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REAL-TIME MONITORING AND ALERTING OF GO-AROUNDS FOR AIR TRAFFIC CONTROL DECISION SUPPORT

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To my wife, Débora, my sons, Luís Pedro, Frederico and Letícia; to my daughter-in-law, Juliana, and my grand-daughter, Luna.

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“Never regard study as a duty but as an enviable opportunity to learn to know the liberating influence of beauty in the realm of the spirit for your own personal joy and to the profit of the community to which your later works belong."

Albert Einstein

Abstract

Go-arounds (GA) are a relevant safety event that may occur during the approach phase of the flight due to several reasons such as unstable approach, loss of separation minima or adverse weather. In dense terminal control areas, this manoeuvre, even though it is a standard procedure, can generate significant and additional air traffic control (ATC) workload as it requires a quick and accurate reaction in order to safely reintegrate the flight into the traffic flow and immediately establish a new approach and landing sequence. In current operations, air traffic controllers typically become aware of a GA during or after their execution, which leads to a very short time horizon for operational decision-making. This research aims to propose and evaluate the operational impacts of a real-time monitoring and alerting solution for ATC decision support in approach control facilities and aerodrome control towers. The solution is based on the use of surveillance data and the application of analytical and machine learning methods for identifying flight trajectory anomalies in real-time and predicting the execution of a GA. Based on a human-in-the-loop simulation of air traffic operations at the Sao Paulo/Guarulhos International Airport, it is assessed how the presence of such an alert that anticipates the occurrence of a GA affects the ATC performance. The results showed an increase in the perceived levels of situational awareness and safety as well as an increase in the efficiency of ATC decisions concerning the go-around, with an observed reduction of nearly two minutes in the flight time from the start of the manoeuvre and the landing when the alert was active.

Keywords: Go-around, situational awareness, air traffic control, machine learning, human-in-the-loop simulation.

Resumo

As arremetidas (GA) são um evento de segurança relevante que podem ocorrer durante a fase de aproximação do voo devido a diversos motivos, como aproximação não estabilizada, perda dos mínimos de separação ou condições climáticas adversas. Em densas áreas de controle terminal, esta manobra, embora seja um procedimento padrão, pode gerar uma carga de trabalho adicional e significativa no controle de tráfego aéreo (ATC), pois requer uma reação rápida e precisa, a fim de reintegrar com segurança o voo no fluxo de tráfego e estabelecer imediatamente uma nova sequência de aproximação para pouso. Nas operações atuais, os controladores de tráfego aéreo normalmente tomam conhecimento de uma GA durante ou após a sua execução, o que leva a um horizonte de tempo muito curto para a tomada de decisões operacionais. Esta pesquisa tem como objetivo propor e avaliar os impactos operacionais de uma solução de monitoramento e alerta em tempo real para apoio à decisão ATC em órgãos de controle de aproximação e torres de controle de aeródromos. A solução baseia-se na utilização de dados de vigilância, na aplicação de métodos analíticos e de algoritmos de aprendizado de máquina para identificar anomalias na trajetória de voo em tempo real e prever a execução de um GA. Com base em uma simulação *human-in-the-loop* das operações de tráfego aéreo do Aeroporto Internacional de São Paulo/Guarulhos, avalia-se como a presença de tal alerta que antecipa a ocorrência de um GA, afeta o desempenho das tomadas de decisão ATC. Os resultados mostraram um aumento nos níveis percebidos de consciência situacional e segurança, bem como um aumento na eficiência das decisões do ATC relativas à arremetida com uma redução observada de quase dois minutos no tempo de voo desde o início da manobra e o pouso quando o alerta estava ativo.

Palavras-chave: Arremetida, consciência situacional, controle de tráfego aéreo, aprendizado de máquina, simulação *human-in-the-loop*.

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List of Abbreviations and Acronyms

4D	Four dimensions
AAL	Above aerodrome level
AD	Aerodrome
ADS-B	Automatic dependent surveillance-broadcast
AI	Artificial Intelligence
ALoSP	Acceptable level of safety performance
ALT	Altitude
ANSP	Air Navigation Service Provider
AO	Aircraft operator
AOC	Airport Obstruction Chart
APP	Approach control
ARR	Arrival
A-SMGCS	Advanced Surface Movement Guidance & Control System
ATC	Air traffic control
ATCO	Air traffic controller
ATM	Air Traffic Management
ATSU	Air Traffic Services Unit
Baro	Barometric
CFIT	Controlled flight into terrain
CoO	Contract of objectives
CWP	Controller working position
DA/H	Decision altitude/height
DBSCAN	Density-based Spatial Clustering of Applications with Noise
DH	Decision height
ELEV	Elevation
FAA	Federal Aviation Administration
FAF	Final approach fix
FDAU	Flight data acquisition unit
FDR	Flight data recorder
FF-ICE	Flight & Flow Information for a Collaborative Environment
FL	Flight level
FN	False negative

FOC	Flight Operations Center
FOQA	Flight Operational Quality Assurance
FP	False positive
FPR	False positive rate
FSF	Flight Safety Foundation
GA	Go-around
GLO	Gol airlines
GMM	Gaussian Mixture Model
GRU	São Paulo/Guarulhos international airport (IATA code)
GS	Glide-slope
HDG	Heading
HDTA	High-density traffic airports
HI	Human interaction
HITL	Human-in-the-loop
HMI	Human machine interface
IAC	Instrument approach chart
IAP	Instrument approach procedure
IAS	Indicated airspeed
IATA	International Air Transport Association
ICAO	International Civil Aviation Organization
ICEA	Airspace Control Institute
ILS	Instrument landing system
IMC	Instrument meteorological conditions
ISA	International Standard Atmosphere
LABSIM	Simulation lab
LOC	Localizer
MAHF	Missed approach holding fix
MDA	Minimum descent altitude/height
NM	Nautical miles
NN	Neural Network
PAELS	Program of Activities and Employment of Simulation Laboratories
PDARS	Performance data analysis and reporting system
QAR	Quick access recorder
QFE	(Q-Code) The atmospheric pressure at aerodrome elevation (or at runway threshold)

QNH	(Q-Code) The altimeter sub-scale setting to obtain elevation when on on the ground
ROC	Rate of climb
ROD	Rate of descent
ROPS+	Runway overrun prevention system
RWY	Runway
SBGR	São Paulo/Guarulhos international airport (ICAO code)
SFO	San Francisco international airport (IATA code)
SID	Standard Instrument Departure Routes
SISCEAB	Brazilian Airspace Control System
SOP	Standard operating procedures
SP	São Paulo (city/area)
STAR	Standard Arrival Route
TBO	Trajectory based operations
THR	Threshold
TMA	Terminal control area
TMI	Traffic management initiative
TN	True negative
TP	True positive
TPR	True positive rate
TW	Target windows
TWR	Airdrome control tower
VAR	Magnetic variation
VMC	Visual meteorological conditions
VPA	Vertical path angle
VP	Vertical path
V_{REF}	Reference speed
WE	Weather effects

Contents

1 Introduction

1.1 Motivation

Approach and landing are the most critical phases of the flight. The high density of operations, the navigation complexity, the number of aircraft configuration changes and the dynamics of weather conditions create a complex environment that places significant workload on both the flight crew and Air Traffic Control (ATC), with a higher likelihood of unanticipated events that can lead to unsafe or inefficient operations. For instance, between 2013 and 2023, the approach and landing phases accounted for 40% of the accidents worldwide, according to the International Civil Aviation Organization (ICAO), as shown in Figure 1-1.

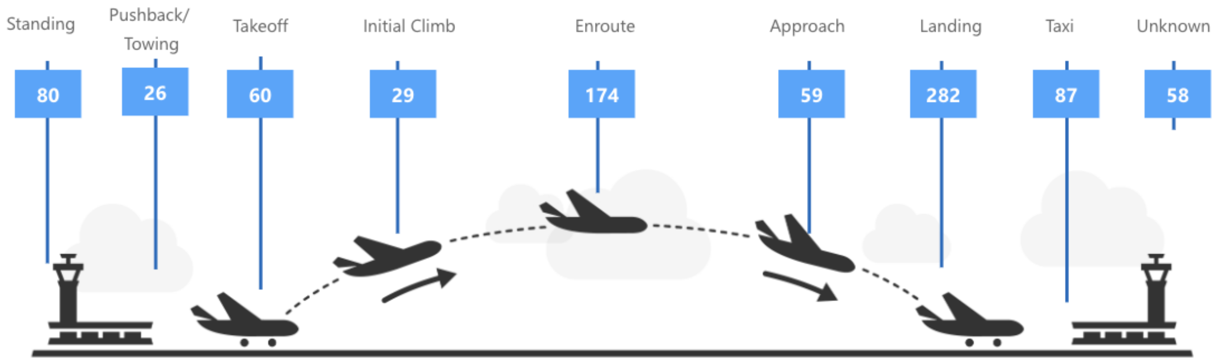

Figure 1-1 - Total number of aviation accidents (fatal and non-fatal) by flight phase between 2013 and 2023. Source: ICAO (2024)

Unanticipated events such as go-arounds (GA) are one of the main contributors for reducing the safety and efficiency levels during the approach. A GA is a missed approach manoeuvre that may be initiated by the pilot or ATC for various reasons, such as unstable approach, loss of separation, or adverse weather. Upon the occurrence of a GA, controllers typically have very short time horizon for decision-making. From the Aerodrome Control Tower (TWR) perspective, ATC instructions must be issued immediately to the pilot to avoid loss of separation between the aircraft performing a GA and other aircraft departing or approaching. At the same time, an effective coordination procedure with the Approach Control (APP) must be performed by the TWR to inform that an aircraft executed a GA and start the transfer of control and communication. APP controllers then must quickly issue ATC instructions to reintegrate the aircraft into the approach sequence while maintaining a safe and expeditious traffic flow. Currently, these actions are performed reactively after the GA is initiated based on information relayed through voice communication.

With the on-going aviation system's digital transformation, several opportunities have arisen to develop novel real-time monitoring and alerting tools to enable more proactive, safe and efficient decision-making. Several initiatives are concentrated on flight crew operations. An example is the Runway Overrun Prevention System (ROPS+), an on-board cockpit technology designed to reduce exposure to runway excursion risk (NAVBLUE, 2018). It continuously monitors total aircraft energy and anticipates the landing performance in wet or dry conditions, aiming to increase pilots' situational awareness during landing. Despite the existence of several studies describing that situational awareness is crucial for the successful performance of decision makers in aviation (ENDSLEY *et al.*, 2001), there is a lack of monitoring and alerting tools, in real time, in support of ATC operations, especially during abnormal conditions.

Recent research has explored the use of increasingly available operational data and machine learning techniques towards the development of real-time monitoring tools for enhanced decision-making in the Air Traffic Management (ATM) context. A particular emphasis has been placed on the detection of anomalies in flight operations data, as anomalies are often related to critical safety events or inefficient operations. While these studies have focused on the development of predictive models that can be applied in online settings for real-time monitoring and alerting of significant anomalous events, the operational impacts of such solutions for ATC decision-making are typically left unexplored.

This work seeks to investigate the use of data-driven predictive models for real-time monitoring of approach trajectories and alerting of GA events while evaluating the contribution of such an alerting solution towards supporting ATC decisions during these events. For illustration of the real-time monitoring solution envisioned in this work, Figure 1-2 shows a hypothetical alert message of a potential GA displayed on the Human Machine Interface (HMI) of an ATC surveillance system, which refers to a screen used by the air traffic controllers (ATCO) – hereinafter referred to as “controller(s)" – to visualize and interact electronically with the labels associated to a flight plan.

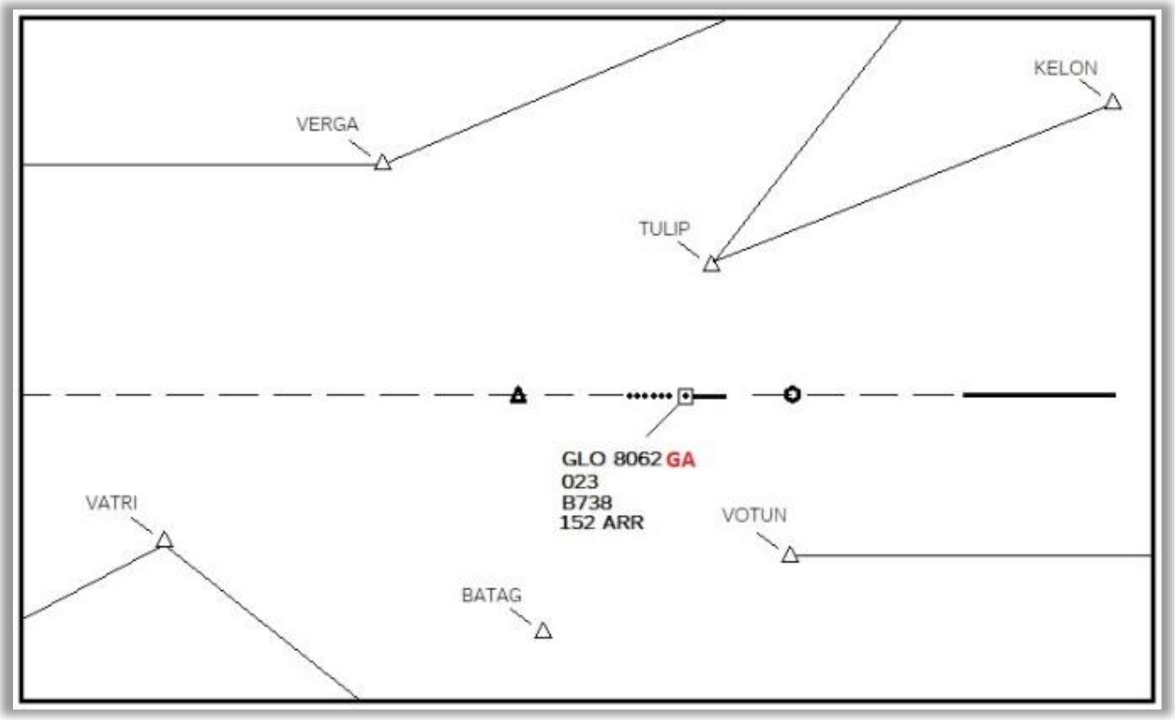

Figure 1-2 - Hypothetical GA alert message displayed on the HMI of an ATC surveillance system

1.2 Thesis Objectives

This thesis aims to develop a data-driven approach for real-time monitoring of approach operations and alerting of GAs and evaluate the operational impacts of such an alerting solution for ATC decision-making and performance. Specifically, the objectives of this thesis are:

- To explore the use of aircraft tracking data generated by surveillance systems and the application of analytical and machine learning methods for online detection of flight trajectory anomalies and prediction of GA events; and
- To develop a Human-In-The-Loop (HITL) simulation study to analyse how the ATC performance, actual and perceived, is affected in the presence of a hypothetical tool that monitors the approach trajectories and anticipates the occurrence of a GA event.

1.3 Organization of the Thesis

This thesis is organized as follows. Chapter 2 provides background information related to flight operations during the final approach and management of GA events by ATC. It also reviews the related literature on data analytics for anomaly detection on flight operations and simulation approaches for ATC operational performance evaluation. Chapter 3 details the methodological approach, describing the data and methods used, the algorithms developed for the detection of GA events and the HITL simulation study conducted to investigate the operational impacts of an ATC decision support tool. Chapter 4 presents and discusses the results of the work. Finally, Chapter 5 summarizes the conclusions and provides potential directions for future work.

2 Background and Literature Review

This Chapter provides background information about flight operations and aircraft performance during the final approach phase, the main contributing factors to a GA event and its potential impact in ATC decision-making and performance. Additionally, we discuss previous studies related to the identification and prediction of flight path anomalies through data analytics and the use of Human-In-The-Loop (HITL) simulations to evaluate the operational performance of ATM processes.

2.1 Flight Operations and Performance on Final Approach

A GA is a missed approach manoeuvre that may be initiated by the pilot or ATC for various reasons. Unstable approaches are one of the most common potential causes for such events. There is no standard definition for the unstable approach, but it can be defined as an approach during which an aircraft does not maintain, at least, one of the criteria, described by ICAO and Federal Aviation Administration (FAA), as the stabilized parameter (SINGH *et al.*, 2020). Accordingly, the Flight Safety Foundation (FSF) Approach and Landing Accident Reduction (ALAR) briefing note 7.1 (FSF, 2000) all flights must be stabilized by 1,000 ft above airport elevation (AAL) in Instrument Meteorological Conditions (IMC) and 500 ft above airport elevation (AAL) in Visual Meteorological Conditions (VMC). An approach should be considered stable when all the following stabilized approach elements are met (IATA, 2017):

● The aircraft is on the correct flight path;

● Only small changes in heading/pitch are necessary to maintain the correct flight path;

● The airspeed is not more than the threshold crossing reference speed V_{REF} + 20 kt indicated speed and not less than V_{REF};

● The aircraft is in the correct landing configuration;

● Sink rate is no greater than 1,000 ft/min; a special briefing should be conducted if an approach requires a sink rate greater than 1,000 ft/min;

● Power setting is appropriate for the aircraft configuration and is not below the minimum power for the approach as defined by the aircraft operating manual;

● All briefings and checklists have been conducted;

Specific types of approach are stable if they also fulfil the following:

- ILS approaches must be flown within one dot of the glide slope and localizer;
- a Category II or III approach must be flown within the expanded localizer band;

An aircraft must meet certain criteria on approach to be able to land safely and an approach can be considered stabilized only if all criteria in the company's Standard Operating Procedures (SOPs) – a framework of common procedures set out by an airline which supports pilots in operating a commercial aircraft safely and consistently – for flight deck crewmembers are met before or when reaching the applicable minimum stabilization height, i.e., 1,000 ft AAL in IMC and 500 ft AAL in VMC (ICAO, 2018). When a unique approach conditions or abnormal situations necessitating a deviation from the elements of a stable approach are identified, a special briefing among the flight crew is required, so that they may foresee the procedures to be executed.

In order to avoid manoeuvres that can deviate that aircraft from the approach axis (i.e., shallow approach – below glide path, low-airspeed manoeuvring – energy deficit, excessive bank angle when capturing the final approach course, etc.), only minor speed adjustments not exceeding plus/minus 40 km/h (20 kt) indicated airspeed (IAS) should be used for aircraft on intermediate and final approach. Additionally, speed control from ATC should not be applied to aircraft after passing a point 7 km (4 NM) from the threshold on final approach (ICAO, 2018).

Despite the established criteria on SOPs, some contributory factors may lead to a GA, such as flight crew fatigue, inefficient approach preparation, ATC instructions, inappropriate management of altitude or speed, adverse meteorological conditions etc (IATA, 2022).

The above-mentioned parameters are closely related to inappropriate management of aircraft energy. This is because an aircraft in flight, and in particular a large aircraft, possesses a great deal of energy that must be dissipated appropriately during descent, landing and rollout. The energy of any aircraft of mass *m* can be written as in Equation (1):

$$\textbf{Total Energy} = \underbrace{\tfrac{1}{2} m v^2}_{\textbf{(Kinetic Energy)}} + \underbrace{m g h}_{\textbf{(Potential Energy)}} \tag{1}$$

where $\boldsymbol{v}$ is ground speed and $\boldsymbol{h}$ is the altitude of aircraft. Though mass is also changing due to fuel consumption, in this dissertation, it is assumed to be constant as the area of study is the final approach and landing, where the change is negligible. Managing an aircraft during the descent and approach phases essentially becomes a task of managing energy, which is provided by aircraft speed and level.

A pilot performing an approach with excessive sink rates and attempting to capture a glide path from above at the same time changes the energy state of the aircraft, which is difficult to manage with the possible consequence of a hard landing or even a Controlled Flight Into Terrain (CFIT). Therefore, a long landing or a landing at excessive speeds can result in a veer off or overrun, excursions in which an aircraft departs the physical edges of a runway/taxiway or departs the end of a runway, respectively.

As mentioned above, the criterion for continuing an approach generally relates to the aircraft's position, height (1,000 ft AAL in IMC and 500 ft AAL in VMC), speed, configuration and should be outlined in SOPs. For each performance criterion, such as speed, rate of descent, etc., the aircraft must be within a certain tolerable "window" (or "envelope") to be classified as "stabilized" and continue the approach to land. Therefore, should the aircraft on approach/final phase not meet these criteria, it is considered to be unstable and a pilot should be expected to execute a GA or missed approach procedure, which is a rare but normal manoeuvre. A GA from an instrument approach should follow the specified missed approach procedure, unless otherwise instructed by ATC. The missed approach should be initiated not lower than the decision altitude/height (DA/H) in precision approach procedures, or at a specified point in non-precision approach procedures not lower than the minimum descent altitude/height (MDA/H).

In that respect, if an approach is not stabilized in accordance with what is outlined in SOPs or has become destabilized at any subsequent point during an approach, this event can be characterized as an anomaly in the flight path of the aircraft performing an instrument approach procedure (IAP), resulting, potentially, in a GA. Furthermore, it is responsibility of the Aircraft Operator (AO) to develop and promulgate a clear policy on GAs, which states that a GA is a normal flight manoeuvre to be initiated whenever a continued approach would not be safe or when the approach does not meet the stabilized approach criteria. In order to prevent this undesired situation, stabilized approaches are more likely when effective collaboration, cooperation and communication occur between all participants, including, among others, the AO, Air Navigation Service Providers (ANSPs), controllers and, of course, the pilots themselves, allowing the aircraft to accurately follow the published IAP.

2.2 Management of Go-around Events by ATC

2.2.1 Reaction Time Following a Go-around

Air traffic controllers and pilots have very short decision time, combined with high workload when a GA is performed, as a consequence of an unstable approach or inefficient operation. This period of time ($\boldsymbol{T}$), as explained in the next paragraph, is crucial and may impact the effectiveness of an ATC instruction provided. From the TWR controllers' perspective, the workload is caused when they must issue, immediately, ATC instructions to the pilot to avoid loss of separation between the aircraft performing a GA and another one, for instance, rolling for a take-off in the same runway, both keeping the same axis. Additionally, and at the same time, an effective coordination procedure with the APP must be performed by the TWR, informing that an aircraft executed a GA and then, start the transfer of control and communication as soon as the coordination is carried out satisfactorily.

Based on the above, the time interval ($\boldsymbol{T}$) can be broken down for each of the following situations happening during a GA:

1. the pilot recognizes the necessity to initiate a GA (*t1*);
2. the pilot configures the aircraft to initiate the GA and manage the high workload in the cockpit (*t2*); and finally
3. the pilot communicates to the ATC that aircraft is executing a GA (*t3*).

The sum of all these times, $\boldsymbol{T} = \sum_{i=1}^{3} ti$, expresses how much time would have passed since the event that gave rise to the GA had occurred until the moment when the TWR controllers received the communication from the pilot that a GA would be executed. For the APP controllers, an additional time *t4* is observed due to the relay of information regarding the GA event through voice communications. With the lack of the information of the exact moment when the pilot could, potentially, initiate a GA, the controllers are not able to plan, in advance, actions to ensure a new, safe and fluid approach sequence.

2.2.2 Workload Considerations

As mentioned in Section 1.1, aircraft operations on final approach and landing are the most critical flight phase and require accurate control and coordination among flight crew, air traffic controllers, and ground operations personnel, which may be considered as contributing factors to increasing the workload for pilots and controllers. Accident and incident analyses have revealed that GA procedures are often imperfectly performed because of their complexity, their high time stress, and their rarity of occurrence that avails little time for practice (DEHAIS, 2017). Considering the operations performed by the flight crew, the pilot performance results showed that two thirds of the crews committed errors including critical trajectory deviations during GAs, a precursor of accidents. It is important to highlight that these "operational errors" may lead to unexpected behaviours from the aircraft on final approach, which can compromise the safety of operations, resulting in increased workload and stress of controllers at the APP and TWR.

From ATC perspective, GA intensify the workload of air traffic controllers, as landing sequences must be amended to accommodate the aircraft that failed to land in a reorganized approach sequence (GARIEL, 2011). Also, their work suggested that having a large number of incoming aircraft increases the probability of having a GA. From a human factor's perspective, a large number of aircraft simultaneously present in the terminal airspace increases the workload of the controllers, probably leading to more "operational errors" and violation of landing minimum separation distance. Socha *et al*. (2020) affirm that even after several years of experience, one abnormal situation, such as a GA, can represent a much higher workload with regards to the capacity of the controller than the control of several aircraft during a standard operation.

While controller workload is a subjective measure, Welch *et al.* (2007) proposed a general macroscopic workload model that considers that any defined controller activity can be uniquely assigned to one of the four following types of task: *background*, *transition*, *recurring*, and *conflict tasks*. When a GA occur, the rate of occurrence of all these tasks (with the exception of *background*) tends to increase, affecting the controller workload. The need for coordination and transfer of control between the TWR and the APP increases the *transition* workload. The need for flight plan changes, status updates and conformance monitoring after the GA contributes to increasing the *recurring* workload. Furthermore, the management of potential conflicts between the GA aircraft and other aircraft in the vicinity of the airport is expected to increase the *conflict* workload.

In that respect, the development of a tool dedicated to anticipating GA events and increase the situational awareness of controllers could improve the reaction time for real-time air traffic control decision support, allowing for better management of the tasks and associated workload resulting from these events.

2.3 Assessing Flight Performance and Identifying Anomalies from Operational Data

Nowadays, significant technological advancement in aeronautical infrastructure and aircraft systems has allowed the use of several sources of data to assess flight performance, such as flight tracking data from surveillance systems and detailed aircraft performance data from modern digital Flight Data Recorders (FDR). GA events are typically characterized by flight path anomalies in the final approach, which can be identified as observations (flight profiles) that are significantly different from others (MORI, 2021). In general, there are two approaches for anomaly detection: unsupervised learning and supervised learning. The difference is that the latter requires the predetermined label for each data. Mori (2021) also explains that most of the previous work applied unsupervised learning, especially because of the common lack of labelled data.

Anomaly detection initiatives have been extensively explored for proactive safety management in airline operations based on Flight Data Recorder (FDR) data and Flight Operational Quality Assurance (FOQA). Gorinevsky *et al.* (2012) demonstrates an application of a data driven monitoring approach called Distributed Fleet Monitoring (DFM) to FOQA data that transforms the data into a list of abnormal performing aircraft, abnormal flight-to-flight trends, and individual flight anomalies by fitting a large scale multi-level regression model to the entire data set. Li *et al.* (2011) also used a set of FDR data, creating subsets by aircraft models, and suggested a new cluster-based anomaly detection method to detect abnormal flights, anomalies and associated risks from routine airline operations. Clustering is an unsupervised learning method used to identify groups of similar observations in a dataset without any prior knowledge (MURÇA, 2021). Chandola *et al*. (2009) affirm that although clustering and anomaly detection appear to be fundamentally different from each other, several clustering-based anomaly detection techniques have been already developed.

Still considering the unsupervised learning approach, Stogsdill *et al.* (2021) proposed the development of a metric concept that distinguishes between normal and abnormal operational data, collected on board the aircraft – FDR – (1,000 Boeing 737–800 flights) to investigate ways of differentiating between “normal” and “abnormal” operations prior to an event occurring. The approach was to develop two construct variables that were designed with the aim to: (1) differentiate between normal and abnormal landings (*row_mean*); and (2) determine if temporal sequence patterns can be detected within the data set that can differentiate between the two landing groups (*row_sequence*). Between these two variables, *row_sequence* seems to be, in a first analysis, more appropriate to be further used in our trajectory assessment, where individual flights can be compared to historically commensurate approaches that ended successfully in the past, representing an offline model operation. Given the aim of the work was to differentiate between normal and firm landing groups, Stogsdill *et al.* (2021) chose to search for two clusters within the data with the explicit intent of separating out normal from firm landings into two different clusters generated by the algorithm. Stogsdill *et al.* (2021) affirm that this variable is dependent upon the logic that a pilot on an approach must make decisions about how to achieve the desired goal (i.e., a safe landing) at touchdown based only on the data available at or before the present.

On the other hand, from the Air Traffic Management (ATM) operations perspective, few studies have explored online anomaly detection on flight tracking data (surveillance data), being mostly focused on offline anomaly detection for post-event air traffic performance analysis (MATTHEWS *et al.*, 2013; MURÇA *et al.*, 2016; OLIVE *et al.*, 2019).

Specifically, Matthews *et al.* (2013) applied anomaly detection algorithms on a portion of the Performance Data Analysis and Reporting System (PDARS – FAA tool) data warehouse. This approach currently focuses on measuring the frequency of occurrence of known events based on previously identified issues. When it comes to focus on offline anomaly detection for post-event air traffic performance analysis, this method provides to the FAA personnel a safety and operational efficiency perspective, considering previously unknown anomalies in the data set.

Taking an empirical approach to identify operational factors at busy airports that may predate GA manoeuvres, Gariel *et al.* (2011) used four years of surveillance data (from 2006 to 2009), from San Francisco International Airport (SFO), extracted from secondary radar, so that, if the causes are identified, mitigation action can be taken in order to reduce the number of GAs without impacting airport throughput. To facilitate the investigation of GAs, Gariel *et al.* (2011) assembled a corpus of samples, each of which is one of two types: *i.*) samples of the airport state during nominal operations in which no GAs occur and *ii.*) samples of the airport state during a window in which a GA does occur.

The following rule was used to label a flight as containing a GA: a flight contains a GA if during the plane's terminal flight phase, the plane's altitude increases for fifteen consecutive measurements following a period in which the plane descended for at least ten consecutive radar measurements. At the sample rate at which measurements were taken, this corresponds to approximately 70 seconds of continuous increase in altitude. Based on a number of airport operational features (weather, traffic density and aircraft mix and ground traffic and delay), each of which is readily accessible to on-duty air traffic controllers, and the role fluctuations in them may play in precipitating a missed approach, and analysing how the distribution of these features varied between nominal and GA operations, Gariel *et al*. (2011) provided a statistical mechanism to gain insight into which factors are more likely to be a discernible precursor to GAs.

By contrast, some studies have leveraged supervised learning techniques for anomaly detection. Deshmukh *et al.* (2019) applied a supervised learning algorithm, from air traffic surveillance and airport operations datasets, to detect precursors for flight anomalies in the terminal airspace from surveillance data. Their work is based on multi-airport (metroplex) terminal airspace, which is one of the most complicated subsystems to manage, especially due to the interactions between closely located airports. Analysis of anomalous behaviours in the metroplex is emerging as a key problem in understanding air traffic management complexity and safety. The proposal is to use a machine learning-based anomaly detection algorithm that generates mathematical models to detect anomalies in metroplex operations. Several machine learning algorithms have been developed to detect anomalies using only air traffic surveillance data, but there is a significant scope of improvement by including airport operational characteristics as well, since integrating such closely controlled metroplex operational datasets allows the developed models to effectively detect anomalies.

Another example of unsupervised learning application, but with a different data source, was the method proposed by Puranik *et al.* (2018). Energy-based metrics are used to generate feature vectors for each flight data record. Density-based clustering and one-class classification are then used together for anomaly detection using energy-based metrics and clustering algorithms with the goal of characterizing the relationship between energy and anomalies in the terminal airspace. Puranik *et al.* (2018) also state that for identifying flight level anomalies, well-defined phases of flight need to be considered as they can be easily compared across different flights, which is entirely aligned with this work that concentrate, specifically, in final approach phase operations.

Puranik *et al.* (2020) advanced their previous research towards, at this time, an online predictive model of aircraft energy state using supervised machine learning models, which has a similar approach of our work, using flight data from the approach phase. The goal of Puranik *et al.* (2020) is to generate a sequential energy states prediction model that can identify risk during approach phase. Aligned with this work, Coelho and Murça (2023) developed a data-driven approach applied to online detection of anomalies from streaming data, which provides the basis for novel real-time monitoring and alerting tools.

While previous studies have shown great potential for the use of flight operations data and machine learning techniques to develop predictive models that can be applied in online settings for real-time monitoring and alerting of significant anomalous events, the actual impacts for ATC decision-making have not been explored.

2.4 HITL Simulation Approaches for Operational Performance Evaluation

The use of Human-In-The-Loop (HITL) simulation has been the primary means for investigating the operational impacts of novel concepts and tools in complex systems with high human factor dependence, allowing for their validation before actual deployment in the real-world. A HITL simulation is based on a reasonably high-fidelity model of the real-world environment, incorporating the active involvement of human participants within the simulated environment. HITL data are often thought to provide the strongest level reliability in testing the interaction between humans and machines (VOLF, 2014). Also, HITL simulations represent one of the most powerful and realistic testing tools and can provide valuable feedback on how new features influence the behaviour of human operators.

In the context of ATM, HITL simulation studies have been extensively performed to investigate how air traffic controllers and managers perform under new operational processes and systems. For example, Bromberg *et al.* (2014) used HITL simulations to analyse the communication process between the flight operations centre (FOC) and Air Traffic Management (ATM), the automation tools required to model, execute and support a capability-aware Traffic Management Initiative (TMI), and roles and responsibilities of various stakeholders in this process. In another example, Guibert *et al.* (2010) used HITL simulation to evaluate the so-called Contract of Objectives (CoO), which is a formal and collaborative commitment of ATM actors (i.e., airspace users, Air navigation services providers (ANSP), airports), to the conduction of each flight. A few HITL studies have evaluated the operational impacts of novel decision support tools for air traffic controllers, such as separation management (PREVOT *et al.*, 2008) and dynamic sectorization tools (AHRENHOLD *et al.*, 2023). Yet, to the best of our knowledge, there is no prior study dedicated to evaluating the potential impacts of a real-time monitoring and alerting tool for ATC decision support during the final approach.

2.5 Research Contributions

This research seeks to propose novel data-driven models for online detection of anomalous approach performance and prediction of GA events towards the development of real-time monitoring and alerting capabilities for ATC decision support. Besides, through a realistic human-in-the-loop simulation of air traffic operations, it is analysed how the presence of an alert presented at the controller working position/human machine interface (CWP/HMI) that anticipates the occurrent of a GA event affects ATC decision-making and performance.

3 Methodology

3.1 Surveillance Data-Driven Approach for Alerting of Go-around Events

This research considers a data-driven approach and uses openly available aircraft surveillance data to model the behaviour of an aircraft on final approach phase. The surveillance data used in this work was mainly from ADS-B, an implementation of the Mode-S Extended Squitter, where the transponder periodically broadcast essential state information of the flight, enabling the aircraft tracking.

3.1.1 Data Description and Pre-Processing

The flight tracking database used for this work was extracted from the *OpenSky Network* (OPENSKY, 2024) and represents a typical month of operations at Sao Paulo/Guarulhos International Airport (SBGR). The original raw data contains 139,411 records, corresponding to 4,864 different flights (identified by its call signs) that operated at SBGR on November 2019. This corresponds to nearly half of the monthly commercial operations at SBGR. The *OpenSky Network* has been collecting valuable flight tracking information since 2017. Although its coverage in the Brazilian airspace is still limited, the platform currently is the only open surveillance data source available for studying the air traffic flows in the region.

Each of the records in the original database, containing 139,411 rows, comprises several data related to a specific flight, presented in columns, representing its descent profile registered every 10 seconds of flight approximately. Some missing data were identified in the original raw data, resulting in intervals of more than 10 seconds between flight records. However, these gaps did not impact the data-driven modelling, as the algorithms for online prediction of GA events either account for the time interval between tracking records or perform resampling as a pre-processing step, as it will be explained in the following sub-sections.

The following flight information were used for the analysis:

a) Call sign;
b) Barometric altitude;
c) Indicated air speed (IAS)/Ground speed (GS);
d) Magnetic heading;
e) Rate of climb/descent (ROC/D)
f) Time (year/month/day/hour/minute/second)

g) Departure airport;

h) Destination (SBGR); and

i) Runway (RWY)

For each specific call-sign in the database, a set of records (rows) represents the flight movement in four dimensions (4D) in the airspace, as presented in Table 3-1.

Table 3-1 - Set of records (rows) for a specific call-sign

CALL-SIGN	ALT	IAS	HDG	ROD	TIME	DEST	STATUS	RWY	AD
TAM8059	9825	302	51	-2175	2019-11-15 19:53:19	SBGR	ARR	27	SBGR
TAM8059	9425	305	60	-2752	2019-11-15 19:53:29	SBGR	ARR	27	SBGR
TAM8059	8975	309	67	-2817	2019-11-15 19:53:39	SBGR	ARR	27	SBGR
TAM8059	8550	310	72	-2047	2019-11-15 19:53:49	SBGR	ARR	27	SBGR
TAM8059	8275	306	72	-1407	2019-11-15 19:53:59	SBGR	ARR	27	SBGR
TAM8059	8025	299	72	-1728	2019-11-15 19:54:09	SBGR	ARR	27	SBGR
TAM8059	7675	295	72	-2240	2019-11-15 19:54:19	SBGR	ARR	27	SBGR
TAM8059	5150	174	275	-961	2019-11-15 19:58:38	SBGR	ARR	27	SBGR
TAM8059	4975	174	275	-961	2019-11-15 19:58:49	SBGR	ARR	27	SBGR
TAM8059	4800	174	275	-961	2019-11-15 19:58:56	SBGR	ARR	27	SBGR
TAM8059	4625	170	276	-896	2019-11-15 19:59:09	SBGR	ARR	27	SBGR
TAM8059	4500	171	276	-961	2019-11-15 19:59:18	SBGR	ARR	27	SBGR
TAM8059	4350	170	276	-896	2019-11-15 19:59:28	SBGR	ARR	27	SBGR
TAM8059	4175	165	276	-961	2019-11-15 19:59:39	SBGR	ARR	27	SBGR
TAM8059	4025	163	276	-896	2019-11-15 19:59:48	SBGR	ARR	27	SBGR
TAM8059	3825	156	276	-768	2019-11-15 19:59:57	SBGR	ARR	27	SBGR
TAM8059	3600	154	275	-768	2019-11-15 20:00:19	SBGR	ARR	27	SBGR
TAM8059	3475	155	276	-896	2019-11-15 20:00:29	SBGR	ARR	27	SBGR
TAM8059	3275	156	276	-768	2019-11-15 20:00:37	SBGR	ARR	27	SBGR
TAM8059	3075	152	276	-833	2019-11-15 20:00:58	SBGR	ARR	27	SBGR
TAM8059	2800	152	276	-833	2019-11-15 20:01:16	SBGR	ARR	27	SBGR
TAM8059	2675	150	276	-833	2019-11-15 20:01:20	SBGR	ARR	27	SBGR

From the original raw data, some unit conversions were necessary to facilitate the association with the international aviation units (ICAO standards) and to help a visual interpretation and assessment of the flight profile for each flight in the database rows. Barometric altitudes were converted from meters (m) to feet (ft), as following: $\mathbf{ALT_{ft} = ALT_{m} \times 3.2808}$. For aeronautical purposes, this work will use, initially, barometric altitude instead of geometric altitude (these values are also available in the database). Barometric altitudes are widely used in aviation today to ensure vertical separation between aircraft and terrain on instrument flight procedures, to define certain vertical approach paths and to determine all the minimum altitudes, in particular the MDA/DA (Minimum Descent Altitude/Decision Altitude). The indicated air speeds were converted from meter per second (m/s) to knots (kt), as following: $\mathbf{IAS_{kt} = IAS_{m/s} \times 1.9438}$.

Specifically for the magnetic heading, the magnetic declination was applied to the "true track" (tt) available in the database, by adding the VAR 22ºW (current value for SBGR), resulting: $\mathbf{HDG_{mag} = HDG_{tt} + 22^{o}W}$. After conversion, values higher than 360º were decreased of 360º, resulting in values corresponding to the circle for magnetic compass (0º/360º), for example: **340^{o}_{tt} +VAR 22ºW = 362^{o}_{mag}**; **362^{o}_{mag} – 360º = 002º $_{mag}$**. This conversion was also necessary to facilitate the visual interpretation of the profile, once the RWY 09 or RWY 27 (magnetic heading 095° and 275°, respectively) of SBGR were used, which differs from the true track by the VAR 22° presented in the original database. The values corresponding to the rate of descent and rate of climb (ROD/C) were also converted from meter per second (m/s) to feet per minute (ft/min), as following: **$ROD/C_{ft/min} = ROD/C_{m/s} \times 196.8504$**.

3.1.2 Identification of Go-around Events Through Sequential Heuristics

In order to develop the algorithms for online prediction of GAs, it was first necessary to identify such events in the database. Flights that performed GA manoeuvres were flagged based on sequential heuristics, applied in all records (rows) of the database. As the same call sign may exist in different days, the first step was to flag flights with the same call sign, operating in the same day and with destination SBGR, which, theoretically, guaranteed to be the same flight. This allowed for a correct two-way association of a flight with its complete descent profile in the database.

In the second step, the database was filtered to keep the records below FL140 associated with terminal area operations. Then, flights in the descent phase (***$ALT_{(r+1)} < ALT_{(r)}$***, *where "**ALT**" is the altitude and "**r**" is the position of a flight in a specific register (row) of the database*) that, from a specific point and for 3 consecutive records, inverted their descent vertical profile (***$ALT_{(r+1)} > ALT_{(r)}$***) by showing, consequently, a sequential "positive" rate of climb, were grouped in a separated subset and flagged as "UP", as demonstrated in Table 3-2.

Table 3-2 - Inversion of descent (red) to climb (green) vertical profile

Inflection point

	A	C	J
1	**Call sign**	**ALT**	**ROD/C**
2	ABC1233	**4000**	**-961**
3	ABC1233	**3850**	**-1089**
4	ABC1233	**2775**	**-1089**
5	ABC1233	**2625**	**-768**
6	ABC1233	**3000**	**2303**
7	ABC1233	**4900**	**256**
8	ABC1233	**4925**	**1407**
9	ABC1233	**5200**	**1344**
10	ABC1233	**5375**	**896**
11	ABC1233	**5675**	**1024**

Conclusively, all flights that were flagged “UP” and showed a “positive” rate of climb (ROC ≥ 0) after the 3 consecutive records were considered to execute a GA and were therefore grouped in the GA flights subset.

Figure 3-1 shows a sample descent trajectory associated with a GA. From 10,000 ft to approximately 3,000 ft, it shows the portion of the trajectory prior to the GA, containing small variations in IAS and negative vertical speed rate (ROD). The instant at which the GA is initiated is indicated with a red arrow. Finally, after this point, the line corresponds to the period of at least 50 seconds of climb following the GA, until reaching the *missed approach holding fix* (MAHF), at 6,000 ft for this specific IAP. It is also observed that the vertical speed rate became positive (ROC) when the GA is executed, followed by a slight increase in IAS. The remainder of the trajectory, including the eventual landing, was not represented here.

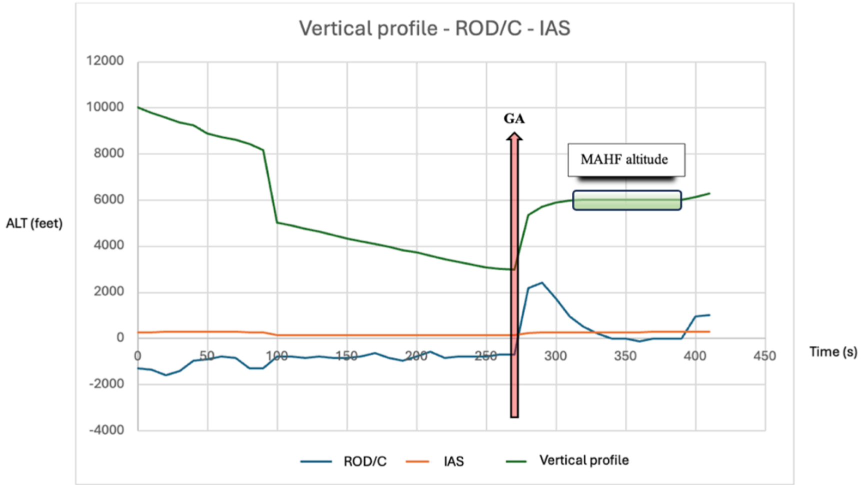

Figure 3-1 - Vertical profile (with ROD/C and IAS) of a flight that executed a GA

After all iterations, **39 flights** were flagged as GAs in the database. Figure 3-2 shows the vertical profile of these flights from the moment they cross the 10 NM distance mark from the runway threshold until landing.

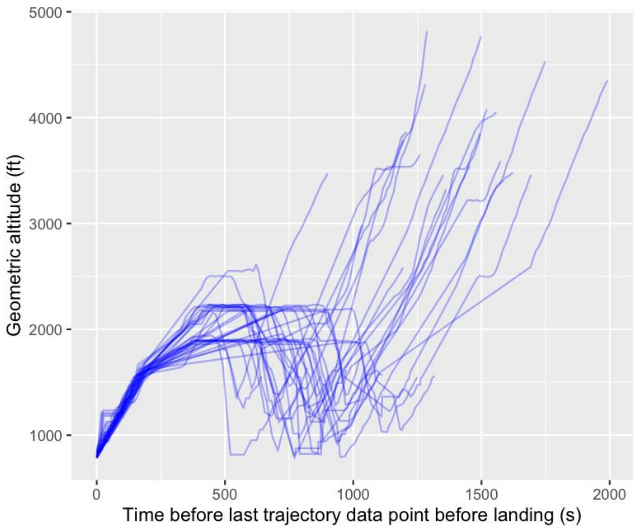

Figure 3-2 - GA flights identified.

3.1.3 Online Prediction of Go-around Events

Based on the labelled dataset, two algorithms were developed for online prediction of GA events. The first one is a rule-based algorithm that considers the evaluation of operational parameters throughout the descent phase. The second one is a machine learning-based algorithm.

3.1.3.1 Rule-Based Algorithm

The rule-based algorithm analyses some operational parameters to identify whether a specific flight profile violates a specified threshold on final approach phase, which may induce to a GA procedure. Among the parameters presented in session 2.1, three of them were selected to create trajectory envelopes that represent acceptable deviations from an ideal operational performance: altitude, airspeed and heading.

The algorithm considers a 3-degree glide-slope (GS) (ICAO, 2018) that refers to the ideal angle of descent that an aircraft follows when approaching a runway for landing. It is a standard angle used for instrument landing systems (ILS) and helps pilots maintain a safe and efficient descent path. The 3-degree glide slope is widely used in aviation as a standard for approach and landing procedures at airports around the world. Also, three gates are selected to evaluate the flight profile with respect to the trajectory envelope.

The three gates established in the final approach are 1,600 ft, 1,000 ft and 500 ft. At these gates, the algorithm calculates the crossing altitude deviation tolerances (±300 ft) and verifies if the aircraft is on the correct flight path according to the established envelope, as presented in Figure 3-3. Specific types of approach may not induce to a GA if the ILS approaches stay within one dot of the glide slope and localizer. One dot represents ± 0.8 degrees of deviation on the localizer (LOC) scale and ± 0.4 degrees on the glideslope scale. Simultaneously, the airspeed should not be more than the threshold crossing reference speed V_{REF} + 20kt indicated speed and not less than V_{REF} and the sink rate should not be greater than 1,000 ft/min (CAMPBELL, 2021; AIRBUS, 2008).

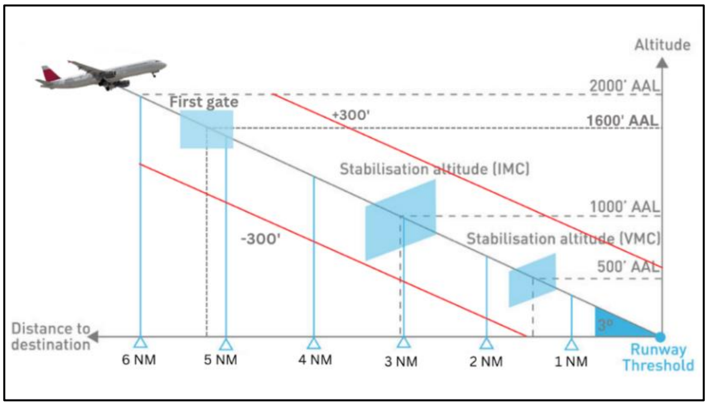

Figure 3-3 - Flight profile on final approach (not to scale)

Calculation of the ideal rate of descent

For a 3º GS, the required rate of descent in feet per minute (ft/min) is approximately equal to the ground speed in knots multiplied by 5. For example, applying this trivial "rule of thumb" generally applied by pilots during their flight operations, at 120 kt, the rate of descent to maintain a 3º GS is approximately 600 ft/min. This can also be demonstrated using simple trigonometry. Considering that tan (descent angle) = descent rate (%), it is possible to calculate the vertical speed as shown in Equation (1) and illustrated in Figure 3-4. For a 3º GS, descent rate = tan (3°) = 0.05240778 ≈ 5.2%.

$$\text{Vertical speed (ft/min) [ROD]} = \text{Descent rate (\%)} \times \text{Ground speed (knots)} \qquad (1)$$

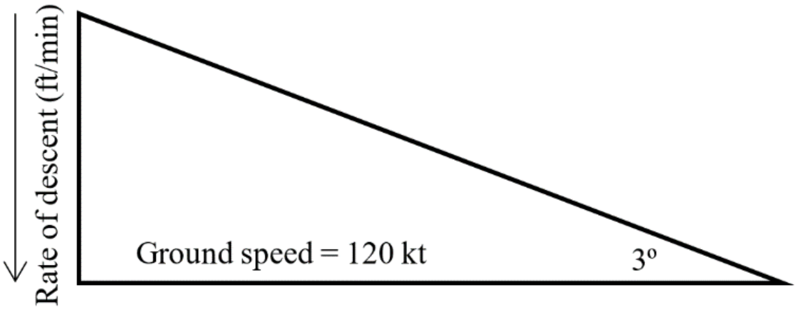

Figure 3-4 - Trigonometry for rate of descent calculation

The rate of descent (ROD) at 120 kt is then obtained as follows:

Tan 3º = ROD / 120 kt

ROD = Tan 3º x 120 kt

ROD ≈ 6.24 NM / h (kt)

ROD = 6.24 / 60 = 0.104 NM / min

ROD = 0.104 x 6076 (from NM to ft)

ROD = 632 ft/min

Calculations between two latitude/longitude points

The flight tracking database does not contain the information of the horizontal distance from the runway threshold (THR) of the current 4D position of the aircraft. To obtain these values, for each 4D position in the database, the "Haversine" formula was applied, as shown in Equation (2). The formula calculates the great-circle distance between two positions, which is the shortest distance over the Earth's surface.

Haversine formula: ***d*** = *distance between two positions* (2)

$$a = \sin^2(\Delta\varphi/2) + \cos\varphi_1 \cdot \cos\varphi_2 \cdot \sin^2(\Delta\lambda/2)$$

$$c = 2 \cdot \operatorname{atan2}(\sqrt{a}, \sqrt{1-a})$$

$$\boldsymbol{d} = R \cdot c$$

Where φ is latitude, λ is longitude, R is earth's radius (mean radius = 6,371km); note that angles need to be in radians to pass to trig functions.

The calculation of the exact linear distance from the THR is crucial to calculate the ideal geometrical altitude of the aircraft for a GS of 3º, in order to compare with the altitude extracted from the flight tracking database. Once the distance is calculated, the tangent of 3º is applied, so that the correspondent altitude of the aircraft may be determined at the GS, as illustrated in Figure 3-5 and described in Equation (3).

Altitude at the GS = Tan 3º x Distance to THR (3)

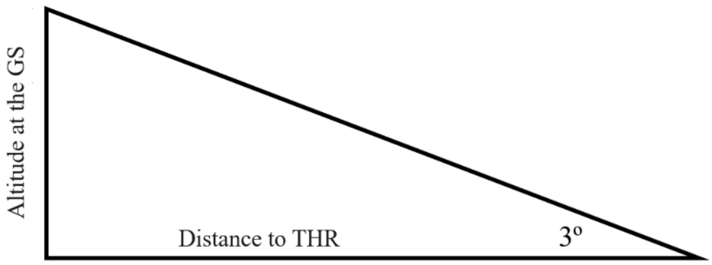

Figure 3-5 - Altitude calculation at the glide slope with 3º angle

In all cases, a more accurate altitude correction should be done in order to compare the true altitude, instead of the one indicated on the altimeter and seen by the pilot (Baro ALT), with the geometrical altitude based on the GS of 3°, at each point. In that respect, the indicated altitude, provided by the flight tracking data, should be corrected, due to the effect of the temperature variation.

There are a number of correction methods that can be used for determining the necessary altimetry correction to compensate the effect of temperature variation (ICAO, 2018; ICAO, 2006). We applied the correction described in Equation (4), which is suitable for practical application and local temperatures above -15ºC. Other methods are more complex and normally used in case of calculating climb gradients or when the conditions are extremely different from ISA (temperatures below -50° C). In temperatures above ISA, the density of the air is lower and consequently the pressure values representing flight levels are even more separated and the true altitude will be higher than the indicated altitude in the altimeter (Baro ALT). Therefore, corrections have to be applied to ensure that the aircraft is following the ideal vertical path angle (VPA) when the temperature is above ISA.

Barometric altimeters measure the air pressure and are calibrated according to the variation of the pressure with height, as specified for the international standard atmosphere (ISA), as shown in Table 3-3.

Table 3-3 - International Standard Atmosphere, Mean Sea Level Conditions

Pressure	p_0 = 101 325 N/m^2 = 1013.25 hPa
Density	ρ_0 = 1.225 kg/m^3
Temperature	T_0 = 288.15°K (15°C)
Speed of sound	a_0 = 340.294 m/sec
Acceleration of gravity	g_0 = 9.80665 m/sec^2

In conditions identical to ISA, the indication on the altimeter indicates the altitude above mean sea level when the reference datum is the local QNH. It is part of the physics of the atmosphere that in case of a temperature deviation from ISA, the true altitude of a certain pressure value does no longer correspond to the altitude indicated on an altimeter that is calibrated to ISA. This variation may indicate, according to the true altitude, that the aircraft is above or below the geometrical altitude (at the GS), depending on the temperature is higher or lower the local ISA conditions, respectively, as presented in Figure 3-6. The temperature variation affects directly the effective VPA, as shown in Figure 3-7.

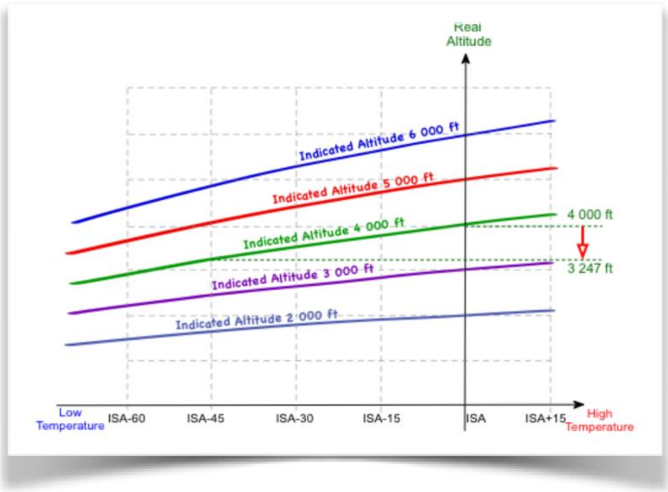

Figure 3-6 - Relation between the altitude and the temperature variation from ISA

Taking as an example the flight GLO1921, at the moment of the approach at SBGR, the temperature was 23.9°C, which indicates an ISA + 13.9 conditions (the ISA at SBGR is 10°C). The true altitude would therefore be above the geometrical altitude and the glide path would be steeper than the normal one, creating a potential and induced scenario for a GA for the pilot. The altimeter is calibrated against an ISA condition, where a particular set of values of temperature is assumed. If the temperature at the moment of operation is different from ISA, the indicated altitude will not correspond to true altitude. The temperature correction is necessary because, when flying close to the ground, it is necessary to know the true altitude, the effective VPA, in order to maintain terrain and obstacle clearance.

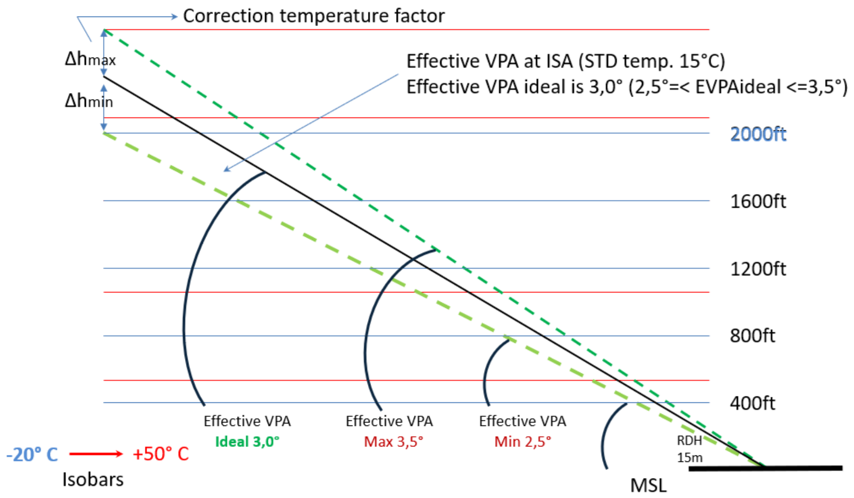

Figure 3-7 - Effective vertical path angle (VPA)

Considering that all altimeter corrections have been made (position error, instrument error) and the correct QNH is set, the indicated altitude differs from the true altitude by temperature variation, which can be corrected using Equation (4):

$$\textbf{True Altitude} = \text{Indicated Altitude} + (\text{ISA Deviation} \times 4/1000 \times \text{Indicated Altitude}) \quad (4)$$

Example: GLO1921

True Altitude = 4025' + (13.9 ºC x 4/1000 x 4025')

True Altitude = 4249' > (Geometrical Altitude (GS) = 3876') (Δ = +373' above the GS)

After applying the corrections for the indicated altitude (Baro ALT extracted from the flight tracking database), several altitude envelope infringements were identified for the flight GLO1921, along with infringements of the other defined operational parameters, as presented in Table 3-4, such as:

a) After the FAF, the sink rate (ROD) was, constantly, greater than 1,000 ft/min, above the limit of 1,000 ft/min;

b) At 3º GS, after the FAF the ideal IAS should be between 120 kt and 150 kt, with a ROD of 700 ft/min (± 50 ft/min). Due to the high ROD, the IAS was constantly above this value;

c) After the FAF, the HDG is 095º (localizer course), however it was observed an important discrepancy from this value, from HDG 090º until 098º, point where the

GA was initiated, far above the tolerance of ±0.8 degrees of deviation on the localizer;

d) And finally, at the gate of ≈1,600 ft (QFE, THR ELEV = 2451 ft, RWY 09) on final approach, the required ALT is 3876 ft, but the flight crossed at 4249 ft (true ALT), a discrepancy of 373 ft above the GS (Table 3-4), where the tolerance is ± 300 ft. It is noted that, in this specific flight profile, the true ALT was constantly above the ideal glide path for a GS of 3º and exceeding the above-mentioned tolerance.

Table 3-4 - Numeric representation of the flight profile of the flight GLO1921

Baro ALT	IAS	ROD	Dist RWY 09	GS 3º	Δ ALT Baro GS	HDG	True ALT	Δ ALT Baro True	Δ ALT True GS
4875	224	-1217	7.3	4779	95	101	5146	271	367
4700	215	-1152	6.7	4587	113	92	4961	261	374
4500	202	-1344	6.1	4389	111	90	4750	250	361
4350	199	-1152	5.7	4264	86	90	4592	242	328
4200	199	-961	5.3	4141	59	92	4434	234	293
4025	201	-1089	4.5	3876	149	93	4249	224	373
3825	200	-1152	4	3735	90	94	4038	213	303
3150	193	-768	3.3	3490	-340	98	3325	175	-165
3050	187	-1089	1.4	2894	156	97	3220	170	326
2850	180	-1152	0.7	2683	167	95	3008	158	325
3125	176	-640	0.4	2576	549	95	3299	174	723
3950	206	1280	1.5	2921	1029	122	4170	220	1249

Bringing together all these violations for this specific flight, GLO1921, it can be better understood the contributing factors that led the flight to execute a GA.

In summary, the rule-based algorithm computes ideal envelopes consisting of acceptable deviations from defined operational parameters and flags a flight as a potential GA whenever its parameters violate any of the established envelopes.

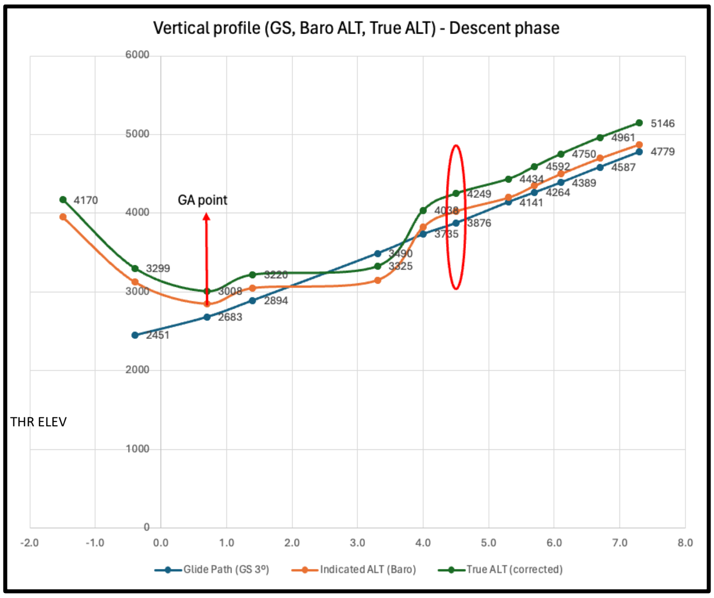

Figure 3-8 - Vertical discrepancies in the vertical profile

3.1.3.2 Machine Learning-Based Algorithm

The machine learning-based algorithm considers the application of clustering analysis to discover nominal patterns in the approach phase followed by probabilistic modelling of these nominal approach patterns to enable the online detection of anomalous behaviours.

First, the approach trajectory is augmented with calculated energy metrics and resampled at every 0.5 NM to create a fixed trajectory feature vector. The Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (ESTER *et al.*, 1996) is applied to identify groups of flight with similar approach performance.

The clusters identified with DBSCAN are then modelled in the form of a Gaussian Mixture Model (GMM) (HAND *et al.*, 1988). We assume that the approach performance variation within the nominal patterns can be modelled with a probability density function given by a weighted sum of Gaussian densities. Given the existence of K clusters (components), the probabilistic model can be written as in Equation (5). Y is a categorical random variable representing the approach pattern. X is a multivariate random variable that represents the approach trajectory. The parameters of the mixture model are given by $\theta = \{\pi_y, \mu_y, \Sigma_y\}$, where π_y are the mixture weights, which satisfy Equations (6) – (7), and μ_y and Σ_y are the mean vector and the covariance matrix of the multivariate Gaussian density that models the y^{th} pattern.

$$p(X) = \sum_{y=1}^{K} \pi_y \, p(X/Y = y) = \sum_{y=1}^{K} \pi_y \, N(X; \mu_y, \Sigma_y) \qquad (5)$$

$$0 \leq \pi_y \leq 1 \qquad (6)$$

$$\sum_{y=1}^{K} \pi_y = 1 \qquad (7)$$

The learned GMM is then applied in an online setting to predict the future trajectory behaviour based on partial trajectory observations through the computation of marginal and conditional densities, which are also known to be Gaussian. Given partial trajectory observations during the approach, the algorithm flags an anomalous behaviour if more than half of the predicted mean trajectory features falls outside the 95% confidence region of the nominal approach patterns.

3.2 Operational Evaluation

A Human-In-The-Loop (HITL) simulation was conducted to evaluate the operational impacts of a real-time monitoring and alert solution for GA events. The goal was to evaluate how the ATC performance, actual and perceived, is affected in the presence of such a decision support tool. The simulation was carried out at the ATC Simulation Laboratory (LABSIM) of *Instituto de Controle do Espaço Aéreo* (ICEA), shown in Figure 3-9. LABSIM is the main facility used for recurrent training of air traffic controllers for the Brazilian Airspace Control System (SISCEAB). The ATC radar simulators at LABSIM provide a very realistic operational environment that allows the controllers to perform their tasks as if they were in the actual ATC facility.

Figure 3-9 - LABSIM premises where the HITL simulation was conducted

The operational environment simulated was the Sao Paulo APP, the ATC facility responsible for the provision of air traffic services to departing and arriving traffic in the Sao Paulo Terminal Manoeuvring Area (TMA-SP), and the TWR of Sao Paulo/Guarulhos International Airport (GRU), the ATC facility responsible for managing the airport landings and take-offs. Three working positions were monitored throughout the simulation: the final approach sector controller (APP FIN), the feeder sector controller (APP FEED) and the local controller (TWR) for GRU.

Four traffic scenarios for the TMA-SP and four teams of controllers were selected for the simulation. The selected scenarios, extracted from the Sao Paulo APP training portfolio, were those having a high level of complexity and workload to explore the most of the controllers' reactivity in the face of dense traffic in the sectors. Each scenario was run twice. In the second run, the difference was the presence of a GA alert for approaches at GRU. A vocal instruction was used to simulate the GA alert for the APP and TWR controllers. For each scenario, a set of randomly selected flights were programmed to initiate a GA at a fixed altitude of 1,600 ft. For each scenario run that considered the presence of a GA alert for approaches, the alert was issued at 2,000 ft. These fixed altitudes were selected based on observed performance for the simulator. The simulation scheme is summarized in Figure 3-10.

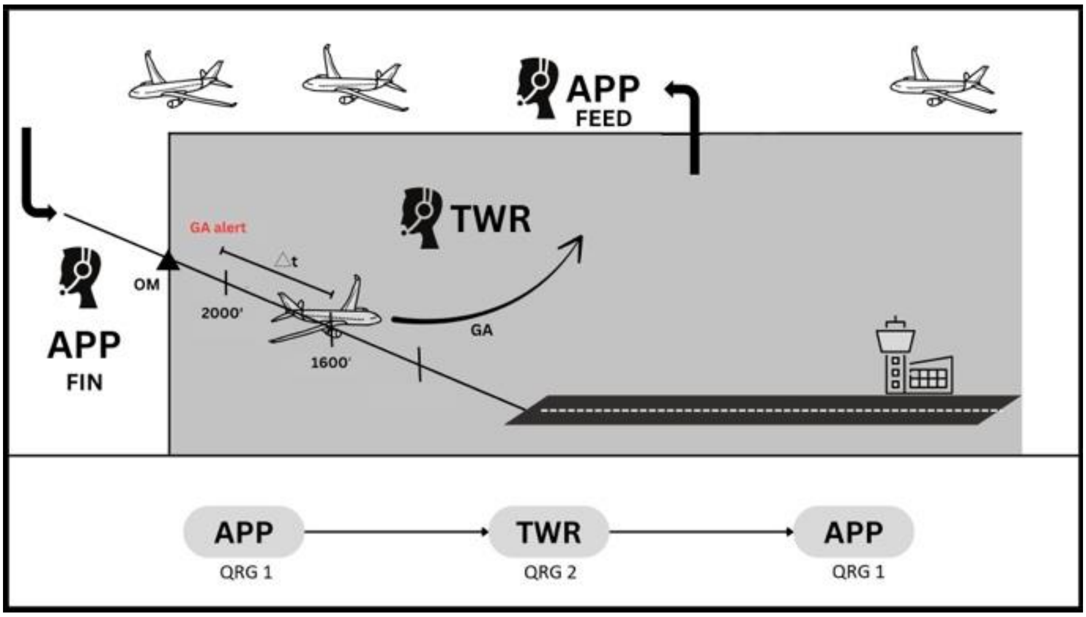

Figure 3-10 - Simulation sectorization scheme

During the real-time simulation, a group of observers was responsible for collecting data regarding the timing of relevant flight events and ATC tasks to enable the quantitative assessment of operational performance. Table 3-5 describes the quantitative metrics computed for each simulation scenario run.

Table 3-5 - Quantitative metrics computed for each HITL simulation scenario run

Metric	Description
M1	Elapsed time (in seconds) between the start of the GA manoeuvre and the first ATC instruction issued by the TWR controller to the flight
M2	Elapsed time (in seconds) between the start of the GA manoeuvre and the first ATC instruction issued by the APP controller to the flight
M3	Elapsed time (in seconds) between the start of the GA manoeuvre and the landing of the flight

At the end of the simulation, the controllers were asked to fill in a questionnaire about the perceived utility and operational impacts of the proposed real-time monitoring and alerting tool. The questionnaire was composed of multiple-choice questions, except for one open question at the end aimed at collecting general comments and observations. The objective questions were designed using the Likert scale (Likert, 1932) to measure the degree of agreement of the respondent with respect to the statement proposed.

It is important to notice that all sessions of HITL simulations were part of the regular refresher training established to provide to the controllers with the competencies required to control air traffic effectively and efficiently within the São Paulo TMA, in accordance with ICAO requirements. Our participation was granted with the condition of not interfering in the established evaluation process of the controllers, design nor conduction of the exercises. The controllers were not informed in advance about what would happen in the exercises, nor about data collection, which ensured that the simulation did not have any prior behavioural interference. The data collection was performed in a very transparent way to the controllers, who were informed about the tool (GA alert) only when they assumed the shift in the controller working position (CWP).

4 Results and Discussion

4.1 Analysis of Predictive Performance

This section discusses the predictive performance of the algorithms developed for online detection of GA events. For this, the True Positive Rate (TPR) and the False Positive Rate (FPR) were calculated, as shown in Equations (7) and (8).

$$TPR = \frac{TP}{TP + FN} \quad (7)$$

$$FPR = \frac{FP}{FP + TN} \quad (8)$$

Where TP is the number of true positives (GA events correctly identified), FN is the number of false negatives (GA events not identified), FP is the number of false positives (completed approaches incorrectly identified as GAs) and TN is the number of true negatives (completed approaches correctly identified).

4.1.1 Rule-based Algorithm

The rule-based algorithm computes ideal envelopes consisting of acceptable deviations from defined operational parameters and flags a flight as a potential GA whenever its parameters violate any of the established envelopes. The analysis is conducted for three envelopes computed with partial trajectory observations available when the aircraft reaches 1600 ft, 1000 ft and 500 ft, simulating an online application. Whenever a specific trajectory observation violates, at least, one of the operational parameters referred to IAS (directly associated with the ROD), ROD or ALT, the observation is registered as an “infringement detection” and the flight is flagged as a potential GA.

The application of the algorithm allowed for the detection of all go-around events since the first gate (1,600 ft), therefore providing a TPR of 100%. However, nearly all flights in the test data presented trajectory observations that violated the operational envelopes. Figure 4-1 shows the average number of envelope infringement detections per flight for each evaluated gate. It is interesting to note the occurrence of envelope violations in altitudes as low as 500 ft. The results indicate that the simple application of operational rules currently used in practice to evaluate the flight profile is not sufficient to successfully anticipate go-around manoeuvres during the approach. This emphasizes the operational variability and complexity of approach operations and the importance of learning this variability from actual data to better understand the actual operational tolerances and identify the deviations that actually lead to a go-around.

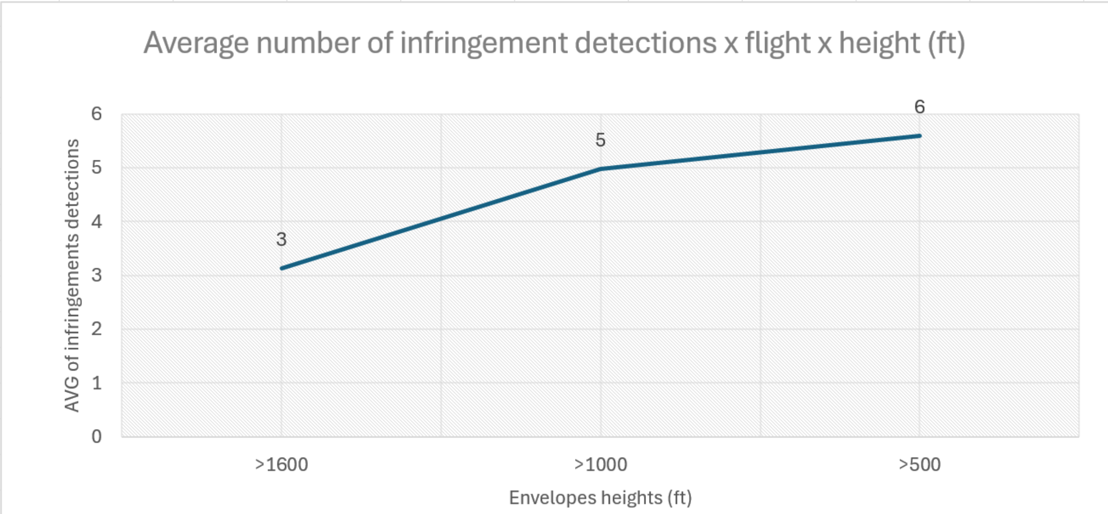

Figure 4-1 - Average number of envelope infringement detections per flight for each evaluated gate

4.1.2 Machine Learning-based Algorithm

Differently than the previous analytical approach, the machine learning-based algorithm tries to predict the go-around events based on knowledge extracted directly from data, not using any prior expert knowledge regarding the flight operational performance during the approach phase. The first step was the identification of the nominal approach patterns through clustering analysis with the DBSCAN algorithm. Figure 4-2 shows that two clusters were identified for SBGR, corresponding to the nominal approach patterns to runways 09 (approach cluster 1) and 27 (approach cluster 2). A Gaussian Mixture Model with two components was then learned for probabilistic modelling of the trajectory behaviour during the final approach. This model was applied in the test data to predict future trajectory points based on partial trajectory observations and identify anomalous behaviours, following the methodology described in Section 3.1.3.2. Figure 4-3 shows an example GA event that was correctly predicted with the algorithm based on trajectory observations at 7.5 NM from the runway threshold.

The blue shaded area shows the 95% confidence region for the total energy feature for the predicted approach pattern. The red line represents the predicted total energy features for the example flight. It is clearly noticeable that most of the features fell outside the confidence region, which made this trajectory to be flagged as an anomalous approach.

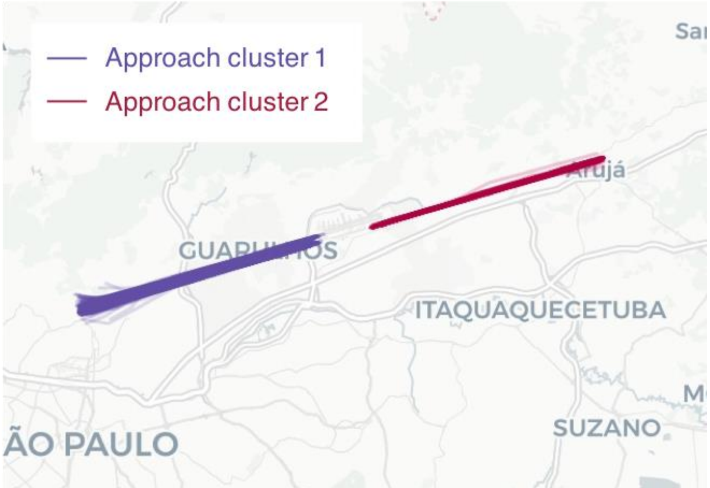

Figure 4-2 - Nominal approach clusters identified for SBGR

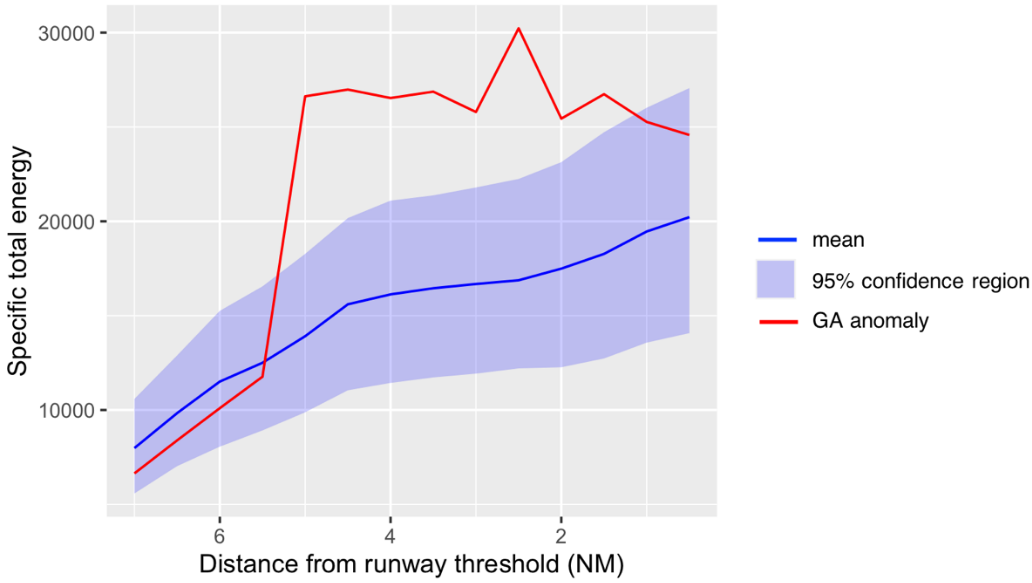

Figure 4-3 - Example prediction of a GA event

The overall predictive performance in the test data is presented in Figure 4-4. While the true positive rate increased as the aircraft gets closer to the airport, the false positive rate remained stable below 5%. At 4 NM from the runway threshold, to model was able to correctly predict 67% of the GAs.

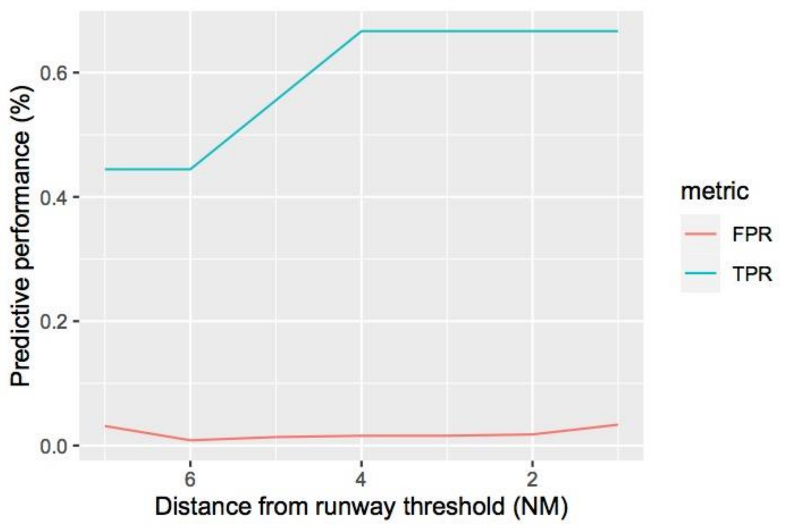

Figure 4-4 - Predictive performance of the machine learning-based algorithm.

4.2 Analysis of Operational Impacts

As planned, the proposed work to assess the operational impact of a novel real-time monitoring and alerting tool was tested through different scenarios in the ATC radar simulator at the LABSIM of ICEA. The data collection was performed during the Program of Activities and Employment of Simulation Laboratories (PAELS), which allows the controllers to receive theoretical and practical instructions, aiming at training in specific and non-routine situations of this important segment of the of Brazilian Airspace Control System (SISCEAB).

Based on the data collected during the HITL simulation, the quantitative metrics listed in Table 3-5 were computed. The results that are displayed in Figures Figure 4-5, 4-6 and Figure 4-7 show the average elapsed time between the start of the GA manoeuvre and the first ATC instruction issued by the TWR controller for each traffic scenario simulated without and with the GA alert. On average, it was observed a reduction of 3.5s on the time required for a positive reaction by the TWR controller in the presence of the GA alert. The reaction time may be understood as the time required for the controller to issue the first ATC instruction regarding the missed approach, such as the level to which the aircraft is to climb and heading instructions to keep the aircraft within the missed approach area and maintain the required safety separations.

The results show that, with the GA alert, the TWR controller was able to issue ATC instructions concerning the missed approach more quickly.

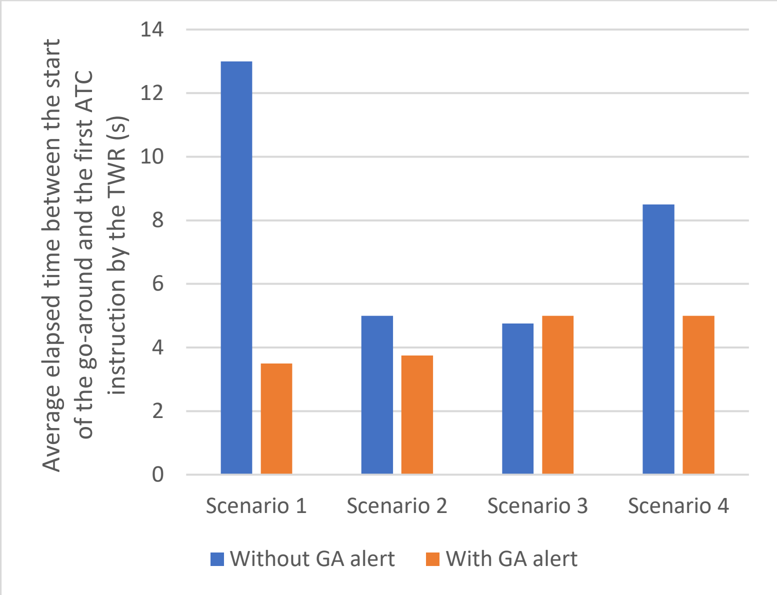

Figure 4-5 - Impacts of the GA alert on the TWR reaction time

A similar behaviour was observed for the APP controller. Figure 4-6 shows the average elapsed time between the start of the GA manoeuvre and the first ATC instruction issued by the APP FEED controller for each traffic scenario simulated without and with the GA alert. On average, a reduction of 8.2s was observed on the time required for a positive reaction by the APP controller in the presence of the GA alert. This suggests that the controller was able to plan, in advance, the actions to reintegrate the flight in the approach sequence, issuing more quickly the ATC instructions to accomplish the task. Interestingly, the results of the simulation showed that such opportunity for planning in advance resulted in more efficient decision-making. Figure 4-7 displays the average elapsed time between the start of the GA manoeuvre and the landing of the aircraft. On average, it was observed a reduction of 141.6s in the flight time from the start of the GA until the landing of the aircraft when the GA alert was active. These results emphasize the importance of ATC decision support tools to increase the efficiency and the environmental performance of the air traffic.

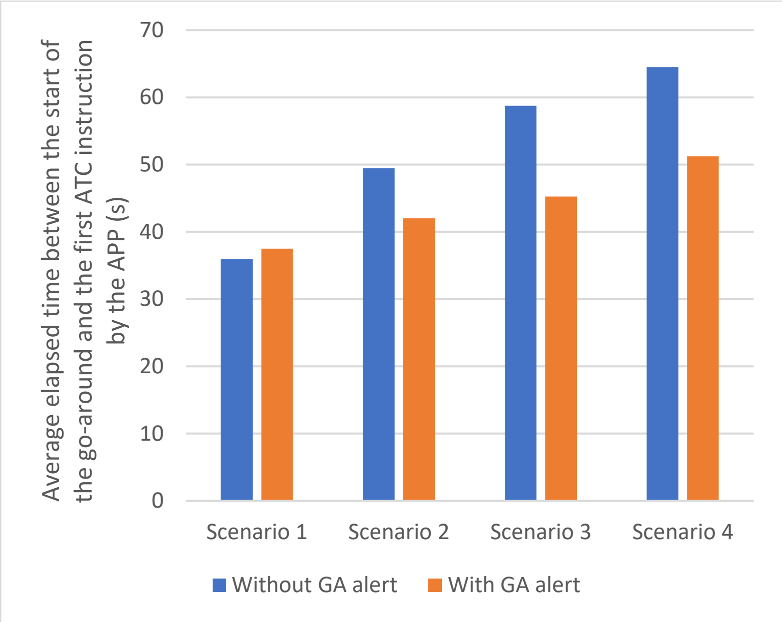

Figure 4-6 - Impacts of the GA alert on the APP reaction time

Figure 4-7 - Impacts of the GA alert on the flight time from the start of the GA until landing

Besides the quantitative assessment of operational performance, a subjective evaluation regarding the perceived impacts of the proposed monitoring and alerting tool was carried out. Figures Figure 4-8, 4-9 and Figure 4-10 present the results of the questionnaire applied to controllers after the end of the simulation.

First, the controllers were asked to compare the perceived levels of situational awareness, workload, and safety during the HITL simulation runs with and without the presence of the GA alert. Figure 4-8 shows that 100% of the controllers considered that the GA alert increased the situational awareness during the GA events, with some indicating that the perceived level of situational awareness was much higher than usual. This very expressive percentage is a potential explanatory factor for the observed reductions in controller reaction time shown in Figures Figure 4-5 and Figure 4-6, as situational awareness is critical for fast and efficient decision-making.

Most of the air traffic controllers (57%) considered that the workload was about the same as usual with the proposed alerting capability. This is a relevant result, as ATC is a high-workload activity that ultimately determines airspace capacity. Therefore, the introduction of any novel automation tool should carefully consider the impacts on controller workload.

In terms of safety, an expressive percentage of 57% of the controllers found that the presence of the GA alert generated a positive impact, with the remaining 43% indicating that the safety level was about the same as usual. As the approach and landing phase accounts for the highest share of accidents worldwide, the positive impact perceived by most controllers emphasizes the potential contribution of the proposed tool to enhance the overall flight safety.

Next, the controllers were asked to assess potential changes in operational performance with the GA alert. Figure 4-9 shows that 100% of the controllers agreed that the alert facilitated the reintegration of the traffic in the approach sequence and 71% agreed that traffic flow efficiency increased. These results corroborate the observed reduction in flight time shown in Figure 6, highlighting the potential benefits of the proposed tool in terms of efficiency besides safety. Regarding the coordination process between the TWR and the APP, controller perception varied. 43% of the controllers disagreed with the statement that the GA alert facilitated the coordination. This result might be related with the fact that the GA alert was present for both the TWR and the APP controller, potentially affecting the form of coordination and the overall perception of its need.

Figure 4-9 also shows that the alert performance is a very important aspect to be considered for practical implementation. A small percentage of the controllers (14%) considered that the alert timing could be more appropriate. Moreover, 43% of the controllers indicated that alert failures would be unacceptable. These results emphasize the importance of the reliability and the antecedence of the information provided by the tool. Since the accuracy of predictive models is affected by the prediction horizon, a trade-off will exist between different alert performance requirements. Therefore, the operational impacts of different levels of alert performance, based on the actual performance of state-of-the-art predictive models, should be analysed in future studies.

Finally, the controllers evaluated the utility of the GA alert for different ATC tasks. Figure 4-10 shows that the totality of the controllers considered that the alert was useful for clearance provision tasks, with 57% of the controllers attributing a medium utility score and 43% a high utility score. A very high percentage of 86% of the controllers also found that the alert was useful for conflict resolution tasks. On the other hand, the perception of the controllers about the utility of the alert for coordination tasks varied from low to high, which is in line with the results shown in Figure 4-9. Overall, there was a positive perception about the global utility of the GA alert, with 57% of the controllers attributing a medium utility score and 43% a high utility score.

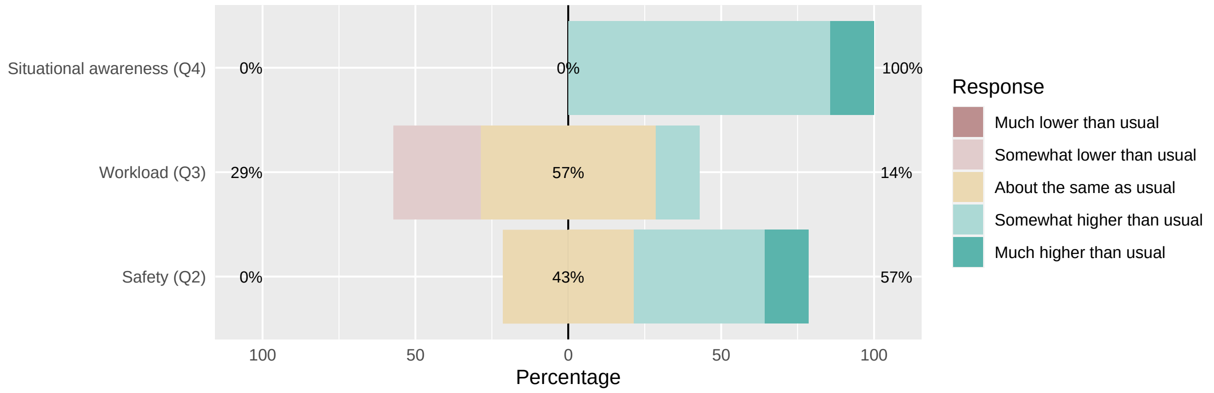

Figure 4-8 - Perceived impacts of the GA alert on situational awareness, workload, and safety

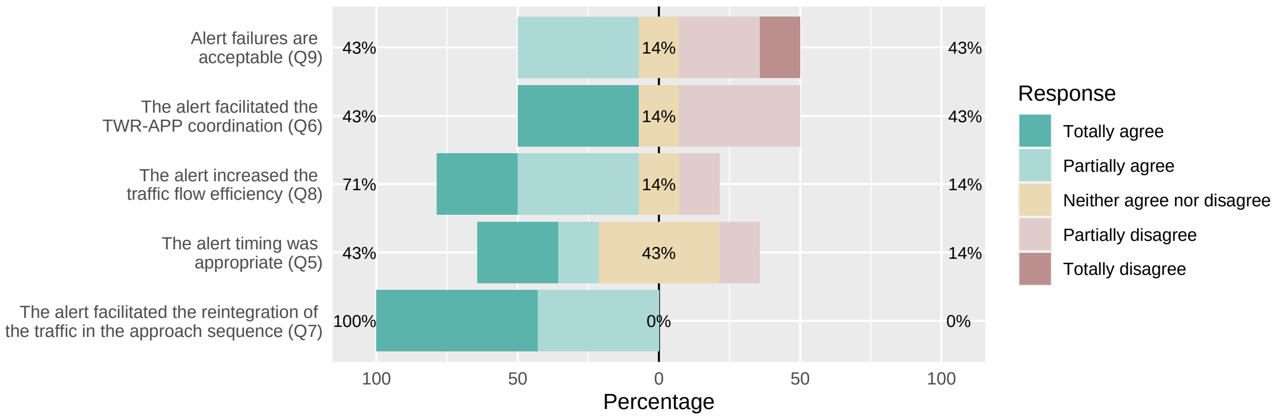

Figure 4-9 - Perceived operational performance with the GA alert

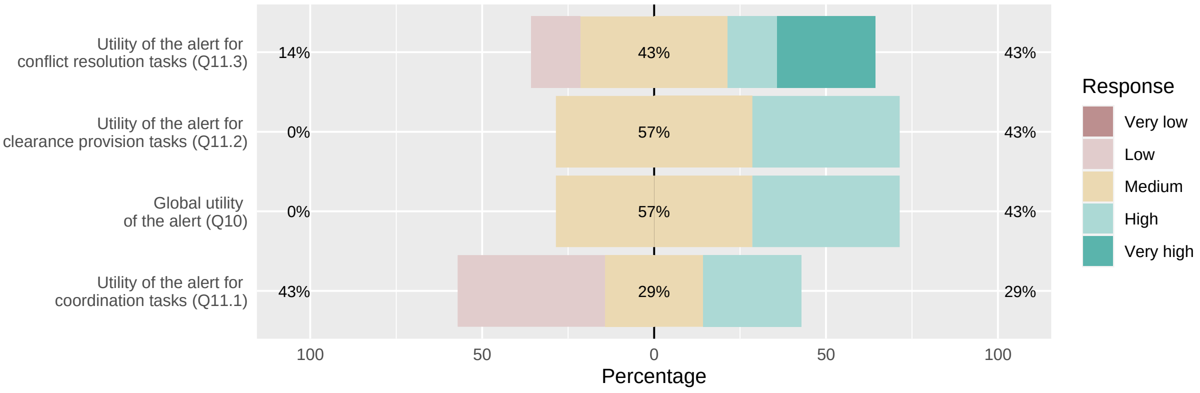

Figure 4-10 - Perceived utility of the GA alert for ATC tasks

5 Final Considerations

5.1 Conclusions

The objectives of this research were to develop a data-driven approach for real-time monitoring of arrival operations and alerting of go-arounds and to evaluate the operational impacts of such an alerting solution for ATC decision-making and performance.

With respect to the first objective, we used surveillance data from an open-source flight tracking platform and developed analytical and machine learning approaches for the online detection of flight trajectory anomalies and prediction of go-around events. We specifically used flight tracking data for one month of arrival operations at Sao Paulo/Guarulhos International Airport.

First, sequential heuristics based on the evaluation of vertical rates were applied to identify go-around events in the database offline. Using the labelled dataset, we developed two algorithms for online prediction of go-around events. The first one is a rule-based algorithm that considers the evaluation of operational parameters throughout the descent phase. The algorithm predicts a go-around whenever the flight profile falls outside trajectory envelopes that represent acceptable deviations from an ideal operational performance. The second one is a machine learning-based algorithm. It considers the application of clustering analysis to discover nominal patterns in the approach phase followed by probabilistic modelling of these nominal approach patterns. The probabilistic model is then applied in an online fashion, using partial trajectory observations, to detect an anomalous behaviour and predict the execution of a go-around.

The algorithms were applied on test data to evaluate their actual operational performance. We found that only the machine learning-based algorithm was capable of discriminating the approach trajectories, enabling the correct detection of 67% of the go-arounds at 4 NM from the runway threshold at a false positive rate lower than 5%. The results emphasized the operational variability and complexity of approach operations and the importance of learning this variability from actual data to better understand the actual operational tolerances and identify the deviations that can actually lead to a go-around.

As a second objective, this work evaluated the operational impacts of a real-time monitoring and alerting solution that anticipates the occurrence of a go-around event towards ATC decision support in approach control facilities and aerodrome control towers.

The evaluation was performed with a human-in-the-loop (HITL) simulation of air traffic operations at Sao Paulo/Guarulhos International Airport. The simulation was based on four traffic scenarios that were run with and without the presence of a go-around alert for air traffic controllers during the approach.

The results showed an increase in the perceived levels of situational awareness and safety as well as an increase in the efficiency of actual ATC decisions concerning the go-around. Overall, we observed a reduction of nearly two minutes in the flight time from the start of the go-around and the landing when the alert was active. This reduction in flight time can be directly associated with the improvement in the perceived level of situational awareness due to information received in advance.

The operational performance metrics computed after the HITL simulation associated with the subjective evaluation results acquired with the questionnaires distributed to the controllers who participated in the simulation indicated that the proposed tool has a great potential to support ATC decision-making in real-time during go-around events, delivering an important contribution towards safer and more efficient flight operations.

5.2 Future work

The proposed data-driven approach for monitoring and alerting of go-around events was based on the use of surveillance data mainly sourced from ADS-B. From a practical perspective, the performance, safety and interoperability requirements of ADS-B should guarantee that the operational service delivery and procedures are working as intended. In reality, the ADS-B data has known inconsistences and faults, where problems or abnormalities may arise during its broadcasting and they should be identified, tracked, analysed to correct the information disseminated as required, at the risk of compromising the integrity and reliability of the alert provided to the controller. It is worth mentioning that trajectory information can also be extracted from radar data of current ATC systems. Towards practical implementation, the use of this type of surveillance data should be explored.

Future work could also explore the use of information extracted from the flight data recorder (FDR), in real-time, that receives various discrete, analog and digital parameters from a number of sensors and avionics systems from a flight data acquisition unit (FDAU). Information from the FDAU to the FDR is sent via specific data frames, which depend on the aircraft manufacturer and, after, this data could be routed to the ATC systems, so that flight trajectory anomalies may be precisely identified in advance. It is important to note that the use of this data may require specific regulation in order to protect the data confidentiality of the airline operators and their standard of operations. Additionally, this would require advanced communication technologies to exchange digital data between air and ground systems.

Another potential future research direction could be the integration of data from air/ground systems, i.e., A-SMGCS (Advanced Surface Movement Guidance & Control System), Flight & Flow Information for a Collaborative Environment (FF-ICE), which also includes complementary procedures that deliver improved situational awareness to TWR controllers. Since runway incursion occurrences associated with the incorrect presence of an aircraft, vehicle, or person on the protected area of a surface designated for the landing and take-off of aircraft may be contributing factors to GA events, this information integrated to the models for the online detection of flight trajectory anomalies from aircraft surveillance data could increase the liability of an alerting solution for ATC decision-making. Weather data, airspace structure data (AOC, IAC, SID, STAR, etc), among other data types, may also be part of the equation in machine learning models, which could bring more precision in the final results.

Regarding the operational evaluation, one important aspect revealed by the questionnaire responses is that the potential occurrence of alert failures might not be easily handled by the controllers. In future studies, additional simulation experiments could be performed to evaluate how the predictive performance of such a decision support tool impacts the usability of the tool and the overall operational performance. For instance, the impact of false alarms on ATC workload and decision-making should be carefully investigated.

Finally, despite the complexity of the ATM, Artificial Intelligence (AI), which is one of the most researched topics in computer science, has not quite reached end users in the ATM domain. In a safety-critical system such as ATM, it is key to ensure the trustworthiness of AI based systems. Developing strategies to enhancing the interpretability of machine learning models and building trust on AI-based decision support tools is another prominent future research direction.

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5. TÍTULO E SUBTÍTULO:

Real-time monitoring and alerting of go-arounds for air traffic control decision support.

6. AUTOR(ES):

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7. INSTITUIÇÃO(ÕES)/ÓRGÃO(S) INTERNO(S)/DIVISÃO(ÕES):

Instituto Tecnológico de Aeronáutica – ITA

8. PALAVRAS-CHAVE SUGERIDAS PELO AUTOR:

Go-around, Situational awareness, Air traffic control, Machine learning, Human-in-the-loop simulation.

9. PALAVRAS-CHAVE RESULTANTES DE INDEXAÇÃO:

Controle de tráfego aéreo; Conciência situacional; Operação em tempo real; Aprendizagem (inteligência artificial); Monitoramento; Segurança do voo; Aeroportos; Transporte aéreo.

10. APRESENTAÇÃO: **X Nacional** **Internacional**

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11. RESUMO:

Go-arounds (GA) are a relevant safety event that may occur during the approach phase of the flight due to several reasons such as unstable approach, loss of separation minima or adverse weather. In dense terminal control areas, this manoeuvre, even though it is a standard procedure, can generate significant and additional air traffic control (ATC) workload as it requires a quick and accurate reaction in order to safely reintegrate the flight into the traffic flow and immediately establish a new approach and landing sequence. In current operations, air traffic controllers typically become aware of a GA during or after their execution, which leads to a very short time horizon for operational decision-making. This research aims to propose and evaluate the operational impacts of a real-time monitoring and alerting solution for ATC decision support in approach control facilities and aerodrome control towers. The solution is based on the use of surveillance data and the application of analytical and machine learning methods for identifying flight trajectory anomalies in real-time and predicting the execution of a GA. Based on a human-in-the-loop simulation of air traffic operations at the Sao Paulo/Guarulhos International Airport, it is assessed how the presence of such an alert that anticipates the occurrence of a GA affects the ATC performance. The results showed an increase in the perceived levels of situational awareness and safety as well as an increase in the efficiency of ATC decisions concerning the go-around, with an observed reduction of nearly two minutes in the flight time from the start of the manoeuvre and the landing when the alert was active.

12. GRAU DE SIGILO:

(X) OSTENSIVO **( ) RESERVADO** **( ) SECRETO**