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OPTIMIZATION OF AIRCRAFT SEQUENCING USING MIXED-INTEGER PROGRAMMING

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ABSTRACT

The rapid growth in global air travel has intensified congestion and delays, highlighting the need for improved aircraft sequencing strategies in air traffic management. In this study, we present a Mixed-Integer Programming (MIP) model to address the Aircraft Landing Problem (ALP), incorporating key operational constraints, including threshold changes. The model is adapted to the context of Guarulhos International Airport using real traffic data from selected days in 2023. Its objective is to minimize cumulative deviations from unimpeded landing times, thereby improving runway use efficiency. Performance is evaluated by comparing model-generated sequences against the First-Come, First-Served (FCFS) baseline across various scenarios, including high-traffic periods and threshold changes. The results demonstrate significant improvements over FCFS, with an average reduction of 39.12% in cumulative deviations on days without threshold changes, and 20.58% under threshold change conditions. These findings confirm the model's potential to enhance sequencing efficiency and support air traffic management.

KEYWORDS. Aircraft Landing Problem. Arrival Manager. Mixed-Integer Programming.

Paper Topics. Logistics and Transportation. Discrete Optimization.

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1. Introduction

Global air travel demand is rapidly increasing, with International Air Transport Association (IATA) projecting 8.2 billion passengers by 2037, nearly double the 4.1 billion in 2017. Eurocontrol forecasts that daily flight delays affecting passengers could grow from 50,000 to 470,000 by 2040 [EUROCONTROL 2018]. This surge in traffic necessitates advanced air traffic management (ATM) techniques to maintain safety and efficiency while mitigating delays. Improved ATM can also reduce environmental impact, as aviation accounts for 2% of global CO2 emissions, expected to rise to 3% by 2050. Efficient management, including minimizing holding patterns and optimizing flight paths, lowers fuel consumption and emissions [Li Long et al. 2021].

Arrival Manager (AMAN) systems assist air traffic controllers by optimizing arrival sequencing through real-time integration of radar, flight plans, weather, and aircraft data [Skybrary 2024]. The sequencing component of AMAN can be enhanced using Operational Research (OR) techniques, particularly Mixed-Integer Programming (MIP), which handles complex scheduling problems involving continuous and discrete variables.

In Brazil, ICEA — the Airspace Control Institute — faces challenges in optimizing landing sequences at busy airports like Guarulhos International Airport, which lacks adequate decision-support tools. Efficient sequencing is critical to manage high traffic and reduce delays.

With rising air traffic and limited possibilities for infrastructure expansion, optimizing runway use has become essential for improving airport capacity Silva et al. [2023]. A key approach is solving the Aircraft Landing Problem (ALP), which assigns landing times and runways to minimize penalties for early or late arrivals within predefined time windows Ikli et al. [2021]. The ALP must also account for safety constraints, such as minimum separation times between aircraft based on their weight categories, as defined by ICAO Fahle et al. [2003]. Mixed-Integer Programming (MIP) has proven effective for modeling the ALP, with studies like Beasley et al. [2000] and Balakrishnan and Chandran [2010] showing its success in reducing delays and improving runway efficiency.

1.1. Objective

This study aims to develop a comprehensive MIP-based model to improve aircraft sequencing efficiency at airports, supporting ICEA in advancing air traffic management through better understanding and use of AMAN systems. The proposed model builds upon a widely recognized formulation from the literature, enhanced with additional operational constraints provided by ICEA — such as potential threshold changes. The model is tested using historical data from Guarulhos Airport and its performance is evaluated by comparing the optimized sequencing results with a First-Come-First-Served (FCFS) baseline, commonly used in current air traffic control practice.

1.2. Literature Review

The most cited MIP approach to the ALP was presented by [Beasley et al. 2000]. They propose the model for a single runway and after expand it to multiple runways. In their formulation, they take into account the minimal separation time between aircraft, enforced by wake vortex (VW) categories, as well as time windows constraints, and additional constraints that strengthen the linear programming relaxations. Their objective function is to minimize the total deviation from the target landing time, considering different costs for earliness and lateness. They also propose a Upper Bound heuristic to the problem. Finally, they solve their model using CPLEX and the proposed heuristic for a increasing number of

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runways in problems from the OR-library [Beasley 1990], involving up to 50 aircraft and 4 runways.

Building upon Beasley's foundational model, [Briskorn and Stolletz 2014] adapted it to include objective functions that depend on aircraft class. They incorporated the Earliest Landing Window rule and achieved better computational times using CPLEX. [Ghoniem and Farhadi 2015] further adapted this model to also encompass aircraft takeoffs, enhancing it with valid inequalities to tackle the complexities introduced by adding multiple runways and aircraft. Their empirical tests indicated that while valid inequalities and preprocessing could handle modest numbers of aircraft and runways, they were insufficient for larger scales. Consequently, they proposed a set-partitioning model solved through a column-generation approach, enabling the management of larger instances within reasonable computation times.

[Faye 2015] used a time-discretization approach on the same model, which presumed integer-valued problem parameters and thus also yielded integer-valued solutions. By discrediting the planning horizon into time slots, the approach limited possible landing scenarios, which simplified the problem into a manageable 0-1 linear problem solved using a dynamic constraints generation algorithm.

In parallel, [Hancerliogullari et al. 2013] proposed a novel MIP formulation inspired by job-shop scheduling, which treated multiple runways as parallel machines, assuming independence in terms of separation requirements. This model also aimed at balancing traffic across available runways by imposing upper and lower bounds on the number of aircraft per runway, though it resulted in large computational times for optimal solutions. Apart from MIP approaches, researchers have explored several alternative methodologies. Heuristic, meta-heuristic and reinforcement learning techniques have become increasingly prominent in solving the complex ALP, offering robust alternatives to traditional optimization methods. Notable studies leveraging Genetic Algorithms, such as those by [Stevens 1995] and [Beasley et al. 2001], have demonstrated the potential of GAs in efficiently navigating the large solution spaces typical of ALP, resulting in high-quality solutions.

Finally, [Veresnikov et al. 2019a,b] and [Ikli et al. 2021] provide extensive reviews of these methods, showcasing a broad spectrum of approaches and techniques developed over the years to solve various instances of the ALP, highlighting the continuous evolution and adaptation of optimization methods in air traffic management.

1.3. Contributions

This work proposes a MIP model tailored to ICEA's operational constraints to optimize aircraft sequencing within AMAN systems. Validated with historical data from Guarulhos Airport, the model demonstrates potential to reduce delays and improve runway capacity management in Brazil. The study advances understanding of AMAN functionality and supports future integration of other methods such as artificial intelligence, aligning with sustainable aviation objectives.

2. Aircraft Landing Problem

When an aircraft approaches an airport, air traffic control must assign it a landing time and a suitable runway. This task is constrained by two main factors: each aircraft's time window for landing and the required separation between consecutive landings. The time window is defined by the earliest and latest acceptable landing times, while the target landing time represents the ideal moment based on preferred speed and trajectory. Landing too early or too late incurs costs.

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To ensure safety, aircraft must maintain a minimum separation due to Wake Vortex turbulence, which depends on the ICAO category of both the leading and following aircraft, classified by maximum takeoff mass.

A widely used method is First-Come-First-Served (FCFS), which sequences aircraft by their Estimated Time of Arrival (ETA). While fair and easy to implement, FCFS may lead to inefficiencies at busy airports, where rigid separation rules can increase overall delays and reduce throughput.

Another important consideration are threshold changes, often required due to weather conditions such as wind and other meteorological conditions. Although these changes can be predicted up to 15 minutes in advance at Guarulhos Airport [ICEA 2023], pilots are usually informed only just before landing, which can cause delays. Incorporating threshold change information into the optimization model allows proactive sequencing and better adaptation, reducing disruptions and improving efficiency. This is particularly valuable in high-traffic environments where small delays can have cascading effects.

2.1. Implemented Model

In this section, we introduce the developed model based on MIP for the ALP. This model is based on inspired by the formulation of [Beasley et al. 2000], with enhancements to accommodate additional constraints designed to meet specific operational demands.

2.1.1. Parameters and Variables

The model considers a set of parameters and decision variables to represent the aircraft landing scheduling problem. Let $N = \{1, 2, \ldots, n\}$ denote the set of aircraft to be scheduled and $R = \{1, 2, \ldots, n_r\}$ the set of available runways. For each aircraft $i \in N$, the parameter T_i represents its target landing time, which is the ideal moment the aircraft should land according to operational plans. The time window within which an aircraft may land is defined by E_i and L_i, indicating the earliest and latest permissible landing times for aircraft i, respectively.

To account for the cost implications of deviations from the target time, the model introduces two parameters: A_i, the cost per unit of anticipation (when the aircraft lands before its target), and B_i, the cost per unit of delay (when the aircraft lands after its target). Safety requirements are incorporated through the parameter S_{ij}, which specifies the minimum separation time required between any two aircraft i and j if they are assigned to the same runway, with $i \neq j$. In scenarios involving a change of runway threshold during the planning horizon, each aircraft i has two possible target times: $T1_i$, which applies if it lands before the change, and $T2_i$, which applies if it lands after. The change itself occurs at a specific time C, a global parameter that influences which target time is active for each aircraft depending on its actual landing time.

The model also defines a set of decision variables. For each aircraft i, the variable t_i represents its actual assigned landing time. Based on this, two auxiliary variables are introduced: a_i, denoting the delay (the amount by which the landing time exceeds the target), and b_i, denoting the anticipation (the amount by which the landing time precedes the target). The effective target time used for comparison is denoted again by T_i, which corresponds to either $T1_i$ or $T2_i$ depending on whether the landing occurs before or after the threshold change time C.

In addition to continuous variables, several binary variables are used to represent logical decisions. The variable x_{ij} is equal to 1 if aircraft i lands before aircraft j, and 0 otherwise, for all distinct pairs $i, j \in N$. The variable z_{ij} equals 1 if aircraft i and j are assigned to the same runway, and 0 otherwise. Runway assignments are captured through

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the binary variable y_{ir}, which is equal to 1 if aircraft i is scheduled to land on runway r, with $r \in R$. To identify the first aircraft to land on each runway, the variable w_{ir} is defined, taking the value 1 if aircraft i is the first to land on runway r, and 0 otherwise. Finally, in the context of a threshold change, the binary variable c_t is used to indicate which threshold is used by aircraft i at the time of landing: it takes the value 1 if threshold 1 is used, and 0 if threshold 2 is used.

2.1.2. Constraints

The first set of constraints ensures that the landing time for each aircraft i is within its defined time window:

$$E_i \leq t_i \leq L_i, \qquad \forall i \in N, \tag{1}$$

Additionally, for each pair of aircraft i and j, we need to ensure that aircraft i must land either before or after aircraft j:

$$x_{ij} + x_{ji} = 1, \qquad \forall i, j \in N,\ j > i. \tag{2}$$

Furthermore, we must ensure that each aircraft i lands on only one runway:

$$\sum_{r \in R} y_{ir} = 1, \qquad \forall i \in N, \tag{3}$$

To adjust the binary variable z_{ij}, we must ensure symmetry such that if aircraft i lands on the same runway as aircraft j, then aircraft j lands on the same runway as aircraft i. This is guaranteed by the set of constraints:

$$z_{ij} = z_{ji}, \qquad \forall i, j \in N,\ j \geq i. \tag{4}$$

Moreover, if there is a runway r where both aircraft i and j land, i.e., $y_{ir} = y_{jr} = 1$, then $z_{ij} = 1$. If $z_{ij} = 0$, then i and j cannot land on the same runway, i.e. y_{ir} and y_{jr} cannot both be 1. This condition is guaranteed by:

$$z_{ij} \geq y_{ir} + y_{jr} - 1, \qquad \forall i, j \in N,\ j \geq i,\ r \in R. \tag{5}$$

To ensure minimum separation between aircraft, we have the constraints:

$$t_j \geq t_i + S_{ij} z_{ij} - M(1 - x_{ij}), \qquad \forall i, j \in N,\ i \neq j, \tag{6}$$

where M is a sufficiently large positive constant. Our approach does not consider minimum separation for aircraft landing on different runways, reflecting the assumption that aircraft on separate runways do not interfere with each other's operations.

To relate the variables t_i with the delay time a_i or the advancement time b_i for each aircraft i, we use the constraints:

$$t_i = T_i + a_i - b_i, \qquad \forall i \in N. \tag{7}$$

Finally, we define intervals for the anticipation and delay time variables:

$$a_i \geq t_i - T_i, \qquad \forall i \in N, \tag{8}$$
$$b_i \geq T_i - t_i, \qquad \forall i \in N, \tag{9}$$
$$0 \leq a_i \leq L_i - T_i, \qquad \forall i \in N, \tag{10}$$
$$0 \leq b_i \leq T_i - E_i, \qquad \forall i \in N. \tag{11}$$

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Equations (8) and (10) ensure that a_i is at least as big as zero and the difference between the landing and target times, and at most the difference between the latest allowed and target times. Equations (9) and (11) ensure are similar, but for b_i.

Additionally, we introduce the following, ensuring that only one aircraft is the first to land on each runway:

$$\sum_{i \in N} w_{ir} = 1, \qquad \forall r \in R, \tag{12}$$

Furthermore, to define as the first aircraft to land on each runway as the one with the least t_i, we have:

$$t_i - t_j \leq M(1 - w_{ir}) - M(2 - \sum_{k \in N'} x_{ikr} - \sum_{k \in N'} x_{jkr}) \tag{13}$$
$$\forall i, j \in N,\ i \neq j,\ \forall r \in R.$$

A key addition is a restriction preventing the first plane predicted to land from advancing beyond its ETA, ensuring minimum separation and reducing the risk of safety issues with aircraft that may have just landed. Therefore, we need to ensure that the first aircraft to land on each runway does not advance beyond its ETA. This is guaranteed by:

$$b_i \leq 1 - w_i + M(1 - w_i), \qquad \forall i \in N, \tag{14}$$

In addition, we must ensure correct landing times for aircraft landing on each threshold. Specifically, we need to guarantee that if an aircraft is assigned to land at threshold 1, it completes its landing before the threshold change time C, and conversely, if it is assigned to threshold 2, its landing occurs after this change. This is enforced through the following constraint:

$$t_i \leq C + M\ c_i, \qquad \forall i \in N; \tag{15}$$

$$t_i \geq C - M\ (1 - c_i), \qquad \forall i \in N; \tag{16}$$

Lastly, we must ensure that the actual target time T_i for each aircraft is correctly assigned. This is achieved through the following constraint:

$$T_i = c_i\ T1_i + (1 - c_i)\ T2_i, \qquad \forall i \in N. \tag{17}$$

The objective function is defined to minimize the total cost of anticipation and delay for all aircraft:

$$\min \sum_{i \in N} (A_i a_i + B_i b_i). \tag{18}$$

3. Methodology

In this section, we outline our approach to evaluating the model's performance across different traffic scenarios, utilizing real data from Guarulhos International Airport. Furthermore, we explain the methods of data acquisition and preparation, ensuring accurate and reliable inputs for analysis.

To evaluate the proposed model, we examined its optimization output, which includes the landing sequence for all aircraft, specific landing times, and required actions to maintain this sequence — whether through applying landing delays or advances. Using this output, we conducted tests to assess the effectiveness of the proposed model with real data from Guarulhos International Airport. The testing process was divided into two stages, which will be explained in the following sections. Prior to testing, the real data had to be acquired and prepared, as described in the next section.

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3.1. Data Acquisition and Preparation

The data used in this evaluation was provided by ICEA and comprised a radar dataset, a BIMTRA table, and a METAR table. The radar dataset contains real-time aircraft positions with geographical coordinates recorded at four-second intervals for aircraft within a 40 nautical mile radius of GRU (C40 zone). The BIMTRA table logs flight information, including details such as aircraft identification, assigned runway, flight category (arrival or departure), landing or departure times, aircraft model, and performance indicators.

Specific days and periods were selected from the radar data to suit each test. Additionally, flights were considered from 40 nautical miles from the airport. This boundary definition ensures that all relevant flights within these control zones are included in the sequence optimization. With the filtered radar data, additional required information was obtained for each flight. The following sections explain the process of data acquisition for each parameter used in the model.

3.1.1. Set of Aircraft and Runways

The set of aircraft (N) varied depending on the number of flights present in the radar data during different time intervals. For each selected period, we created a set of active aircraft, with each aircraft represented by a unique identifier. The set of runways (R), however, remained fixed, as Guarulhos International Airport operates with only one active runway for landing sequences.

3.1.2. Target landing time

A critical parameter in the optimization model is the target landing time, representing the ideal time for each aircraft to land under optimal sequencing conditions. For this study, the unimpeded time was used as the target landing time. This approach was chosen because scheduled airline arrival times are often conservative, including buffers that do not necessarily reflect ideal operational timing. Moreover, there is no reliable mechanism to infer true target landing times from operational data alone.

According to Brazilian aeronautical procedures [DECEA 2020b], the unimpeded time corresponds to the time an aircraft would take to land from a predefined distance in the absence of any sequencing intervention. This value depends on the aircraft's type, the landing runway, and the sector of entry into the control area. Unimpeded times were estimated following a statistical analysis of historical flight data provided by ICEA. Flights were grouped by entry sector, runway, and wake turbulence category (Light, Medium, Heavy, or Super). The unimpeded time for each group was calculated as the 20th percentile of observed landing times under similar conditions, representing an ideal case scenario. When needed, interpolation was applied between predefined distances.

3.1.3. Additional Time in the Terminal Area

The Additional Time in the Terminal Area (KPI08) is the primary performance metric used in this evaluation. It quantifies the time spent by an aircraft in the terminal area beyond its unimpeded transit time and reflects the impact of sequencing interventions [DECEA 2020b]. KPI08 is calculated as the difference between the actual and unimpeded times. A positive value indicates delay, while a negative value indicates an advance. In this study, the model was designed to treat early and late arrivals symmetrically, with the objective of minimizing the absolute deviation from the unimpeded time. This approach encourages balanced adjustments across the arrival stream and allows the model to optimize runway use while maintaining fairness and predictability in sequencing.

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3.1.4. Earliest and latest landing times

Estimating the earliest and latest feasible landing times is challenging due to the unavailability of sensitive operational data, such as fuel status and aircraft-specific speed constraints. These factors are proprietary and cannot be inferred from public sources. To address this, the study used a statistical estimation method based on historical performance data from the BIMTRA table. For each of the 256 aircraft models that landed at Guarulhos in 2023, the 90th percentiles of both positive and negative KPI08 values were computed. These percentiles represent the maximum delay and maximum advance typically observed for each aircraft type.

3.1.5. Minimum Separation Times

Separation times between arriving aircraft were defined based on ICAO and Brazilian air traffic control standards [DECEA 2020a]. Aircraft are classified into four wake turbulence categories: Super, Heavy, Medium, and Light, based on their certified takeoff weight. The corresponding minimum separation times between leading and trailing aircraft in different categories are established in DECEA's regulatory document on air traffic control procedures [DECEA 2020a].

3.1.6. Data Retrieval Process

Radar data was used to identify flights entering the designated airspace boundary, capturing their entry coordinates, entry time, and unique flight identification codes. From these coordinates, each aircraft's distance from the airport and sector of entrance were calculated to classify the approach direction. Using the flight IDs, detailed information was retrieved from the BIMTRA database, including the assigned runway, wake turbulence category, aircraft model, and KPI08 values. Maximum allowable delay and advance times for each aircraft model were obtained from historical data, defining feasible scheduling windows for landing sequence optimization.

The unimpeded transit time — from the boundary to the runway threshold — was calculated based on aircraft size, sector of entrance, and assigned runway, with interpolation applied when necessary to estimate times for intermediate distances. All relevant flight information was compiled into a dataset of active flights, forming the basis for the subsequent optimization process.

3.2. Testing the Model

The model's performance was evaluated through two efficacy tests: one without runway threshold changes and another including threshold changes. It is important to note that the model was not tested against real landing sequences. This decision ensures a fair comparison, as real-world operations are influenced by external factors which are not modeled in our simulations.

3.2.1. Efficacy Test without Threshold Change

Three days with clear weather and traffic volumes at or above the 2023 annual average were selected. Periods without threshold changes or significant weather disruptions were confirmed using METAR reports. Aircraft trajectories were simulated from initial radar detection until landing. As flights entered the monitored airspace, they were added to an active list, and the model optimized landing times to minimize additional time spent in terminal airspace (KPI08) compared to unimpeded transit times. A First-Come-First-Served (FCFS) baseline was also simulated, sequencing flights by estimated arrival times and applying delays only when necessary to maintain separation. The evaluation compared cumulative KPI08 values between the optimized model and the FCFS baseline, focusing on flights entering during the simulation period.

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3.2.2. Efficacy Test with Threshold Change

This test examined the model's ability to handle these threshold changes, selecting three dates with documented threshold shifts and adequate traffic volumes. The model received 15 minutes advance notice of threshold changes, allowing it to dynamically adjust estimated arrival times and optimize sequencing accordingly. The FCFS baseline was also adapted to be threshold-aware. Both approaches were simulated, and their cumulative KPI08 values compared to assess the benefits of threshold awareness on landing efficiency.

4. Results

The model was evaluated through a series of experiments in the C40 airspace configuration against the FCFS baseline. The evaluation focused on minimizing cumulative deviations from scheduled landing times, measured using the KPI08 metric. The numerical tests were performed on a computer with an Intel Core i7-1260P processor and 16GB of RAM, running Ubuntu 22.04, using the Gurobi 11.0.2 solver API.

4.1. Efficacy without Threshold Change Test

Figures 1 to 3 illustrate the landing sequences produced by the model and the FCFS baseline for traffic samples from January 28, March 21, and April 24, 2023. In these comparisons, aircraft are sorted according to their FCFS order, and the lines represent the actual sequencing in each model. Figure 4 summarizes the cumulative absolute KPI08 values across the three days.

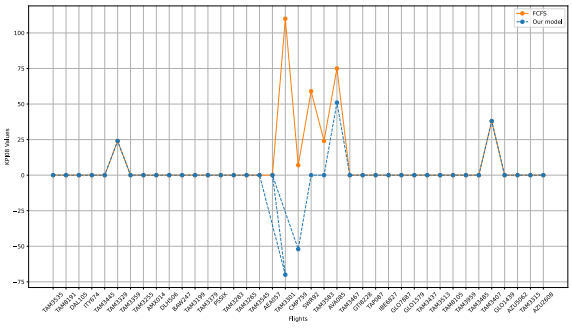


Figure 1: KPI08 comparison for January 28, 2023, during the 08:00 to 10:00 period.

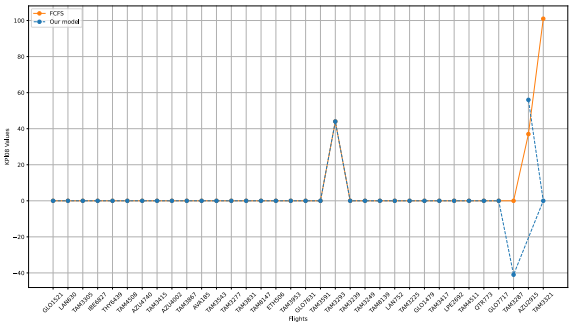


Figure 2: KPI08 comparison for March 21, 2023, during the 18:00 to 20:00 period.

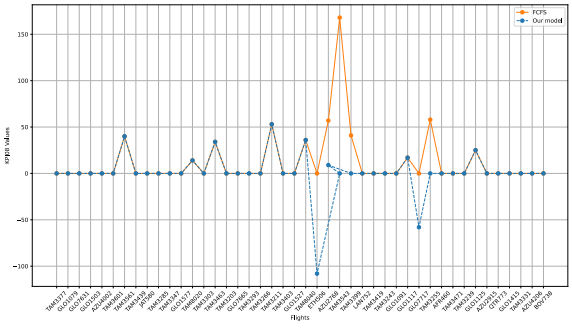


Figure 3: KPI08 comparison for April 24, 2023, during the 08:00 to 10:00 period in the C40 scenario.

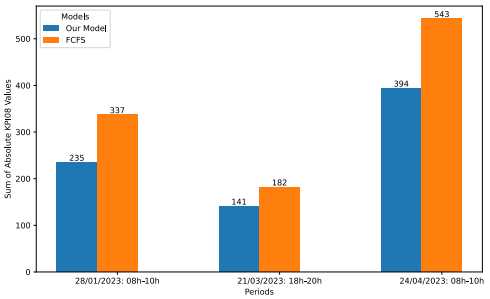


Figure 4: Cumulative absolute KPI08 values for January 28, March 21, and April 24, 2023.

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The model consistently reduced cumulative deviations compared to the FCFS baseline, achieving an average improvement of 39.12%. These reductions resulted both from precise adjustments to scheduled landing times and, when beneficial, changes in landing order. For example, in Figure 1, the model reorders AEA057 (Heavy) and TAM3301 (Medium), allowing TAM3301 to land earlier and thus reducing required separation. Similar reorderings in Figures 2 and 3 further contributed to improved sequencing outcomes.

Even when the sequence remained unchanged, the model was able to reduce KPI08 values through fine-tuned time optimization. This flexibility in adjusting both sequence and timing proved effective in minimizing delays and advances within the arrival stream.

4.2. Efficacy with Threshold Change Test

Figures 5 to 7 show the results for March 01, March 29, and May 20, 2023, in scenarios involving threshold changes. Figure 8 presents the cumulative KPI08 values for these dates.

In this setting, the model continued to outperform the FCFS baseline, with an average KPI08 reduction of 20.58%. Advance knowledge of threshold changes allowed the model to adjust sequences and scheduled times accordingly, mitigating the impact of anticipated rerouting. The observed improvements stemmed from a combination of optimized sequencing and more precise time adjustments, which together helped to absorb the disruptions caused by the threshold transitions.

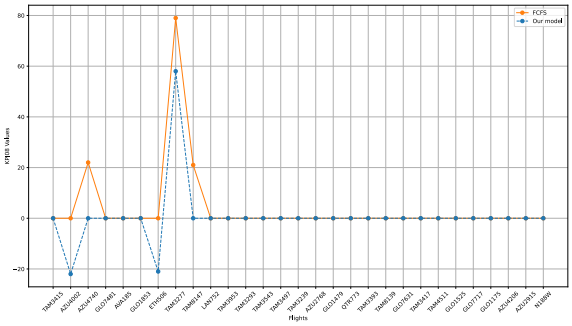


Figure 5: KPI08 comparison for March 01, 2023, during the 18:00 to 20:00 period with threshold change.

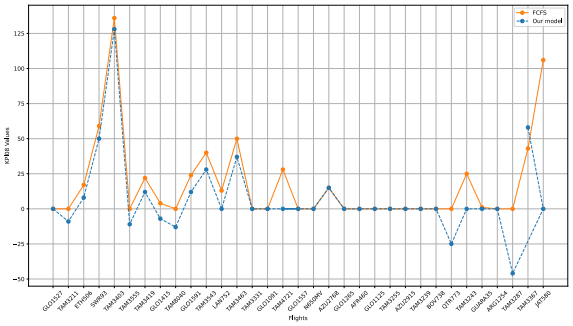


Figure 6: KPI08 comparison for March 29, 2023, during the 15:00 to 17:00 period with threshold change.

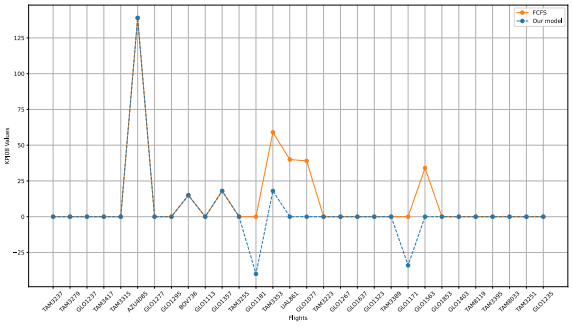


Figure 7: KPI08 comparison for May 20, 2023, during the 19:00 to 21:00 period with threshold change.

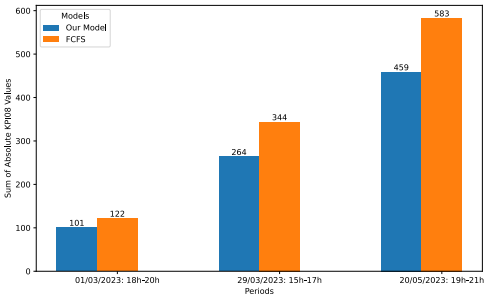


Figure 8: Cumulative absolute KPI08 values for March 01, March 29, and May 20, 2023.

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5. Conclusion

This study developed a MIP model to optimize aircraft landing sequencing at Guarulhos Airport, incorporating key operational constraints provided by ICEA — such as threshold changes. The model is based on a widely accepted formulation in the literature and extended to reflect the specific challenges of the Brazilian airspace environment.

Using historical arrival data, the model was tested across multiple high-traffic scenarios. Its results were compared to the commonly used FCFS sequencing strategy. In all instances, the model produced more efficient landing sequences than FCFS, particularly by reducing total deviation from target landing times. The comparison also highlighted how FCFS can lead to suboptimal outcomes due to its inability to account for separation costs and aircraft heterogeneity. The model's consideration of dynamic threshold changes demonstrates its potential to support more adaptive and resilient sequencing strategies. By anticipating and integrating these changes during optimization, the model helps mitigate potential disruptions and enhances scheduling flexibility.

In summary, this study illustrates the value of optimization-based approaches in air traffic management. The proposed model serves as a solid foundation for improving AMAN systems and can support decision-making in complex, high-demand airport environments. Future applications may further enhance its effectiveness by integrating real-time data or expanding to multi-runway operations.

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