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PROCESS OPTIMIZATION AS A TOOL FOR ANALYZING PERFORMANCE INDICATORS OF ADDITIONAL TAXI-OUT AND TAXI-IN TIME OF THE BRAZILIAN AIRSPACE CONTROL SYSTEM

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ABSTRACT

This study aims to improve the efficiency of Brazilian air traffic by analyzing the Brazilian Airspace Control System (SISCEAB) performance indicators. The methodology used combined alternative data sources, namely BIMTRA, TATIC FLOW, and VRA, which were employed to examine the impact of different variations in taxiing times. Specifically, Additional Taxi-Out Time (KPI 02) and Additional Taxi-In Time (KPI 13) were analyzed to identify discrepancies among these data sources and determine the most precise combination. The results indicate that airport layout, gate distribution, and runway threshold selection significantly impacted taxiing times. Statistical analysis revealed substantial variations in unimpeded taxi times across different gates and runway thresholds, emphasizing optimizing operational flows. Based on these findings, integrating BIMTRA and VRA is recommended for more accurate KPI measurement. Therefore, this study contributes to implementing operational enhancements, optimizing airport operation flow, and leading to a more efficient management of Brazilian air traffic.

I. INTRODUCTION

The increasing complexity and competitiveness of the air traffic sector impose significant operational challenges on organizations responsible for airspace control. In Brazil, the Department of Airspace Control (DECEA) establishes processes and methods to enhance organizational planning in Air Traffic Management (ATM) [1].

However, the lack of reliable data for analyzing performance indicators compromises operational efficiency assessment, particularly regarding Additional Taxi-Out Time (KPI 02) and Additional Taxi-In Time (KPI 13).

The absence of consolidated data sources and the difficulty in accessing reliable information limits the ability to diagnose and improve airport operations, directly impacting performance management and the efficiency of air navigation services.

Process optimization contributes to safety and air traffic organization, creating a more efficient operational environment. Within the ATM context, performance indicators play a key role in providing a comprehensive view of operational performance, enabling comparisons between airports. Their analysis is crucial for improving performance-based management and enhancing navigation service efficiency [2].

Thus, implementing process optimization strategies emerges as a fundamental approach to continuous sector improvement. The systematic review and enhancement of methods, procedures, and workflows create significant opportunities for reducing operational costs and promoting economic and environmental sustainability.

This study proposes optimizing the Brazilian Airspace Control System (SISCEAB) performance through a critical evaluation of key performance indicators and available data sources. The research analyzes taxi time variability and the influence of variable combinations on KPI calculations, aiming to identify discrepancies and opportunities for process improvement.

This study's main contribution lies in identifying alternative and reliable data sources for evaluating operational performance and establishing a benchmarking framework for the databases currently used in air traffic monitoring. This structured approach enables an in-depth analysis of the Key Performance Areas (KPA) for Efficiency, facilitating more accurate airport comparisons.

Additionally, this study proposes enhancements for performance-based management, focusing on Efficiency and sustainability in airport operations. Considering that fuel costs account for approximately 41% of airline operating expenses, optimizing these processes can generate significant cost reductions and mitigate environmental impacts [3].

Therefore, this research advances theoretical knowledge on process optimization and performance indicator analysis within the ATM context and proposes practical solutions to improve the Efficiency of Brazilian airspace control. By addressing complex operational challenges, this study contributes to a safer, more effective, and sustainable air traffic management system in the country.

II. THEORETICAL REFERENCE

II.1 AIR TRAFFIC

II.1.1 Characterization of the Brazilian Airspace Control System

The Brazilian Airspace Control System (SISCEAB) is a critical infrastructure designed to ensure the safety and efficiency of air traffic. It comprises control towers, area control centers, radar systems, and advanced communication networks, coordinating operations from takeoff to landing.

The integration of international regulations, rigorous procedures, and technological advancements highlights the system's complexity. Challenges such as increasing air traffic and the introduction of unmanned aircraft drive ongoing research efforts aimed at enhancing efficiency and safety.

II.1.1.1 Responsible Organizations

The Brazilian Airspace Control System (SISCEAB) is responsible for managing and controlling airspace, as well as providing air navigation services throughout the country. It is a comprehensive and effective system that ensures the organization and safety of air traffic flow [4].

The Aeronautics Command Directive (DCA) establishes the flexible use of Brazilian airspace and assigns the Department of Airspace Control (DECEA) the responsibility for controlling and administering an area of 8,511,965 km² of national territory, including the oceanic region up to the 10°W meridian, totaling 22 million km² [5].

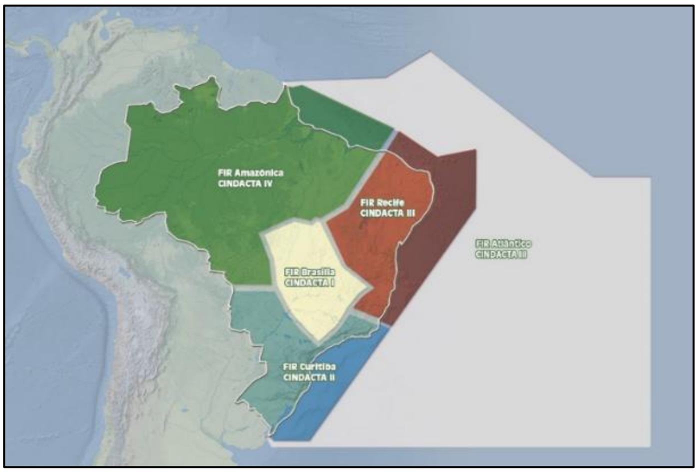

Figure 2: Air Traffic Control Jurisdiction in Brazil.
Source: Authors, (2025).

The Air Navigation Management Center (CGNA), a unit under DECEA, is responsible for balancing demand and capacity at airports and control sectors, working in collaboration with airlines, Air Navigation Service Providers (ANSPs), and control centers to optimize air traffic flow in Brazil [6].

Brazilian controlled airspace is divided into five Flight Information Regions (FIRs), managed by the Integrated Air Defense and Air Traffic Control Centers (CINDACTA), ensuring supervision and operational safety of air traffic within national territory.

II.1.1.1 Air Traffic Management

Air traffic refers to the coordinated movement of aircraft within airspace, regulated by specific systems and procedures to ensure safety, efficiency, and order in operations. This complex system involves Air Traffic Control (ATC), airports, navigation systems, communication networks, and regulations that maintain the smooth and secure flow of operations, both on the ground and in the air [7].

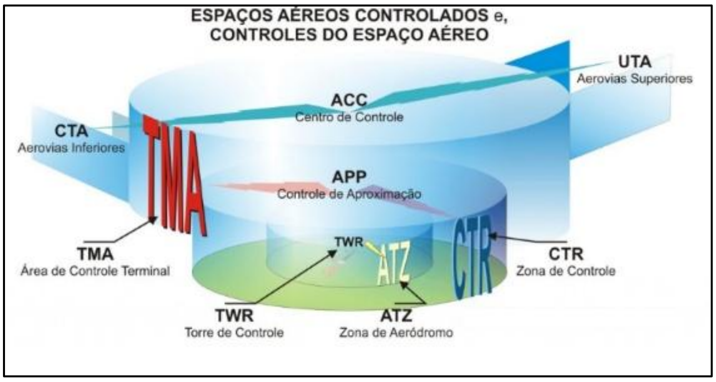

Figure 3: Operational Authority Jurisdiction.
Source: Authors, (2025).

Air Traffic Management (ATM) aims to dynamically and integratively coordinate air traffic and airspace, ensuring safety, efficiency, and cost-effectiveness in operations, while fostering collaboration among stakeholders [7][8].

ATM is directly related to air traffic demand, influencing flight planning and managing delays in landings and takeoffs at airports. Its structure is based on three key components: Air Traffic Service (ATS), Airspace Management (ASM) and Air Traffic Flow Management (ATFM)

Air Traffic Flow Management (ATFM) is a service designed to ensure safe, organized, and efficient traffic, enabling Air Traffic Control (ATC) to operate at full capacity, in accordance with the declared capacity set by the competent authority [8],[9].

ATFM seeks to balance capacity and demand, making the definition and understanding of key operational parameters essential for service efficiency. Its measures aim to maximize available capacity, adjusting the traffic flow along a route or at an aerodrome, preventing operational imbalances [10].

II.1.2 Performance-Based Management

The evaluation of organizational performance focuses on financial aspects, quality, and productivity, categorized into strategic goals (long-term objectives), tactical goals (process and personnel monitoring), and operational goals (real-time evaluation) [11],[12].

The International Civil Aviation Organization (ICAO) develops air navigation principles and promotes global transportation, encouraging performance benchmarking and the use of Key Performance Indicators (KPIs) to optimize sector management [13].

In Brazil, performance-based management seeks to optimize and efficiently utilize air traffic controllers' workforce, prioritizing performance, capacity, and resource management [14].

Performance indicators play a fundamental role in measuring results, ensuring higher quality and efficiency in decision-making and risk mitigation [15]. These indicators are classified as objective (unambiguous measurement) and subjective (requiring contextual interpretation) [16]. Their proper application enhances strategic decision-making and optimizes available resources [17].

Additionally, these indicators help in defining priorities and continuously evaluating processes, enabling adjustments and effective monitoring of organizational impacts [18]. In the corporate sector, they support structured strategic planning [19] and establish technical foundations for regulatory recommendations and program implementation [20].

In the air transport sector, performance analysis is becoming increasingly relevant, highlighting the importance of indicators for evaluating revenues, costs, and airport operations [21]. Identifying the relationship between demand, airport capacity, and flight punctuality underscores the importance of operational planning [22].

KPIs are essential for continuous improvement, providing an objective view of organizational performance. They monitor, communicate objectives, motivate teams, and drive improvements, serving as essential tools for efficient and sustainable management [23].

The definition of Key Performance Areas (KPA) represents management methodologies that reflect an organization's strategic vision [24]. The critical elements for process management include monitoring and effective process control, with the identification of relevant KPIs being essential for evaluating the analyzed processes [25].

KPIs represent key metrics in quantifying process performance and are widely recognized as fundamental elements in planning and control. Their relevance lies in providing critical information that supports more precise decision-making [26],[27].

The Department of Airspace Control (DECEA) adopted ICAO's 2016 performance indicators through DOC 9750-NA/963 – 2016-2030 (Global Air Navigation Plan - GANP), which established 19 KPIs aimed at verifying whether these indicators accurately express the intent of specific objectives [28].

Thus, metrics can represent past, present, and future performance, correlating with organizational objectives to support a more effective performance management strategy.

II.1.3 Application of the Business Process Management Cycle

Business Process Management (BPM) is an approach that has gained increasing interest among administrators and managers due to its ability to optimize organizational outcomes. The collaborative nature of BPM emerged in the 1990s, introducing a new administrative approach focused on restructuring and improving organizational processes [29].

BPM is widely recognized in specialized literature as an essential strategy for improving operational efficiency. According to [30], early studies highlighted the importance of process reengineering as an effective means to transform organizations and achieve substantial performance gains.

The theory of processes, as proposed by [31], provides the foundation for BPM by viewing organizational activities as interconnected elements aimed at continuous optimization. At the same time, the continuous improvement perspective promotes an incremental approach to enhancing efficiency and quality [32].

In the context of organizational innovation, [33] emphasizes the importance of adopting innovative practices aligned with BPM, encouraging the integration of advanced technologies, such as automation and process analytics.

The practical application of BPM is supported by numerous benefits, including: Increased operational efficiency, Improved process visibility and control, Greater adaptability to business environment changes na Enhanced quality and consistency of products and services. These aspects are widely discussed in [34] and [35].

Furthermore, [36] highlights the growing relevance of process automation and the integration of emerging technologies, such as artificial intelligence and predictive analytics, within BPM. These innovations reflect the continuous development and adaptation of BPM to the modern business landscape.

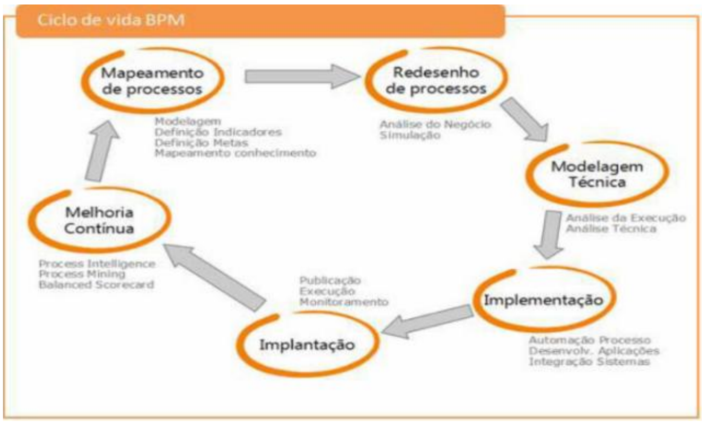

Figure 4: BPM Cycle.
Source: [36].

III. MATERIALS AND METHODS

In 2016, DECEA initiated a study to implement performance-based management as a method for measuring results. The initial findings were published in the SISCEAB Performance Report 2017, marking a significant milestone in the analysis of performance-based management in Brazil.

From this standpoint, airports were selected based on their relevance and flight volume within Brazilian airspace. In the São Paulo Terminal Control Area (TMA – SBXP), the international airports of Guarulhos (SBGR), Congonhas (SBSP), and Campinas (SBKP) were chosen due to their status as major national hubs. Additionally, Belém Val-de-Cans International Airport (SBBE) and Manaus Eduardo Gomes International Airport (SBEG) were included in the Northern Region because of their high traffic volume, significant cargo transportation, and important strategic infrastructure. This thoughtful selection allows for a comprehensive analysis of national air traffic, encompassing both key connection hubs and regional logistics centers.

The calculation of Key Performance Indicators (KPIs) in this study follows the ATM indicators methodology from SISCEAB. Airlines aim to optimize their gate-to-gate operational costs through flight efficiency by using KPI 02 and KPI 13 to measure discrepancies in unimpeded times.were included in the

Northern Region due to their high movement volume, cargo transportation, and strategic infrastructure. This strategic selection enables a comprehensive analysis of national air traffic, covering both key connection hubs and regional logistics centers.

The calculations of the Key Performance Indicators (KPIs) in this study follow the methodology of ATM indicators from SISCEAB [37]. Airlines, through flight efficiency, aim to optimize gate-to-gate operational costs by using KPI 02 and KPI 13 to measure discrepancies in unimpeded times

It is important to highlight that taxi time is defined as the difference between gate departure and takeoff for KPI 02, and the difference between landing and gate arrival for KPI 13.

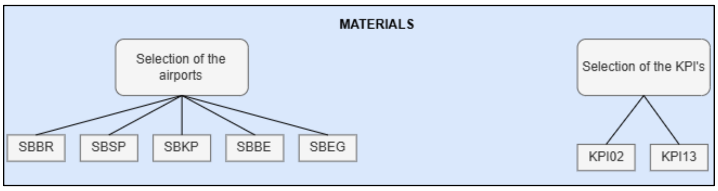

Figure 5: Selection of Airports and KPI's.
Source: Authors, (2025).

The variability of these times directly impacts the planning of air operations. Thus, taxi time indicators are essential for airlines and airport administrators, as they support the optimization of operational efficiency by providing data-driven insights based on reliable sources.

The study adopted a retrospective, documentary, exploratory, descriptive, and analytical approach, using data from the Airspace Control Institute (ICEA), under the jurisdiction of DECEA, as well as the ATM Performance Reports from SISCEAB and ANAC (2023).

The research covers all Air Navigation Service Providers (ANSPs) in Brazil that use the TATIC FLOW System, with the sample comprising records of landings and takeoffs from scheduled commercial flights registered in this system in 2023 at airports monitored under the Aeronautics Command Plan and selected for this study [38].

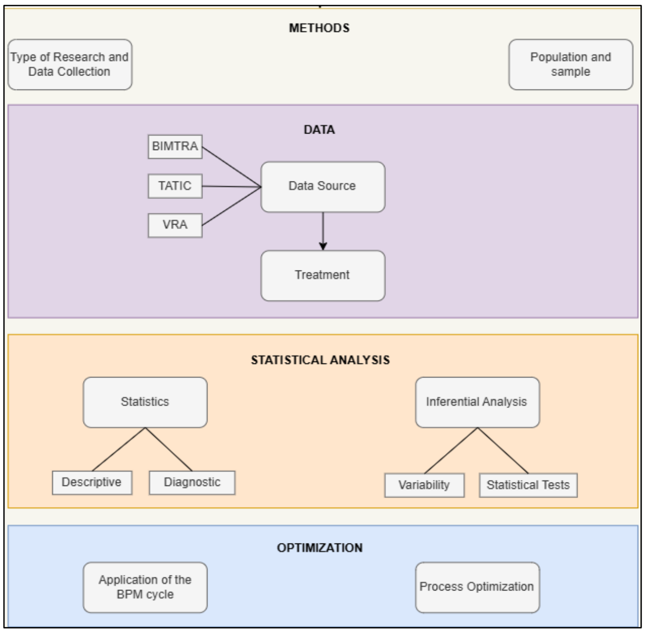

Figure 6: Methodology.
Source: Authors, (2025).

The data sources used in the study included TATIC FLOW, the Air Traffic Movement Information Database (BIMTRA), and the Active Scheduled Flight (VRA) system, which are used to measure air traffic control tower (TWR) performance and assess the operational efficiency of the selected indicators. Data processing involved the preparation, organization, and cleaning of the collected information, ensuring its quality and reliability before analysis.

Thus, two datasets were constructed from commercial flight records based on movements registered in the TATIC FLOW System: the first dataset analyzed KPI 02, containing 290.133 records, of which 0.57% (1,649 records) were excluded due to negative times or values exceeding 40 minutes. The second dataset, related to Additional Taxi-In Time (KPI 13), included 291.170 records, with 0.39% (1,138 records) removed for not meeting the established criteria.

Additionally, cross-validation was performed between the BIMTRA, TATIC FLOW, and VRA systems to ensure data consistency. In other words, the same movement recorded in the TATIC FLOW system was also found in BIMTRA and VRA, allowing for accurate comparisons.

After applying the exclusion criteria, 288.484 takeoff movements and 290.032 landing movements were considered, ensuring a solid foundation for subsequent analyses.Statistical analysis was essential for data interpretation and followed complementary steps to ensure a detailed and robust approach. Initially, a descriptive and diagnostic analysis of the data was conducted, identifying patterns and discrepancies through graphs, measures of central tendency, and dispersion statistics.

Next, variability analysis was performed using metrics such as variance, standard deviation, and interquartile range to assess data fluctuation. To test hypotheses, non-parametric statistical tests such as Mann-Whitney and Kruskal-Wallis were applied. The choice of tests was based on the most suitable approach given the characteristics of the data, including distribution, variability, and independence, ensuring a systematic and reliable analysis.

A Business Process Management (BPM) cycle was applied, focusing on optimizing efficiency and the quality of organizational processes. This cycle involved six key phases: Planning, Analysis, Modeling, Implementation, Monitoring, and Process Optimization.

IV. RESULTS AND DISCUSSIONS

The application of the BPM Cycle was designed to integrate new data sources for obtaining ATM performance indicators in Brazil. During the Planning phase, processes and responsible parties were identified using flow diagrams and quality tools, such as the Cause-and-Effect diagram.

This highlighted the need for more reliable sources to enhance the accuracy of indicator calculations. In the Process Analysis phase, we evaluated inefficiencies and explored new data sources, including BIMTRA and VRA. Key variables, such as takeoff (ATOT) and gate departure (AOBT) for KPI 02, as well as gate arrival (AIBT) and landing (ALDT) for KPI 13, were analyzed. These variables are crucial for measuring taxi times and improving the accuracy of calculations.

Table 1: Combination for KPI 02.

Combination	Metric 01	Metric 02
1ª Combination	ATOT (TATIC FLOW)	AOBT (TATIC FLOW)
2ª Combination	ATOT (TATIC FLOW)	AOBT (VRA)
3ª Combination	ATOT (BIMTRA)	AOBT (TATIC FLOW)
4ª Combination	ATOT (BIMTRA)	AOBT (VRA)

Source: Authors, (2025).

The Process Modeling phase proposed four combinations of data sources for each KPI, allowing for comparisons and greater efficiency in the indicators, as shown in Tables 1 and 2.

Table 2: Combination for KPI 13.

Combination	Metric 01	Metric 02
1ª Combination	AIBT (TATIC FLOW)	ALDT (TATIC FLOW)
2ª Combination	AIBT (TATIC FLOW)	ALDT (BIMTRA)
3ª Combination	AIBT (VRA)	ALDT (TATIC FLOW)
4ª Combination	AIBT(VRA)	ALDT (BIMTRA)

Source: Authors, (2025).

For the statistical tests, significance levels were considered as described in Table 3.

Table 3: Test Statistic.

p-Value	Level of Significance
*	< 0.05
**	< 0.01
***	< 0.001
ns	>= 0.05

Source: Authors, (2025).

Process implementation integrates advanced technologies and training to optimize activities, reducing manual interventions.

Process Monitoring established a control system to measure KPI effectiveness, ensuring agile adjustments and identifying opportunities for continuous improvement.

Finally, Process Optimization leveraged monitored data for operational adjustments and refinement of analyses, enhancing efficiency and adaptability to organizational needs. Using KPIs and dashboards ensured data-driven decision-making, reinforcing the application of the BPM Cycle in air traffic management.

Table 4 presents the number of landings and takeoffs per airport in 2023.

Table 4: Movimento de aeronaves.

Operação	Aeroporto				
	SBGR	SBSP	SBKP	SBBE	SBEG
Decolagem	110.095	91.557	59.518	14.365	12.949
Pouso	110.904	92.202	59.738	14.335	12.853
Total	**220.999**	**183.759**	**119.256**	**28.700**	**25.802**

Source: Authors, (2025).

Guarulhos Airport (SBGR) recorded the highest number of operations, totaling 220.999 movements, followed by Congonhas (SBSP) with 183.759 and Campinas (SBKP) with 119.256. In the North Region, Belém (SBBE) and Manaus (SBEG) had lower volumes, with 14.365 and 12.949 takeoffs and 14.335 and 12.853 landings, respectively. These figures highlight the concentration of traffic in the country's main TMAs, particularly in São Paulo, while also emphasizing the lower operational demand in Northern airports, despite their strategic importance in air transport and logistics.

The analysis of Taxi-Out Times revealed an average close to 15 minutes and a median around 14 minutes, indicating slight asymmetry in the distribution, as the mean is slightly higher. The standard deviation ranges between 0.0035 and 0.0038, suggesting moderate variation but no significant fluctuations, reinforcing operational consistency.

Comparing different data sources, the 3rd and 4th combinations showed similar averages and medians, demonstrating that the use of TATIC or BIMTRA does not significantly impact the recorded times. Thus, the analysis suggests that the Taxi-Out process is stable and predictable, supporting efficient air traffic management, as shown in Figure 6.

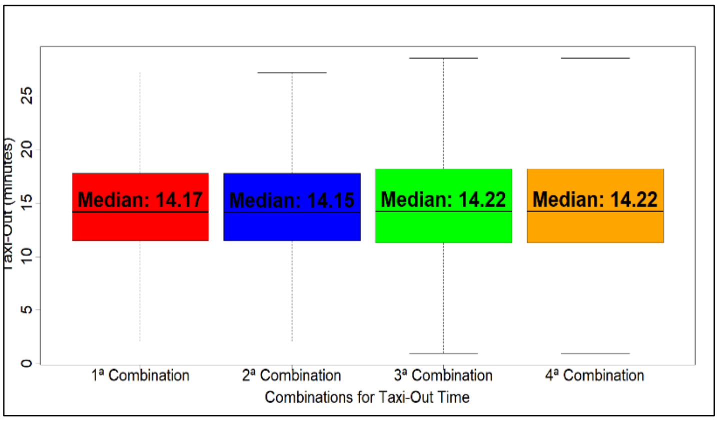

Figure 6: *Taxi-Out* Time.
Source: Authors, (2025).

The variability analysis of Taxi-In Time at the studied airports revealed significant differences among the data source combinations, as shown in Figure 7.

In the 1st and 2nd combinations, which considered only variants from the TATIC source, the mean values were 2m46s and 2m49s, respectively, while the medians were 1m45s and 1m46s, suggesting the presence of outliers that increase the mean. The standard deviation of 0.13s indicates that most values are concentrated near the median.

In the 3rd and 4th combinations, the distributions were more symmetrical, with means of 6m06s and 6m09s and medians of 5m23s and 5m25s, respectively. The standard deviation remained low at 0.14s, suggesting greater homogeneity. Overall, the 1st and 2nd combinations exhibited higher positive skewness due to extreme values, whereas the 3rd and 4th combinations were more balanced.

The low standard deviations reflect high consistency in the recorded times. However, the outliers in the 1st and 2nd combinations should be further investigated, as they may be related to atypical operational conditions. Additionally, the average Taxi-In times in the 3rd and 4th combinations, around 6 minutes, indicate the need for a comparative analysis with industry benchmarks to identify potential improvements in operational efficiency.

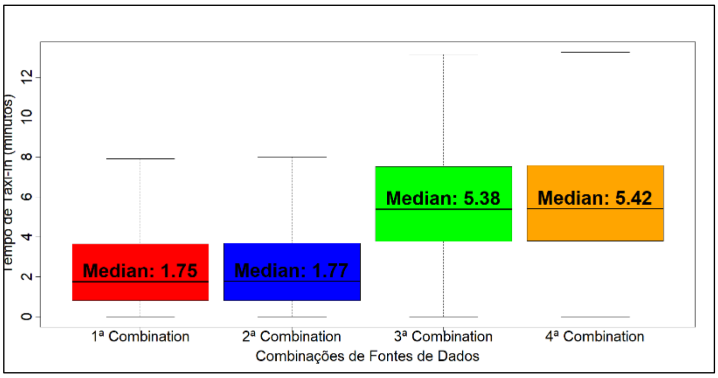

Figure 7: *Taxi-In* Time.
Source: Autor, (2024).

The analysis of Taxi-Out Time at the studied airports revealed significant variations across locations, reflecting traffic volume and the operational complexity of each airport, as shown in Figure 8 and Figure 9.

Congonhas (SBSP) recorded the highest average time (16m13s), followed by Guarulhos (SBGR) with 15m42s, while lower-traffic airports, such as Belém (SBBE) and Manaus (SBEG), had shorter times (11m27s and 13m, respectively).

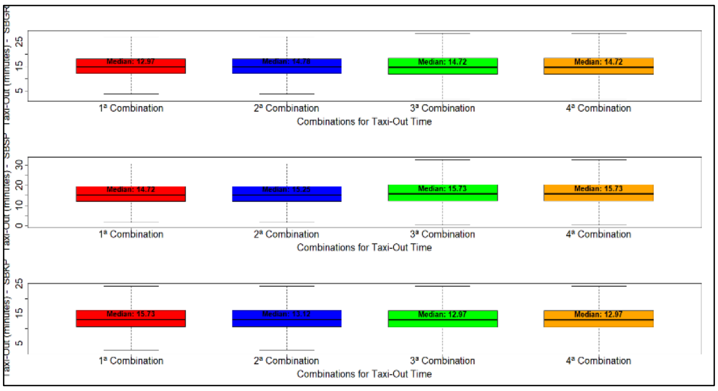

Figure 8: *Taxi-Out* Tima for SBGR, SBSP and SBKP.
Source: Authors, (2025).

The medians follow the same pattern, with SBSP and SBGR recording the highest values (15m15s and 14m47s), while SBBE and SBEG showed more stable times (11m04s and 12m22s).

The standard deviation, which measures time dispersion, was higher in SBSP (0.00384) and SBGR (0.00335), indicating greater variability, possibly due to high slot demand. In contrast, SBBE (0.00226) and SBEG (0.00229) had lower dispersion, suggesting higher operational efficiency.

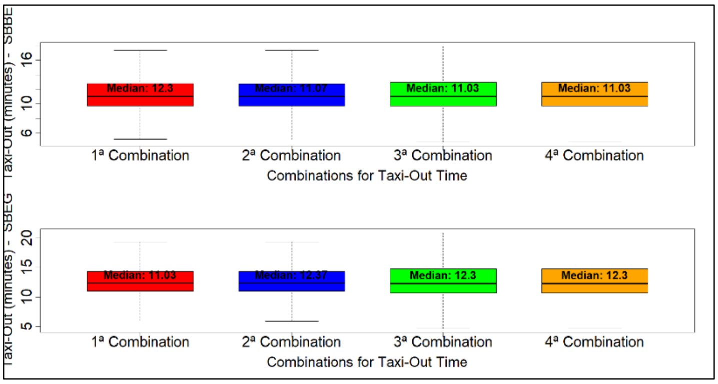

Figure 9: *Taxi-Out* Time for SBBE and SBEG.
Source: Authors, (2025).

The analysis of Taxi-In Times at the studied airports, as shown in Figure 10 and Figure 11, revealed distinct patterns in central tendency and dispersion. Guarulhos (SBGR) recorded the highest average times, reaching 3m56s in the 1st combination and 7m54s in the 3rd, reflecting a higher traffic volume and potential congestion. In contrast, Manaus (SBEG) had the lowest times, with 1m15s in the 1st combination, suggesting faster and more efficient taxiing.

The medians confirm this trend, with SBGR at 2m45s and SBEG at just 28s in the 1st combination, indicating greater dispersion in SBGR, where some flights experience significant delays. The standard deviation further reinforces this variability, being higher in SBGR (0.00257 in the 3rd combination) and lower in SBEG and SBKP, suggesting greater operational predictability at these airports.

These results highlight areas for improvement, such as traffic management adjustments and infrastructure optimization at SBGR, while SBEG can serve as a model for airports seeking greater efficiency and reduced taxiing times.

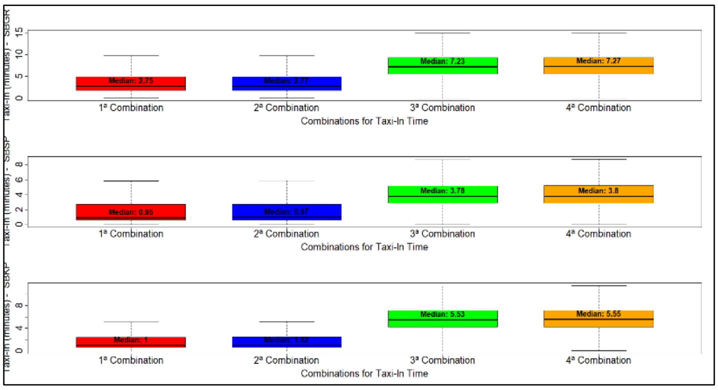

Figure 10: *Taxi-In* Time for SBGR, SBSP and SBKP.
Source: Authors, (2025).

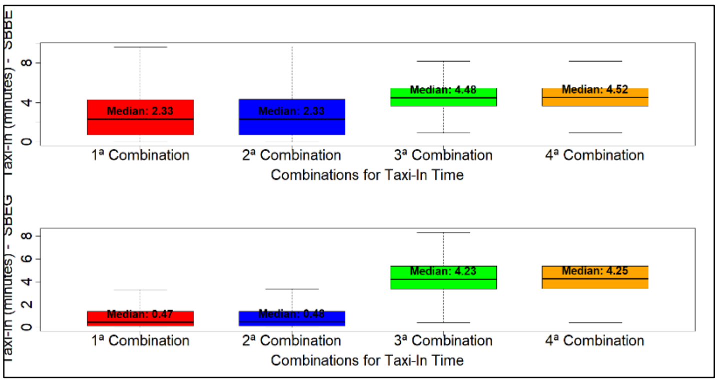

Figure 11: Taxi-In Time for SBBE and SBEG.
Source: Authors, (2025).

In this context, the study aimed to verify the existence of significant differences in taxiing times across the analyzed airports.

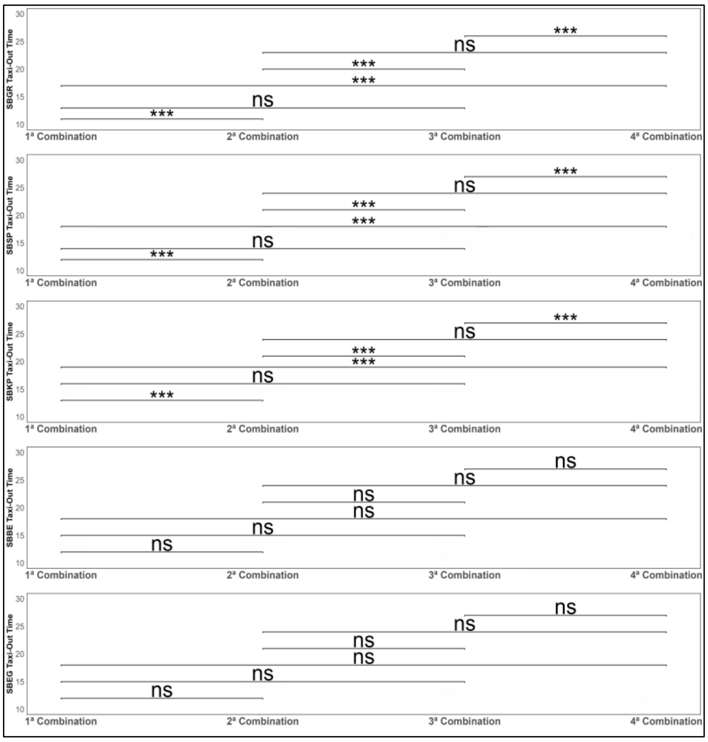

Figure 12: Combinations for *Taxi-Out* Time
Source: Authors, (2025).

Figure 12 showed statistically significant differences in Taxi-Out Time between certain combinations of data sources for airports SBGR, SBSP, and SBKP. In contrast, at Belém (SBBE) and Manaus (SBEG) airports, these variations were not as pronounced.

SBGR, recognized as one of the busiest airports in Brazil, exhibited low p-values, indicating considerable variability in taxi times due to its complex operations and high traffic volume. Congonhas (SBSP) also demonstrated significant differences, likely influenced by the high volume of domestic flights and infrastructure limitations. Campinas (SBKP), an essential hub for both cargo and passenger transport, also showed variations in taxi times, reflecting its connectivity for domestic and international flights.

In contrast, Belém (SBBE) and Manaus (SBEG) had no statistically significant differences between data combinations, possibly due to their lower traffic volumes and operational stability. Nevertheless, taxiing times at these airports are still affected by infrastructure, weather conditions, and logistical operations.

Given the relevant differences in taxiing times observed at SBGR, SBSP, and SBKP, operational efficiency could be enhanced by considering factors such as airport layout, taxiing routes, runway holding times, and distances between gates and runway thresholds. The key performance indicators (KPIs) associated with these times provide valuable insights to optimize air traffic flow, reduce excessive taxiing durations, and improve overall airport efficiency.

The analysis of Taxi-In Time comparisons (Figure 11) revealed statistically significant differences across all airports except for the comparisons between the 1st and 2nd datasets, as well as the 3rd and 4th datasets, as illustrated in Figure 13.

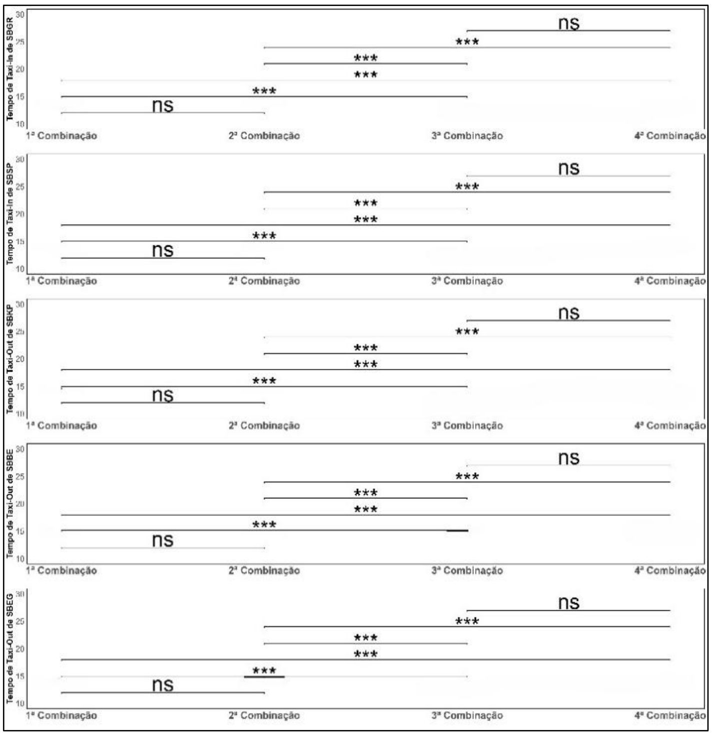

Figure 13: Combinations for *Taxi-In* Time.
Source: Authors, (2025).

At SBGR, SBSP, and SBKP, the comparisons between the 1st and 2nd combinations did not show significant differences (p = 0.61, 0.51, and 0.49, respectively).

However, when comparing the 1st combination with the 3rd and 4th, highly significant differences were observed (p < 2e-16), while the comparison between the 3rd and 4th combinations was not significant (p = 0.92, 0.91, and 0.93), indicating a higher similarity between the latter two.

At SBBE and SBEG airports, the results followed a similar pattern. Comparisons between the 1st and 2nd combinations, as well as between the 3rd and 4th combinations, showed no significant differences ($p \approx 0.99–1.00$). However, when the 3rd and 4th combinations were compared to the 1st, the differences were highly significant (p < 2e-16), suggesting that the 1st and 2nd combinations are more homogeneous, while the 3rd and 4th differ significantly.

These results indicate that while some combinations are statistically similar, others reflect more pronounced variations in Taxi-In Times, influenced by differences in data sources and the operational dynamics of the airports.

Additionally, considering the distances between gates and runway thresholds was essential, as they directly impact additional taxi time, affecting the airports' operational efficiency.

From this perspective, the study also aimed to assess whether taxi time variations, as combined from different data sources, would impact the efficiency of unimpeded taxi time indicators when considering different gate and runway threshold combinations.

For Guarulhos Airport (SBGR), the existence of two runways for landing and takeoff operations 10R/28R and 10L/28L was verified, as described in the airport chart (Figure 14).

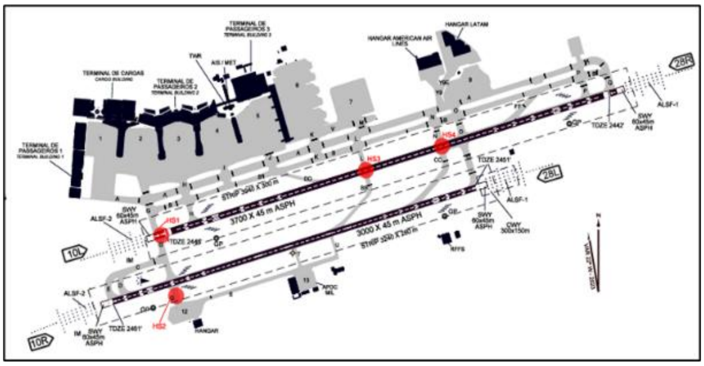

Figure 14: SBGR Airport Chart.
Source: Adapted from [39], (2025).

For departures, the most frequently used threshold was 10L, accounting for 75,04% (82.624) of movements, followed by 28R, 10R, and 28L, with 23,94% (26.353), 0,92% (1.012), and 0.10% (106) movements, respectively. For arrivals, 110.994 movements were recorded, with runway 10R handling the highest volume at 81.729 operations, while 28L registered 25.907 landings. Runways 10L and 28R had lower volumes, with 2.611 and 657 landings, respectively.

SBGR presented 462 possible gate and runway threshold combinations, a significant number that reflects its importance as the busiest airport in the country. The analysis of gate distribution revealed that demand was concentrated in six distinct aprons, with the combinations featuring the highest volume of landings and takeoffs selected for each of them.

Gate 207 with runway threshold 10L was the most frequent combination, recording 2.125 takeoffs (1,93%), followed by gates 309 (2.009; 1,82%), 102R (1.979; 1,80%), 401 (1.414; 1,28%), 501 (654; 0,60%), and 604 (288; 0,26%).

At runway threshold 28R, the most utilized gates were 102R, 209, 309, 401, 507R, and 606. Gate 209 led with 765 recorded takeoffs (0,70%), followed by gates 311 (711; 0,28%), 102R (648; 0,59%), 401 (547; 0,50%), 507R (189; 0,17%), and 606 (111; 0,10%). For arrivals (landings), 552 gate and runway threshold combinations were identified. Gate 208 was the busiest, with 2.183 landings (1,97%), followed by gates 310 (2.051; 1,85%), 102R (1.873; 1,69%), 401 (1.531; 1,38%), 504R (553; 0,50%), and 612L (181; 0,16%), all combined with runway 10R.

At runway threshold 28L, gates 102R, 209, 309, 401, 507R, and 606 recorded the highest landing volumes. Gate 209 was the most utilized (765 landings; 0,69%), followed by gates 309 (707; 0,64%), 102R (648; 0,58%), 401 (528; 0,48%), 507R (173; 0,15%), and 606 (58; 0,05%). Figure 15 revealed significant differences between the gates and runway threshold 10L in most comparisons, indicating relevant operational variations. Gates 102R, 207, 309, 401, and 501 showed consistent differences among themselves, reflecting distinct impacts on taxi times.

However, the comparison between gates 501 and 604 resulted in $p = 0.07$, suggesting no significant difference, possibly due to operational similarities or physical proximity. These findings reinforce the need to consider gate variability in airport planning, optimizing operational efficiency and air traffic flow.

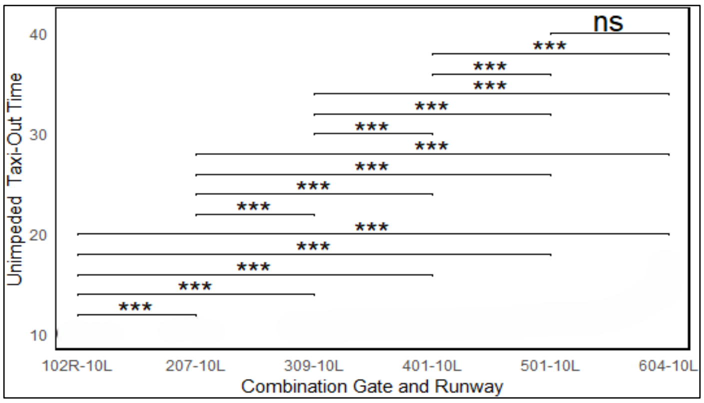

Figure 15: Combination of gate and runway 10L for KPI 02.
Source: Authors, (2025).

The analysis of Unimpeded Taxi-Out Times for gates using runway threshold 28R revealed statistically significant differences among gates 102R, 209, 311, 401, 507R, and 604, as presented in Figure 16.

These variations indicate relevant operational differences, suggesting that gate allocation directly influences taxi time efficiency. The results reinforce the need for strategic adjustments in gate utilization to optimize airport resource management and improve operational flow at runway threshold 28R.

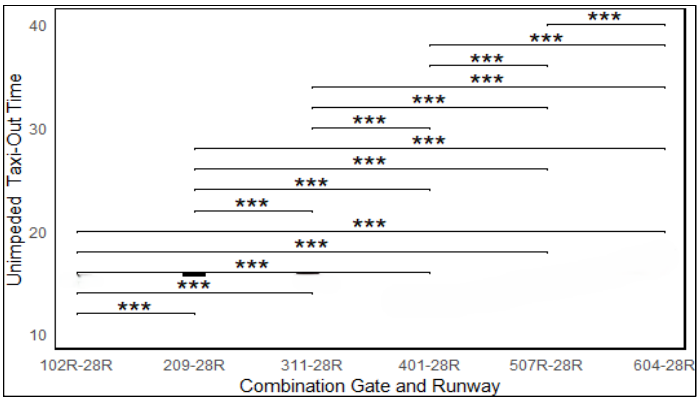

Figure 16: Combination of gate and runway 28R for KPI 02.
Source: Authors, (2025).

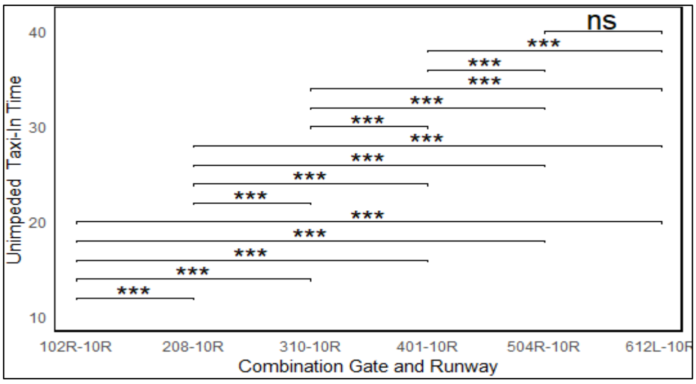

Figure 17: Combination of gate and runway 10R for KPI 13.
Source: Authors, (2025).

Figure 17 showed the combination of gate and runway threshold at threshold 10R, revealing statistically significant differences among gates 102R, 208, 310, 401, 504R, and 612L, with $p < 0.001$ for most comparisons. The exception was the comparison between gates 504R and 612L ($p = 0,48$), which showed no significant difference.

Figure 18 described the combinations of gate and runway threshold 28L, revealing statistically significant differences among gates 102R, 209, 309, 401, 507R, and 606, except for the comparison between gates 507R and 606 ($p = 0.94$), which showed no relevant variation. For all other combinations, *p-values* were below 0.001.

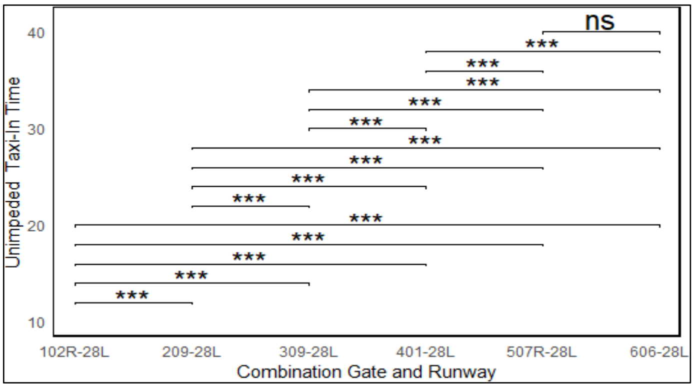

Figure 18: Combination of gate and runway 28L for KPI 13.
Source: Authors, (2025).

At Congonhas Airport (SBSP), landing and takeoff operations take place on two runways: 17R/35L and 17L/35R, as described in the airport chart (Figure 19).

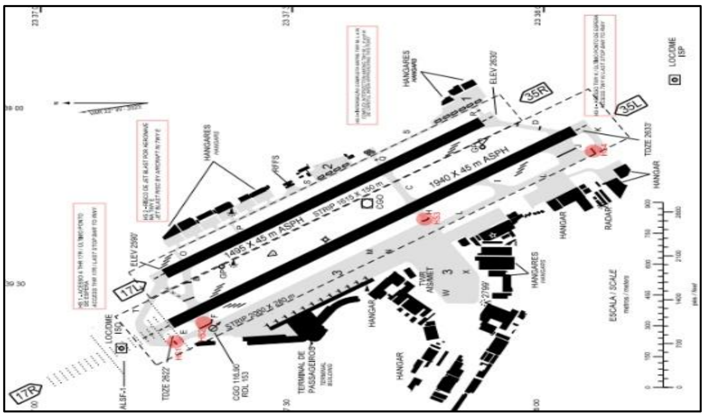

Figure 19: SBSP Airport Chart.
Source: Adapted from [39], (2025).

Runway threshold 17R was the most frequently used for takeoffs, accounting for 59,47% (54.449 movements), followed by 35L (38,55%; 35.296 movements), 17L (1,10%; 1.006 movements), and 35R (0,88%; 806 movements). For landings, threshold 17R also predominated, with 59,81% (55.145 movements), highlighting its significance in the distribution of air traffic at SBSP. The gate layout for Apron 3 at Congonhas Airport (SBSP) covered 84,75% (100) of possible modifications and 99,97% of movements (91.532). The apron has 30 gates, organized into six groups of five gates each, with each group represented by the gate with the highest number of movements.

SBSP identified 118 gate and runway threshold combinations for takeoffs, with gate 05 standing out, recording 2.622 departures (2,86%) when combined with runway 17R. At threshold 35L, gates 04, 06, 11, 16, 22, and 26 were analyzed as they had the highest traffic volumes. Gate 06 led with 1.712 recorded takeoffs (1,87%), followed by gates 04 (1.704; 1,86%), 11 (1.573; 1,72%), 16 (1.030; 1,12%), 22 (976; 1,07%), and 26 (915; 1,00%).

For arrivals, 130 gate and runway threshold combinations were identified, with gate 04 standing out, recording 2.644 landings (2,87%) when combined with runway 17R. Additionally, movements recorded at threshold 35L were analyzed, where gates 04, 06, 11, 16, 22, and 26 had high traffic volumes. Gate 04 had the highest number of recorded landings, with 1.753 arrivals (1,90%), followed by gates 06 (1.726; 1,87%), 11 (1.608; 1,74%), 16 (1.005; 1,09%), 21 (910; 0,98%), and 26 (843; 0,91%).

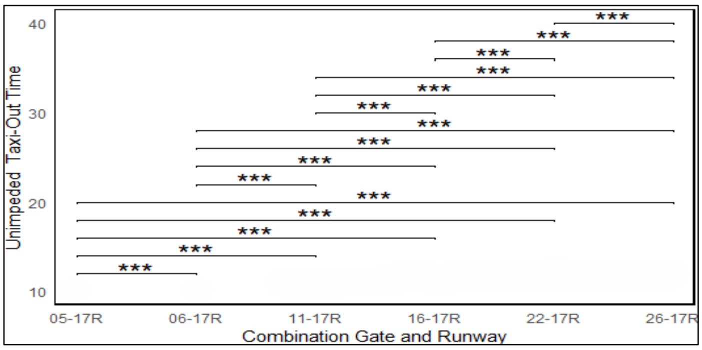

Figure 20: Combination of gate and runway 17R for KPI 02.
Source: Authors, (2025).

Figure 20 presents the analysis of Unimpeded Taxi-Out Times for each gate and runway threshold combination, revealing statistically significant differences for gates 05, 06, 11, 16, 22, and 26 when compared to runway threshold 17R.

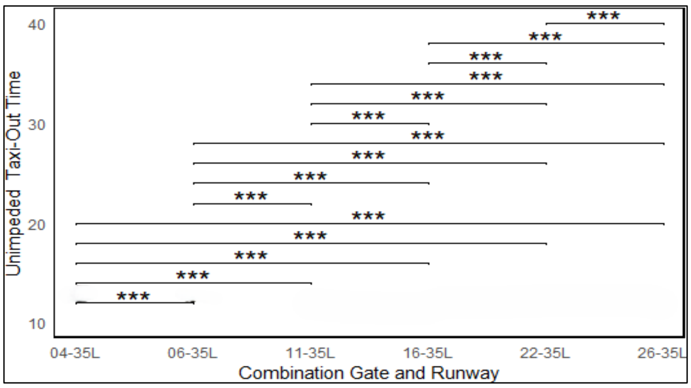

Figure 21: Combination of gate and runway 35L for KPI 02.
Source: Authors, (2025).

Figure 21 presented the combinations among the six groups, highlighting significant differences. In other words, variations were observed in the medians of the Unimpeded Taxi-Out Times for gates 04, 06, 11, 16, 22, and 26 at runway threshold 35L.

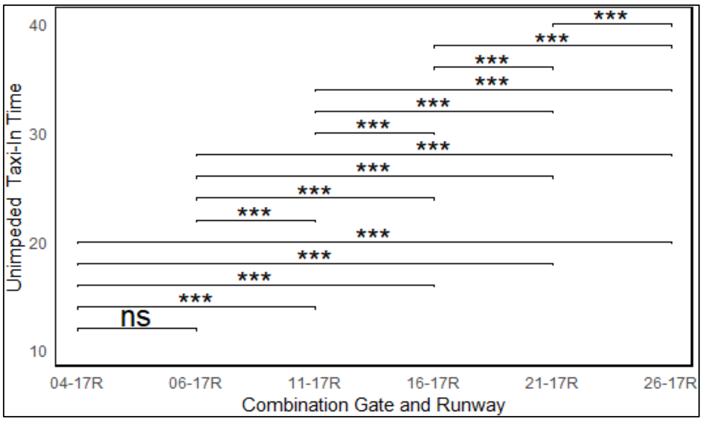

Figure 22: Combination of gate and runway 17R for KPI 13.
Source: Authors, (2025).

Figure 22 shows the combination of gate and runway threshold, revealing significant differences in the medians of gates 05, 06, 11, 16, 21, and 26 at runway threshold 17R. Except for the comparison between gates 04 and 06, where no significant difference was observed, all other combinations exhibited substantial variations in taxi times, with p-values below 0,001 in all comparisons.

Figure 23 presents the combinations of gate and runway threshold 35L, highlighting gates 04, 06, 11, 16, 22, and 26. Statistically significant differences were found among the medians.

The only exception was observed between gates 04 and 16, where no significant difference was found (p = 1.00). For all other comparisons, *p-values* were below 0,001, indicating highly significant differences and reinforcing the heterogeneity in taxi times among the analyzed groups.

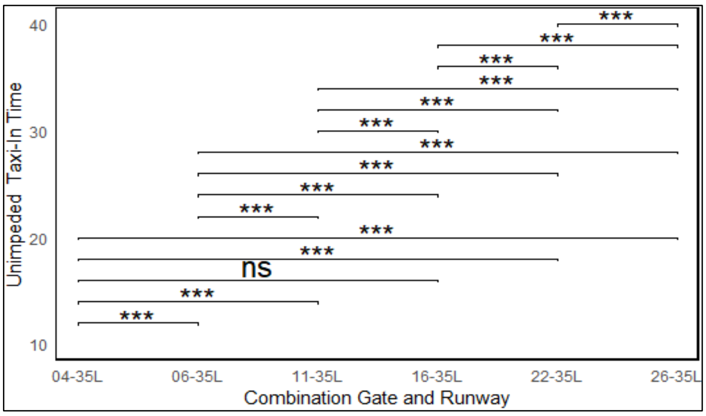

Figure 23: Combination of gate and runway 35R for KPI 13.
Source: Authors, (2025).

Campinas Airport (SBKP) has a single runway for landing and takeoff operations (15/33, Figure 24).

For takeoff operations, runway threshold 15 was the most utilized, accounting for 69,61% of the total (41.430 movements), while threshold 33 recorded 30,39% (18.088 movements). Similarly, threshold 15 predominated for landing operations, with 68,75% of movements (41.069 records).

These data highlight a clear operational preference for runway threshold 15 for landings and takeoffs, emphasizing its importance in the distribution of air traffic flows.

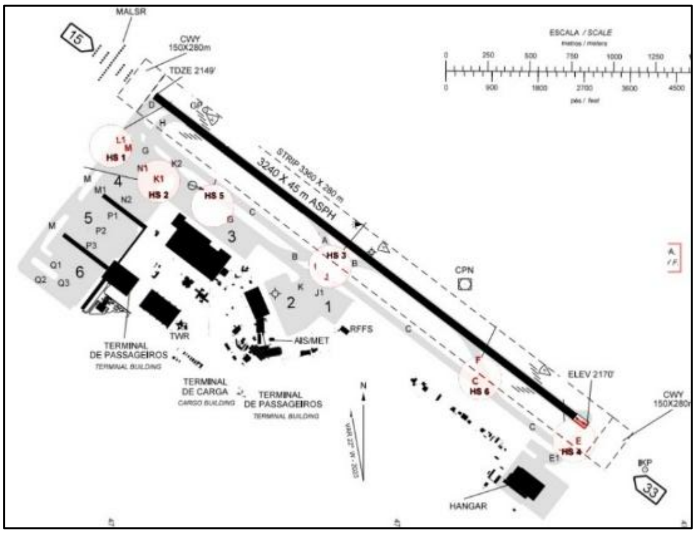

Figure 24: SBKP Airport Chart.
Source: Adapted from [39], (2025).

SBKP identified 177 gate and runway threshold combinations for takeoffs, with gate C02 standing out, recording 1.732 departures (2,91%) when combined with runway 15.

For threshold 33, gates B02, B13A, C02, M5, R7, and R9 were analyzed as they had the highest traffic volumes. Gate C02 led with 757 recorded takeoffs (1,27%), followed by B02 (631; 1,06%), B13A (293; 0,49%), M5 (139; 0,23%), R7 (129; 0,22%), and R9 (89; 0,15%).

For arrivals, 184 gate and runway threshold combinations were identified, with gate B02 standing out, recording 1.501 landings (2,51%) when combined with runway 15.

Similarly, gate and threshold combinations for runway 33 were analyzed, selecting gates B11, C04, C05, M5, R7, and T04, which had the highest traffic volumes. Gate C04 had the highest number of recorded movements, with 776 operations (1,30%), followed by C05 (661; 1,10%), B11 (290; 0,48%), R7 (136; 0,23%), M5 (128; 0,21%), and T04 (28; 0,05%).

Figure 25 reveals statistically significant variations in the medians of Unimpeded Taxi-Out Times for gates B02, B13A, C02, M5, R7, and R9 in relation to runway threshold 15. However, some differences among M5, R7, and R9 were not significant, as indicated by the *p-values*.

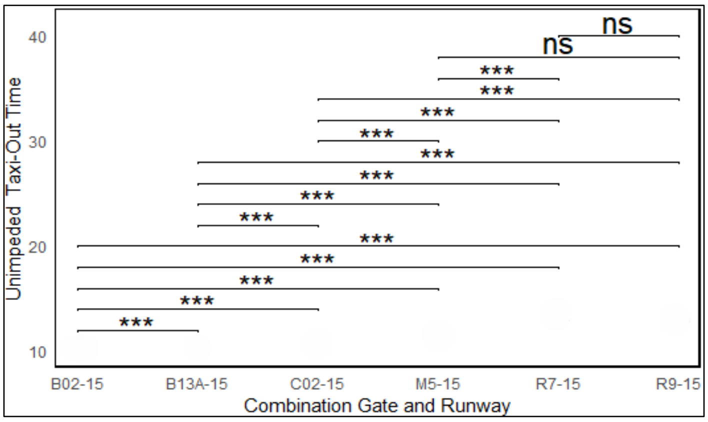

Figure 25: Combination of gate and runway 15 for KPI 02.
Source: Authors, (2025).

Figure 26 revealed statistically significant differences in the medians of Unimpeded Taxi-In Times for gates T3, R8, M5, C06, B02, and B13A in relation to runway threshold 15. The only exception was the comparison between T3 and R8 (p = 0.85), which showed no relevant variation.

Combinations involving M5, C06, B02, and B13A exhibited consistent differences among themselves, with *p-values* below 0,001, highlighting the variability in KPI 13 as a function of the gates and the runway threshold used.

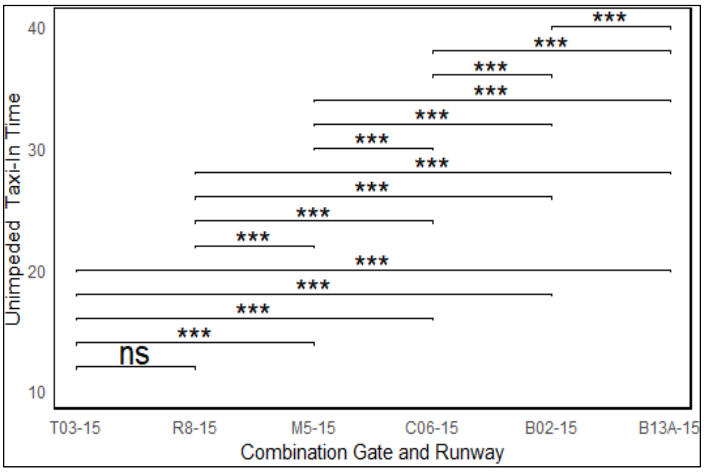

Figure 26: Combination of gate and runway 15 for KPI 13.
Source: Authors, (2025).

For Belém Airport (SBBE), the existence of two runways for landing and takeoff operations 06/24 and 02/20 was verified (Figure 27).

It was verified that, for both takeoffs and landings, runway threshold 06 was the most utilized, accounting for 90,94% (13.064) and 92,28% (13.229) of movements, respectively.

The analysis of gate and runway threshold combinations at Belém Airport (SBBE) identified 72 combinations for departures and 63 for arrivals, with aprons 3 and 4 concentrating 98,30% of departure movements (14.121 records in 2023). These aprons contain 12 gates, divided into six groups of two, represented by the gates with the highest traffic volumes.

Gate 04 recorded 1.969 departures (13,71%) and gate 05 had 1.959 departures (13,64%), both combined with runway threshold 06. For threshold 02, gates 02, 04, 05, 07, 08, and 12 had the highest departure volumes, with gate 04 leading (160 records; 1,11%), followed by gates 05 (150; 1,04%), 02 (147; 1,02%), and 12 (145; 1,01%).

For arrivals (landings), gate 04 was also the busiest, with 1.942 recorded landings (13,54%), followed by gate 05 (1.915; 13,36%), both combined with runway threshold 06. For threshold 02, gates 02, 04, 05, 07, 10, and 12 recorded the highest landing volumes, with gate 05 being the most utilized (163 records; 1,14%), followed by gates 04 (150; 1,05%) and 02 (134; 0,46%).

The data indicate that gates 04 and 05 were the most active for both departures and arrivals, highlighting an operational concentration and a decreasing distribution among other gates, reflecting strategic traffic management patterns at SBBE.

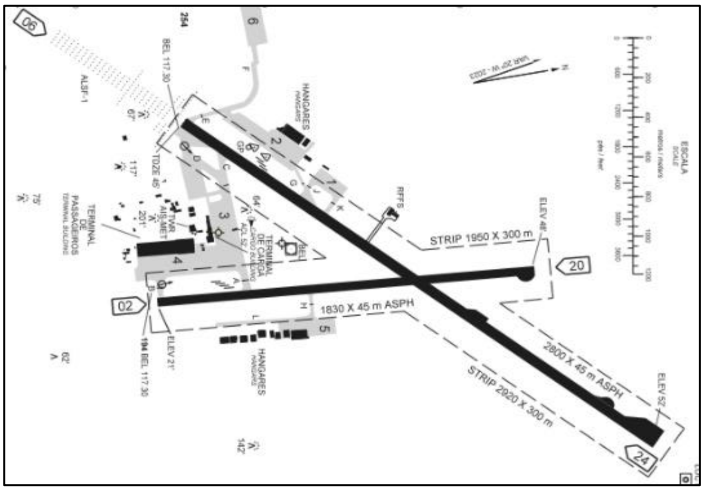

Figure 27: SBBE Airport Chart.
Source: Adapted from [39], (2025).

Figure 28 presents the analysis of Unimpeded Taxi-Out Times for each gate and runway threshold combination, revealing statistically significant differences.

Observing the combinations of gates 02, 04, 05, 07, 08, and 12 with runway threshold 06, the differences in the medians of Unimpeded Taxi-Out Times were found to be highly significant, as indicated by the *p-values*. This result suggests that, for runway threshold 06, there are substantial variations in taxi times depending on the gate used, reflecting operational and logistical differences for each combination.

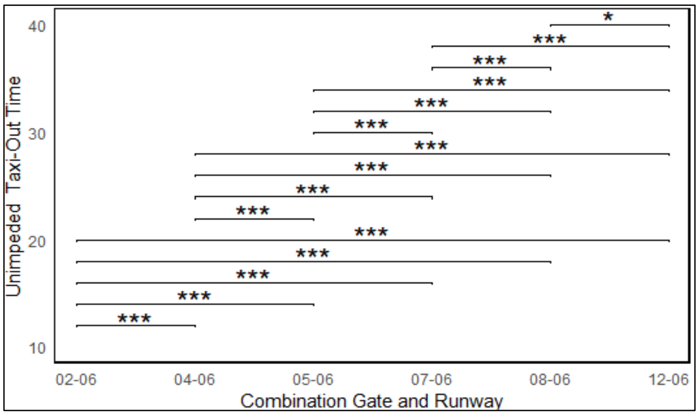

Figure 28: Combination of gate and runway 06 for KPI 02.
Source: Authors, (2025).

Figure 29 presents the analysis of combinations among gates 02, 04, 05, 07, 08, and 12, considering runway threshold 06, revealing statistically significant differences in the medians of Unimpeded Taxi-Out Times in most comparisons. The exceptions were the combinations between gates 02 and 07, 04 and 07, 07 and 08, and 08 and 12, which showed no statistically relevant variations.

These results indicate that, although some combinations did not exhibit significant differences, Unimpeded Taxi-Out Times show substantial variations among the analyzed gates. Notably, gate 12 stood out for having the largest observed difference, suggesting a significant impact on operational efficiency depending on the configuration used.

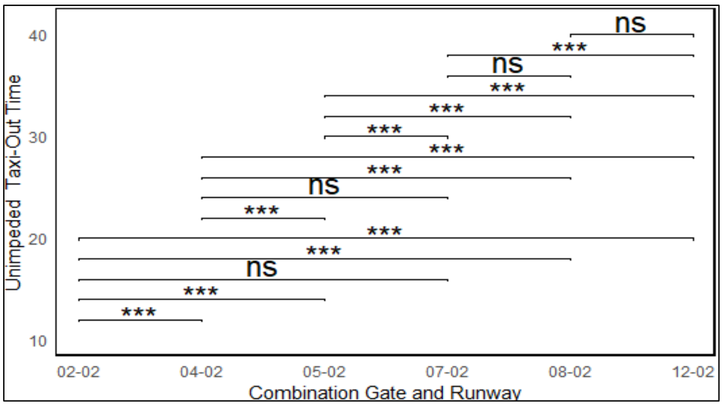

Figure 29: Combination of gate and runway 02 for KPI 02.
Source: Authors, (2025).

The analysis of runway threshold 02 revealed statistically significant differences among the median times of the analyzed gates, as shown in Figure 30.

Comparisons between gates 02 and 04, 02 and 05, 02 and 07, 02 and 10, and 02 and 12 presented *p-values* < 0.001, indicating significant variations in Unimpeded Taxi-In Times for these combinations. The only exception was the comparison between gates 10 and 12, which did not show a statistically significant difference.

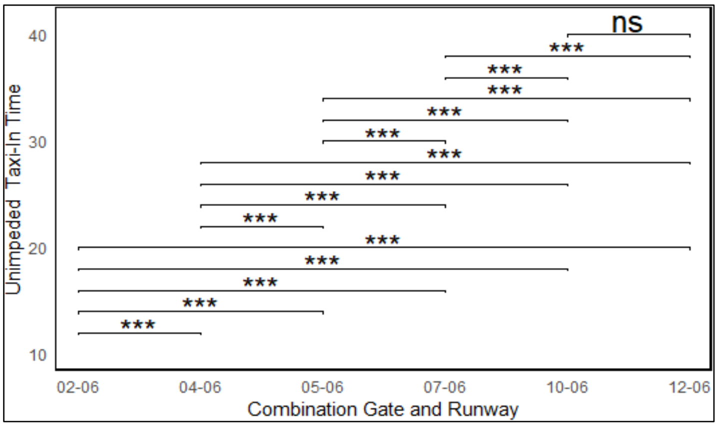

Figure 30: Combination of gate and runway 06 for KPI 13.
Source: Authors, (2025).

Figure 31 illustrates the runway threshold 02 combination, revealing statistically significant variations among gates 02, 04, 05, 07, 10, and 12, except for comparisons between gates 04 and 12, and gates 07 and 10, which showed no relevant differences.

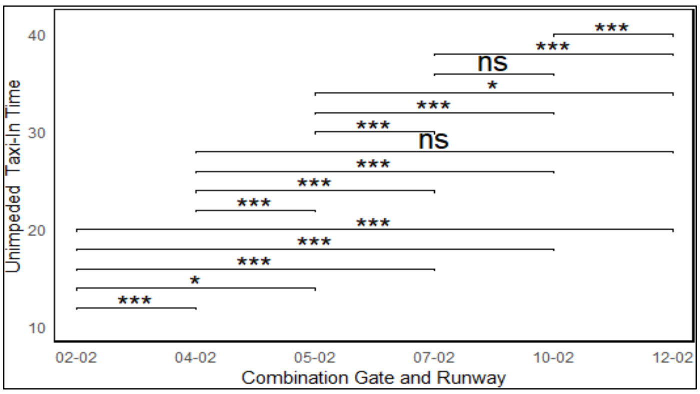

Figure 31: Combination of gate and runway 02 for KPI 13.
Source: Authors, (2025).

The results indicate that Taxi-In Unimpeded Times differ substantially among gate combinations, notably between gates 02 and 10 ($p < 0.001$), and between gate 05 and other gates, demonstrating statistically significant differences.On the other hand, gates 04 and 12 showed similar taxi times, as did gates 07 and 10, whose comparison yielded a *p-value* of 0,3988, suggesting comparable taxi-in times. At Manaus Airport (SBEG), there is a single runway (11/29) used for both landing and take-off operations (Figure 32).

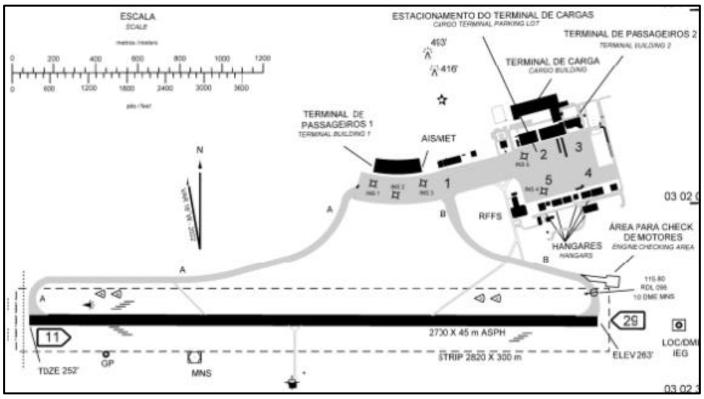

Figure 32: SBEG Airport Chart.
Source: Adapted from [39], (2025).

For departures, runway threshold 11 was the most frequently used, representing 94,49% of the operations (12.235 movements), whereas runway threshold 29 accounted for only 5,51% (714 movements). In landings, runway threshold 11 also predominated, accounting for 97,02% of operations (12.470 movements), while runway threshold 29 was utilized in just 2,98% of cases (383 movements). These data indicate a strong operational preference for runway threshold 11, both for takeoffs and landings, possibly influenced by factors such as prevailing winds, airport infrastructure, and the established air traffic flow patterns.

At SBEG, 67 combinations of gates and runway thresholds were identified for departures and 78 for arrivals. Apron 1 concentrated 87,79% of departures (11.369 movements in 2023) and is configured with 18 gates divided into 6 groups of 3, each represented by the gate with the highest activity. The most frequently used combination for commercial flights was gate B18 with runway threshold 11, totaling 1.764 departures (13,62%). In the analysis of operations using runway threshold 29, gates B18, E15, R20, R21, R23, and R26 were selected due to their higher traffic volumes. Gate R20 registered 121 movements (0,93%), followed by gates R21 (81; 0,63%), B18 (70; 0,54%), R23 (36; 0,28%), E15 (31; 0.24%), and R26 (13; 0.10%).

For arrivals (landings), 78 combinations of gates and runway thresholds were identified, notably gate B18, which received 1,774 landings (13,80%), followed by gates C17 (1.725; 13,42%), R20 (1.052; 8,18%), R26 (600; 4,67%), F14 (485; 3,77%), and R22 (268; 2,08%), all operating with runway threshold 11. Similarly, for runway threshold 29, gates B18, C17, F14, R20, R22, and R25 were selected due to their higher landing volumes.

Figure 33 shows gate-runway threshold combinations at SBEG, revealing statistically significant differences among gates A19, B18, E15, R21, R24, and R25 for runway threshold 11. Comparisons between gates A19 and B18 indicated statistically relevant differences ($p < 0.001$), suggesting distinct taxi times between these gates. The same pattern was observed for gate E15, which demonstrated significant variations compared to gates A19 and B18.

Significant differences were also identified in comparisons among gates R21, R24, and R25, all presenting extremely low *p*-values ($p < 0.001$), reinforcing the substantial variation in taxi times across the analyzed gates.

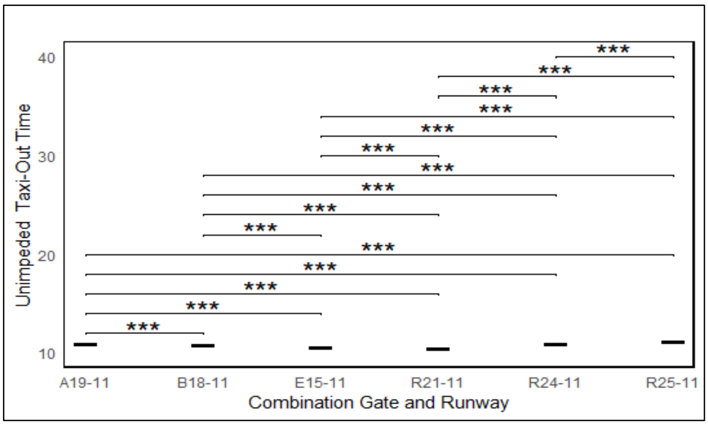

Figure 33: Combination of gate and runway 11 for KPI 02.
Source: Authors, (2025).

Figure 34 presents gate-runway threshold 29 combinations, revealing statistically significant differences. Comparisons indicated substantial variations among median unimpeded taxi-out times for gates B18, E15, R20, R21, R23, and R26. However, no significant differences were observed in the combinations between gates B18 and R23, B18 and R26, and E15 and R26, suggesting these gates have similar taxi times.

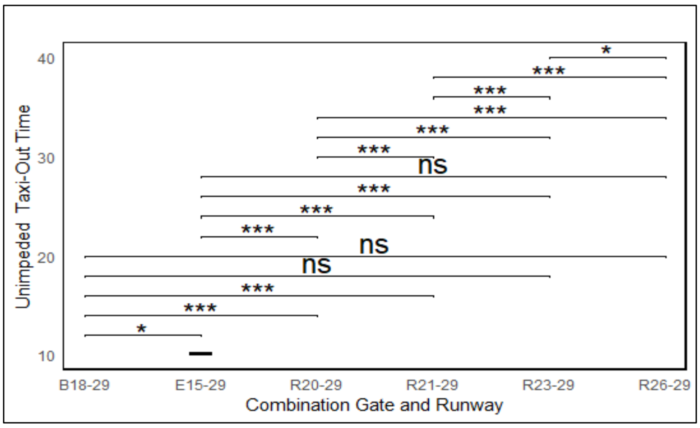

Figure 34: Combination of gate and runway 29 for KPI 02.
Source: Authors, (2025).

Figure 35 shows the gate-runway threshold 11 combinations, revealing statistically significant differences.

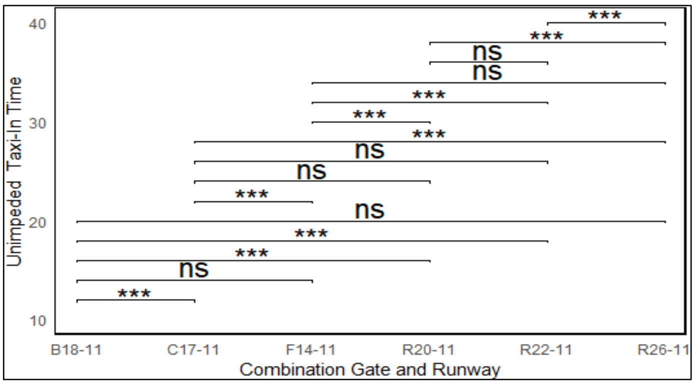

Figure 35: Combination of gate and runway 11 for KPI 13.
Source: Authors, (2025).

Gates B18, C17, F14, R20, R22, and R26 showed variations in median unimpeded taxi-in times, indicating distinct operational impacts among these combinations. However, no significant differences were observed in comparisons between gates B18 and F14, B18 and R26, C17 and R20, C17 and R22, F14 and R26, and R20 and R22, suggesting these gate pairs have similar taxi times.

Finally, Figure 36 describes gate-runway threshold 29 combinations, revealing statistically significant differences. Gates B18, C17, F14, R20, R22, and R25 showed variations in median unimpeded taxi-in times, indicating operational discrepancies among these combinations. However, no significant differences were observed in comparisons between gates B18 and F14, B18 and R20, C17 and R25, and R20 and R22, suggesting similar taxi times among these gate pairs.

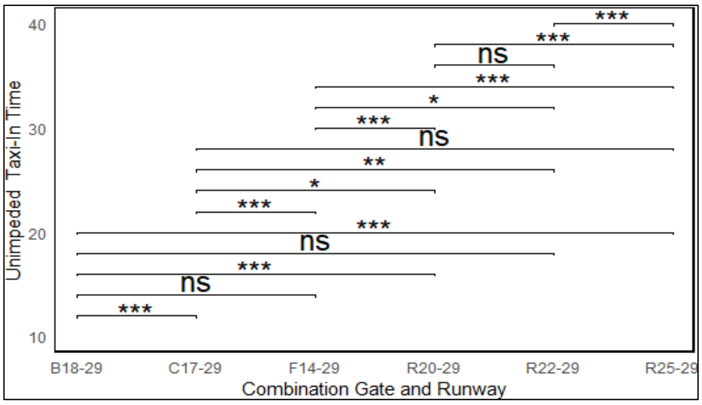

Figure 36: Combinação de Gate e Runway 29 para KPI 13.
Source: Authors, (2025).

V. CONCLUSIONS

The assessment of key performance indicators of the Brazilian Airspace Control System (SISCEAB) was essential to this study. It highlighted that out of the 19 KPIs and 7 IDBRs described in MCA 100-22, only 10 KPIs and 1 IDBR are currently monitored by DECEA.

An analysis of data sources (TATIC FLOW, BIMTRA, and VRA) revealed significant discrepancies in the records, underscoring the necessity for an integrated approach to enhance the accuracy of KPI 02 and KPI 13.

The selection of data sources directly influences the reliability of indicators, while operational and environmental factors may impact taxi time variability.

The analysis found that BIMTRA and VRA provide greater representativeness and accuracy in calculations despite their inherent limitations.

The study revealed an overall efficiency of 0,35% for KPI 02 and 207% for KPI 13. When examining KPI 02 individually, the airport combinations displayed similar efficiencies, except for SBEG, which notably achieved 3,15%. Regarding KPI 13, the efficiency results varied considerably across airports: SBGR had an efficiency of 163%, SBSP reached 298%, SBKP recorded 453%, SBBE obtained 92%, and SBEG stood out significantly at 800%.

The optimal data source combination for KPI 02 includes take-off time (ATOT) from BIMTRA and gate departure (AOBT) from VRA, whereas for KPI 13, gate arrival time (AIBT) from VRA and landing time (ALDT) from BIMTRA proved to be most effective.

Therefore, integrating these data sources enables more accurate and reliable measurements, optimizing air traffic management, reducing congestion, and improving operational efficiency, particularly at high-flow airports.

It is recommended to use these databases jointly as the most effective strategy for enhancing KPI 02 and KPI 13, thus contributing to more efficient and secure airport operations management.

VI. AUTHOR'S CONTRIBUTION

Conceptualization: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Methodology: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Investigation: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Discussion of results: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Writing – Original Draft: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Writing – Review and Editing: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Supervision: Alessandro Soares de Freitas, Edilson Marques Magalhaes
Approval of the final text: Alessandro Soares de Freitas, Edilson Marques Magalhaes

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VIII. REFERENCES

[1] NSCA 351-1, *Brazilian Air Force Command System Standard: Brazilian Airspace Control System (SISCEAB)*. Rio de Janeiro: DECEA, 2024.

[2] A. D. Silva *et al.*, "ATM performance report of the Airspace Control System (SISCEAB)," DECEA, 2019.

[3] ANAC, "Air Transport Yearbook." in *National Civil Aviation Agency. Air Transport Indicators Panel 2022*, ANAC, 2024.

[4] *DCA 351-7*, Air Force Command Guideline: Guideline for Airspace Control, DECEA, Rio de Janeiro, Brazil, 2025.

[5] *DCA 100-2*, Guideline of the Air Force Command: Flexible Use of Airspace, DECEA, Rio de Janeiro, Brazil, 2017.

[6] *Aeroespaço*, Special Edition commemorating the 10th anniversary of CGNA, DECEA, Rio de Janeiro, Brazil, Dec. 2017.

[7] *DCA 351-2*, Guideline of the Air Force Command: National ATM Operational Concept, DECEA, Rio de Janeiro, Brazil, 2021.

[8] *ICA 100-22*, Instruction of the Air Force Command: Air Traffic Service, DECEA, Rio de Janeiro, Brazil, 2023.

[9] L. P. Oliveira, "System for optimizing Brazilian air traffic management with the Collaborative Trajectory Options Program," Undergraduate Thesis, University of Brasília (UNB), Brasília, Brazil, 2018.

[10] P. C. F. Barbosa, *Imbalance of aerodrome runway capacities: A calculation for obtaining the maximum per type of operation*, M.S. thesis, Professional Master's Program in National Network Mathematics, Graduate Studies, Research, Extension, and Culture Office, Pedro II College, Rio de Janeiro, Brazil, 2021.

[11] R. Tezza, A. C. Bornia, and I. H. Vey, "Performance measurement systems: A review and classification of the literature," *Management & Production*, vol. 17, pp. 75–93, 2010.

[12] A. C. Fernandes, "Analysis and forecasting of Brazilian air traffic performance indicators," Undergraduate Thesis, Aeronautics Institute of Technology, São José dos Campos, Brazil, 2022.

[13] DECEA, "ATM performance report of the Airspace Control System (SISCEAB)," DECEA, 2023.

[14] DECEA, "ATM performance report of the Airspace Control System (SISCEAB)," DECEA, 2024.

[15] A. C. R. A. Duarte, "Implementation of operational safety indicators in Cape Verde aviation," M.S. thesis, Master's Program in Air Transport Operations, Higher Institute of Education and Sciences, Lisbon, Portugal, 2023.

[16] O. T. Muniz, *Performance Management*, 1st. Rio de Janeiro, Brazil: SESES, 2016.

[17] P. M. Jannuzzi, *Social Indicators in Brazil*, 6th. ed. Campinas, Brazil: Alínea Publishing, 2017.

[18] L.O. Bahia, *Reference guide for the construction and analysis of indicators*, 1st ed. Brasília, Brazil: ENAP, 2021.

[19] R. B. Santana and V. A. G. Zanoni, "Brazilian housing indicators: comparative analysis of the historical series 1995-2018," *Cadernos Metrópole*, vol. 24, no. 53, pp. 409–428, 2022.

[20] H. O. Gomes *et al.*, "The impact of Embraer's intellectual property assets indicators on strategic decision-making for the company," *Peer Review*, vol. 5, no. 5, pp. 353–365, 2023.

[21] A. C. Fernandes, "Analysis and forecasting of Brazilian air traffic performance indicators," Undergraduate Thesis, Aeronautics Institute of Technology, São José dos Campos, Brazil, 2022.

[22] B. Bubalo, *Airport Capacity and Performance in Europe: A Study of Transport Economics, Service Quality and Sustainability*, Ph.D. dissertation, Department of Economics, University of Hamburg, Hamburg, Germany, 2021.

[23] Francischini, A. S. N., and Francischini, P. G. *Performance Indicators*. 1st ed. Rio de Janeiro, Brazil: Alta Books, 2017.

[24] A. W. Dougall and M. Mmola, "Indentification of key performance áreas in the Southern African surface mining delivery environment". Journal of the Southern African Institute of Mining and Metalurgy, V. 115, n. 111, pp. 1001-1006, 2015.

[25] P. Gackowiec *et al*. "Review of Key Performance Indicators for Process Monitoring in the Mining Industry." Energies, V. 13, n. 20, pp. 30-59, 2020.

[26] R. Domigues *et al.*, "Key performance indicators in marketing," *Iberian Journal of Information Systems and Technologies*, no. E35, pp. 128–140, 2020.

[27] F. R. M. S. Montenegro and A. L. C. Callado, "Contingency factors and the use of performance indicators associated with the Balanced Scorecard perspectives," *Revista Gestão Organizacional*, vol. 12, no. 1, pp. 73–91, 2019.

[28] ICAO, *Global Air Navigation Plan (GANP)*, 7th ed. Montreal, Canada: ICAO, 2021.

[29] R. L. Pereira, "Management of the methodology for air traffic controllers' shift scheduling: a perspective based on EUROCONTROL concepts," M.S. thesis, Graduate Program in International Security and Defense, Superior War College, Rio de Janeiro, Brazil, 2022.

[30] M. Hammer and J. Champy, *Reengineering the Corporation: A Manifesto for Business Revolution*, New York, NY, USA: HarperCollins Publishers, 1993.

[31] T. H. Davenport, *Process Reengineering: How to Innovate in the Company T hrough Information Technology*, 4th ed. Rio de Janeiro, Brazil: Campus, 1994.

[32] M. Imai, Kaizen: The Path of Continuous Improvement, Sa˜o Paulo, Brazil: McGraw-Hill, 1986.

[33] J. Tidd and J. Bessant, *Innovation and Business Process Management*, 5th ed. , Porto Alegre, Brazil: Bookman, 2015.

[34] J. Jeston and J. Nelis, *Business Process Management: Practical Guidelines to Successful Implementations*, 5th ed. Abingdon, UK: Routledge, 2018.

[35] P. Harmon, *Business Process Change: A Guide for Business Managers and BPM and Six Sigma Professionals*, 2ª ed., Burlington, MA: Morgan Kaufmann, 2010.

[36] W. van der Aalst, *Process Mining: Data Science in Action*, 2nd ed. Heidelberg, Germany: Springer, 2016.

[37] *MCA 100-22*, Air Force Command Manual: ATM Indicators Methodology of SISCEAB. Rio de Janeiro, Brazil: DECEA, 2020.

[38] *PCA 100-3*, Brazilian Air Force Command Plan: ATM Performance Plan. DECEA, Rio de Janeiro, Brazil, 2024.

[39] Adapted from SBGR ADC Chart (AISWEB), (2024). file:///C:/Users/LAB%2020%20ITEGAM/Downloads/sbgr_adc-sbgr_adc_20240905.pdf