ANALYSIS OF GUARULHOS POINT MERGE ADHERENCE BASED ON ADDITIONAL TIME IN TMA AND TRAJECTORY CLUSTERING

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Abstract

The increasing global air traffic requires efficient management systems. One way to achieve that is optimizing arrival sequences, reducing flight duration, and enhancing operational safety. A method to address these requirements is a sequencing technique called Point Merge system (PM). This study analyzes the adherence to the PM at Guarulhos International Airport (GRU), aiming to understand the peak and off-peak usage times, and provide a detailed sector-by-sector analysis. Two methods were applied for trajectories classification according to their adherence to the PM: A method based on the 8th ICAO's Key Performance Indicator (KPI08-based method), which consists of thresholding based on additional time in terminal area, and clustering by the agglomerative method using trajectories data. The experimental data were collected from: KPI08 dataset, airport movements and radar synthesis, focusing on medium-sized commercial aircraft. The total number of flights analyzed was 2427. The results obtained indicate a better performance of the KPI08-based method, which achieved a more defined representation between the classified trajectory groups. The results highlighted a behavior pattern in relation to peak and off-peak times in the use of PM in all periods analyzed. Evaluating the North and West sectors, it was possible to show that some time slots exhibited similar behaviors when using the KPI08-based method. The time slots 8h-9h and 18h-19h stand out as they show that more than 70% of flights execute the PM. The time slot 20h-22h showed similar behavior in both sectors, with approximately 50% of flights executing the PM. This work contributes by proposing the KPI08-based method, an innovative method to classify flights according to the adherence to the PM, which proved to be more accurate than the agglomerative trajectory clustering method. Additionally, this study may indicate an improvement in the arrival flow management at GRU, due to demand predictability. This predictability enables better route planning, which may result in additional fuel reduction.

Keywords: Air Traffic Flow Management, Additional Time in TMA, Point Merge, Trajectory Clustering, Agglomerative clustering.

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1. INTRODUCTION AND BACKGROUND

The significant increase in global air traffic requires the implementation of more efficient methods for managing the air traffic flow. According to the International Air Transport Association (IATA), global air passenger numbers are expected to reach 8.2 billion by 2037, doubling from the 4.1 billion passengers in 2017 (IATA, 2018). One such method to address this growing demand is the Point Merge system, an innovative air traffic sequencing technique designed to optimize aircraft arrival sequences, reduce flight times, and enhance operational safety.

Point Merge operates efficiently under high traffic loads without the need for radar vectoring. It relies on a specific Precision-Area Navigation (P-RNAV) route structure, comprising a merge point and equidistant pre-defined legs known as sequencing legs. Sequencing is achieved through a “direct-to” instruction to the merge point at the appropriate time. The sequencing legs are used to delay aircraft only when necessary, a process known as path stretching. The length of these legs reflects the required delay absorption capacity, ensuring a streamlined and predictable arrival flow. This method simplifies controller tasks, reduces communication and workload, enhances pilot situational awareness, and improves the predictability and efficiency of flight trajectories (Eurocontrol, 2014). Figure 1 illustrates the Point Merge system and its components.

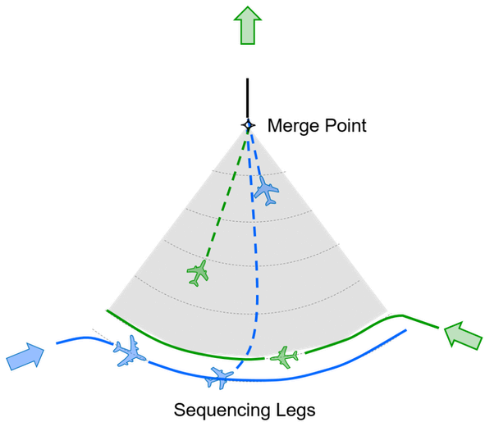


Figure 1 Point Merge structure. Source: Eurocontrol (2014).

The Point Merge system has been successfully implemented in various airports worldwide, demonstrating its ability to improve airspace efficiency and minimize the environmental impact of fuel consumption (Eurocontrol, 2014; ICAO, 2016). For example, a study conducted at Tokyo International Airport (Haneda) highlighted that the Point Merge system improved sequencing efficiency during peak traffic periods (Sakamoto *et al.*, 2019). Similarly, a research at Dublin Airport demonstrated that Point Merge significantly enhanced predictability and reduced fuel consumption compared to traditional vectoring methods (Christien *et al.*, 2017).

In Brazil, Guarulhos International Airport (GRU) stands as one of the busiest hubs in Latin America, facing daily challenges associated with high traffic density. Analyzing the implementation of the Point Merge system at GRU is therefore highly relevant to evaluate its benefits and challenges in a complex and busy operational environment. Improper fuel loading decisions result in carrying excessive weight during flight operation, which will burden the airline operation cost and cause extra waste emission (Yi Lin *et al.* 2024). Therefore, the final goal of this study was to understand the use of the Point Merge system to enable the possibility that, if it is not used during certain periods of the day, aircraft would not need to carry extra fuel for it. This would save fuel, reduce the load, lower flight costs, and potentially reduce ticket prices for passengers.

To classify the adherence to the point merge two distinct approaches were applied: KPI08-based classification and Trajectory Clustering. The dataset used for both analyses included: Radar data for each flight, as well as Control tower movement data for the airport. The time period analyzed was December 18, 2023, as a proof of concept, then the period from September 15 to 21, 2023, and finally the period from April 15 to 21, 2023, to cover different times of the year. The total number of flights analyzed was 2,427.

The KPI08 is a Key Performance Indicator defined by ICAO (ICAO, 2023) that measures the additional time in terminal area. It compares the time an aircraft spends in the terminal airspace (within the 40NM cylinder, known as C40) with the time it would spend under ideal conditions, called the unimpeded time. The unimpeded time is calculated based on past flights and is set as the 20th percentile time of this historical dataset. Thus, the difference between the actual time spent in the Terminal Airspace and the unimpeded time is the KPI08. By analyzing the KPI08, we can understand how much the flight was delayed compared to the ideal scenario.

Another type of analysis that can be conducted to determine the adherence to the Point Merge is the study of aircraft trajectories. Related works suggest the use of unsupervised learning for understanding trajectory patterns. Murça *et al*. (2016) and Gariel *et al.* (2011) highlight how the utilization of the vast amount of available data on trajectories and their groupings can bring considerable gains to air traffic efficiency. Moreover, different clustering techniques have been used in other studies, such as DBSCAN (Bolić, 2022) and Deep Autoencoders and Gaussian Mixture Models (Zeng *et al.*, 2021), proving to be effective in clustering trajectories and extracting relevant information from them.

This study aims to analyze the use of the Point Merge system in São Paulo terminal, with a focus on GRU Airport, using time metrics and trajectory clusterization to identify usage patterns and efficiency. This work contributes by proposing an innovative method to classify flights according to the adherence to the point merge (KPI08-based method). The findings provide valuable insights to improve local operation, to plan future implementations of the Point Merge system in other airports and regions in Brazil, and to support the continuous evolution of air traffic operations in the country (IATA, 2019).

2. METHODOLOGY

2.1. Data Collection and Processing

Data was collected from a combination of different sources, including KPI08 data, Control towers movement), and radar data. By merging these datasets, it was possible to consolidate information about the flights conducted on the studied dates: December 18, 2023, from September 15 to 21, 2023, and from April 15 to 21, 2023, as mentioned in the Introduction. These dates were selected because they are considered typical periods of movement at airports, unaffected by national festive events or holidays. Additionally, the data were filtered to include: only commercial medium-sized aircraft (wake turbulence category 'M') to ensure data uniformity and avoid speed variations that could affect the results; and only flights from Azul, Gol, and Latam airlines, aiming to standardize the data, remove potential outliers, and result in a more representative dataset that aligns with the goal of optimizing costs for the end user.

To use the trajectory data as input for clustering algorithms, the data was processed so that each trajectory became an object for unsupervised learning. Thus, each latitude and longitude coordinate, ordered over time, is an attribute of this object. To ensure each trajectory had the same number of points over time, the number of points in each was truncated to the quantity that encompassed all trajectories above the first quartile when ordered by the number of points. This way, the data could be used in the algorithms.

Finally, it is worth noting that the analysis was separated by entry sectors into the Terminal Airspace. For sector classification, the angle at which the aircraft entered the C100 (100NM cylinder) was considered, measured from zero (North direction) and increasing clockwise. Figure 2 shows the sectorization used, based on the results presented by Lima et al. (2023), where sectorizations in C40 were found using unsupervised machine learning from flight approach data at Guarulhos. Thus, trajectories with an entry angle (θ) into the terminal area such that $-20° \leq \theta < 50°$ were considered as the North sector, $50° \leq \theta < 180°$ were considered as the

East sector, and 180° ≤ θ < 340° were considered as the West sector. The study focused on the North and West sectors, which effectively make use of the Point Merge system.

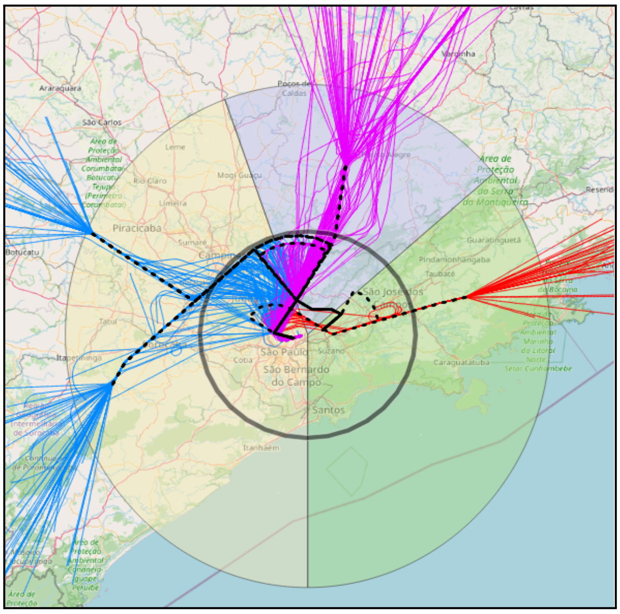


Figure 2 Flights arrived at GRU Airport on 18/12/23. North sector in light blue with trajectories in pink. East sector in green with trajectories in red. West sector in yellow with trajectories in blue.

2.2. Metrics and Classification

2.2.1. KPI08-based method

Initially, the only classification parameter was the KPI08, which hindered the classification in some cases since it can be difficult to distinguish a higher KPI08 due to the Point Merge contour from one due to vectoring near the runway. As seen in the aeronautical chart procedures in Figure 2 (dashed lines), there is both the deviation of the Point Merge and a smaller arc closer to the runway, both within the C40. Therefore, using only the additional time parameter within the C40 (KPI08) did not yield good analysis results.

To overcome this problem, the 20NM cylinder, C20, was also considered. This allowed us to separate the KPI08 time into time between C40 and C20, where the delay is more likely due to the use of Point Merge, and time between C20 and landing, where the delay is due to the deviation closer to the runway, not the Point Merge.

With this, the classification sought to separate the flights into three distinct classes:

- Class 1: Direct flights that do not use Point Merge or deviate near the runway;
- Class 2: Flights that do not use Point Merge but deviate near the runway;
- Class 3: Flights that use Point Merge and deviate near the runway, meaning slower flights.

To ensure that the classification based on the times from C40 and C20 reflected this described classification, several empirical tests of classification intervals were performed, mainly on the September 2023 days and later validated on the April 2023 days. After this, the classification shown in Table 2 below was established.

Table 2 KPI08 classification based on times from C40 to C20 and from C20 to landing.

Sector	KPI08 Class	C40 to C20 time	C20 to landing time
North	1	<= 350	<= 585s
	2	<= 350	> 585s
	3	> 350	-

West	1	<= 460s	<= 550s
	2	<= 460s	> 550s
	3	> 460s	-

2.2.2. Clustering

With the data divided into sectors, proof-of-concept tests of the clustering algorithm were conducted using flights from only one day, specifically December 18, 2023. The algorithms tested were DBSCAN and Agglomerative for the northern and western sectors of arriving flights at GRU. To determine which algorithm to use in the final analysis, evaluation metrics of the classifications were compared alongside a visual analysis of the results. Evaluations were performed using the silhouette method, Davies-Bouldin index, and Calinski-Harabasz criterion. (Vendramim *et al,* 2010) Thus, the hyperparameters were adjusted considering the results obtained, and ultimately, the best clustering identified. The chosen algorithm was hierarchical agglomerative clustering, and the optimal number of clusters was determined to be two, as testing by the elbow method revealed that this configuration provided the highest information gain. Also, this configuration achieved the best scores across the evaluation metrics mentioned above.

After selecting the best algorithm, it was applied to each main sector (North and West) for the flights defined on the study dates, from September 15 to 21, 2023, and from April 15 to 21, 2023. The evaluative metrics of the clusters were also applied to the new data to verify the validity of the choice of the best algorithm in the proof of concept. Thus, the choice of the Agglomerative algorithm, a type of hierarchical algorithm, was confirmed. The tree of the hierarchical algorithm was pruned with the number of clusters set to 2, to classify the trajectories as either having performed the merging point or not.

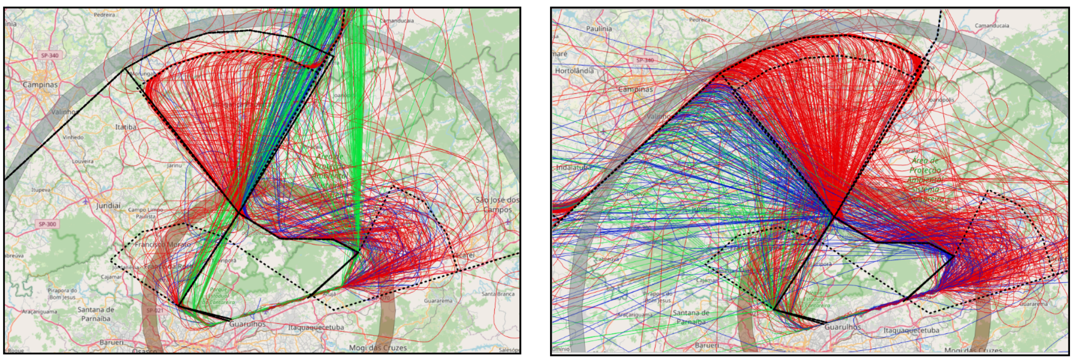
3. RESULTS

3.1. KPI08-based classification

In this section, the results obtained from the classification using the KPI08 metric for each sector and period considered will be presented.

3.1.1. April 15-20, 2023

This subsection details the classification of flights based on the KPI08 metric from April 15 to April 20, 2023. Figure 3 shows the classification of flights in the North (a) and West (b) sectors. In the figure, the red color indicates the flights that performed the point merge, while the green and blue colors represent the flights that did not perform the point merge, according to the classification based on KPI08, as shown in Table 2. A total of 1,124 flights were observed for a 5-day sample in April 2023. Of these, 55.60% (n=625) performed the point merge, whereas 44.40% (n=499) did not perform the procedure in the North and West sectors.



(a) (b)

Figure 3 Classification of flights (a) in the Northern sector and (b) in the Western sector from April 15, 2023, to April 20, 2023.

Figure 4 shows the average point merge utilization curves by time of day for each sector studied. It is noteworthy that, in the time slots from 0h to 1h, 8h to 9h, 9h to 10h and 18h to 19h, more than 70% (n=304) of the flights performed the point merge. While in the time slots from 3h to 5h, 12 flights were registered, none of which used the point merge. It is important to highlight that 93% (n=38) of the flights in the time slot from 8h to 9h, in the North sector, performed the point merge. In contrast, in the time slot from 18h to 19h, 87% (n=39) of the flights performed the point merge in the West sector, this being the time slot with the highest number of performances of this maneuver in this sector.

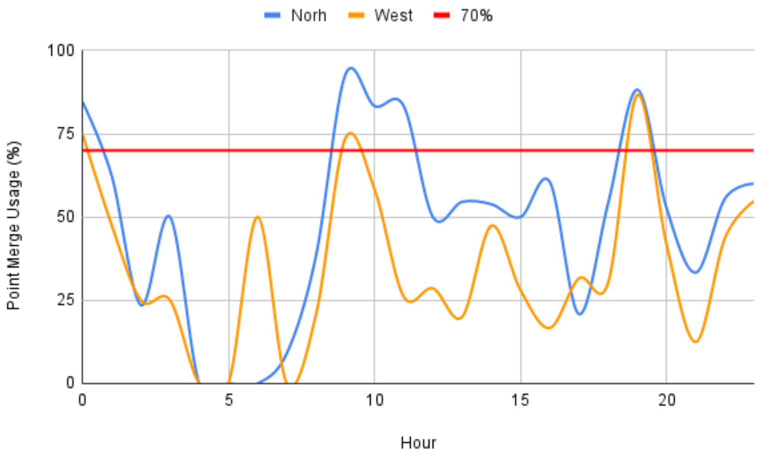
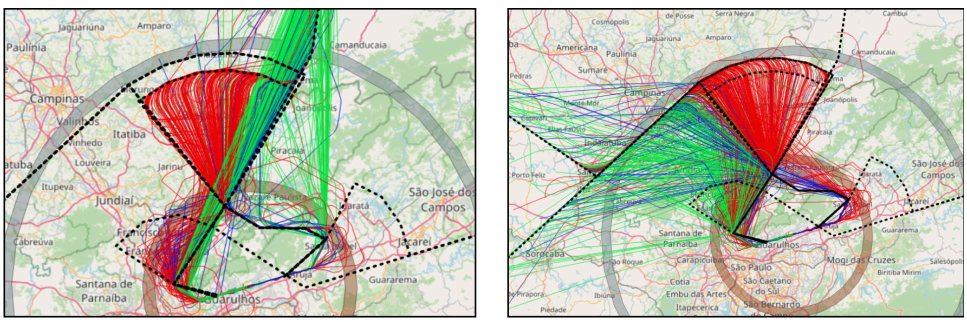


Figure 4 Average percentage of Point Merge Utilization in the Northern and Western sector from April 15, 2023, to April 20, 2023, by hour (UTC) of the day, according to the KPI08-based method.

3.1.2. September 15-20, 2023

Analogously, this subsection details the classification of flights based on the KPI08 metric from September 15 to September 20, 2023. Figure 5 shows the classification of flights in sectors (a) North and (b) West. A total of 1,303 flights were observed in the 5-day sample of September 2023. Of these, 46.58% (n=607) performed the point merge, while 53.42% (n=696) did not perform the point merge in the North and West sectors.

Figure 6 presents the average point merge utilization curves by time of day, in which the results showed that the time slots from 0h to 1h, 8h to 9h, and 18h to 19h stood out, with more than 70% (n=285) of the flights performing the point merge. In particular, the time slot from 0h to 1h stood out, with approximately 85% of the flights performing the point merge in both periods analyzed. On the other hand, in the time slots from 2h to 3h and from 5h to 6h, 23 flights were registered, in which none performed the point merge. In addition, it is important to highlight that in the time slots from 0h to 1h and from 8h to 9h, 78% (n=107) of the flights in the North sector and approximately 91% (n=108) of the flights in the West sector performed the point merge. Overall, there was a difference of approximately 9% in the number of flights that did not perform the point merge when comparing the 5-day sample from April with the sample from September.



(a) (b)

Figure 5 Classification of flights (a) in the Northern sector and (b) in the Western sector from September 15, 2023, to September 20, 2023.

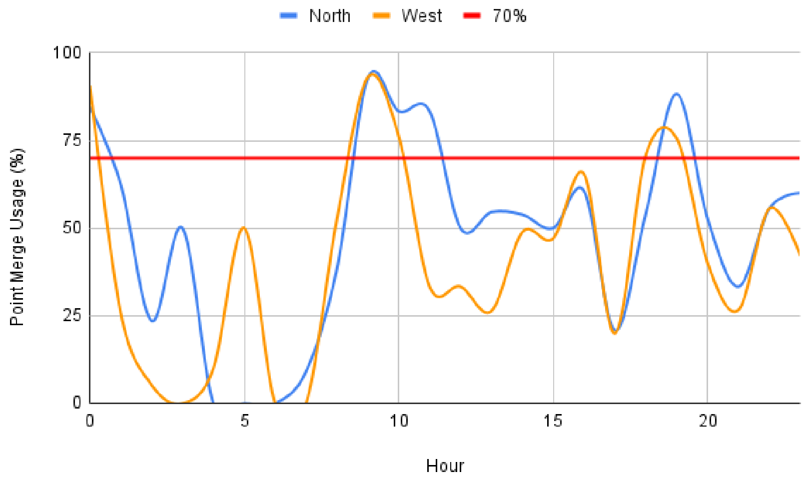


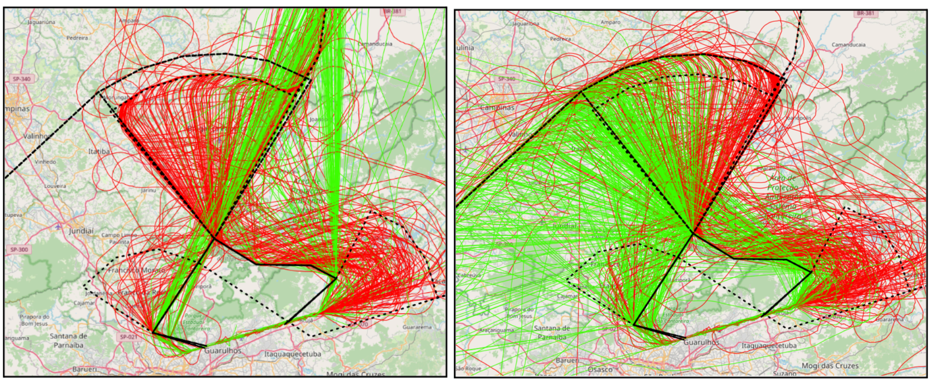
Figure 6 Average percentage of Point Merge Utilization in the Northern and Western sector from September 15, 2023, to September 20, 2023, by hour (UTC) of the day, according to the KPI08-based method.

3.2. Clustering

The Agglomerative Clustering algorithm was applied to the trajectory data described in Section 3. The results are presented in the following subsections.

3.2.1. April 15-20, 2023

This subsection presents the application of the Agglomerative Clustering algorithm to flight trajectories from April 15 to April 20, 2023. Figure 8 shows the flight clusters in the North (a) and West (b) sectors from April 15 to 20, 2023. In the figure, the red color indicates the cluster of flights that executed the point merge, while the green color represents the cluster of flights that did not execute the point merge, according to the hierarchical cluster analysis. Of the 1007 flights analyzed, it was observed that 38.53% (n=388) executed the point merge, while 61.47% (n=619) did not execute, according to the defined clusters.



(a) **(b)**

Figure 8 Clusters of flights (a) in the Northern sector and (b) in the Western sector from April 15, 2023, to April 20, 2023.

Figure 9 shows the average point merge usage curves by time of day, based on the defined clusters. The results indicate that the intervals from 0h to 1h and 8h to 9h stand out, showing more than 70% (n=50) of the flights that used Point Merge in the North sector. On the other hand, the intervals from 3h to 6h, 11h to 12h and 20h to 21h registered flights that did not execute the point merge. In the West sector, only the interval from 8h to 9h presented 73% (n=27) of the flights that executed the point merge. In addition, the intervals from 4h to 7h and from 12h to 13h did not register flights executing the point merge.

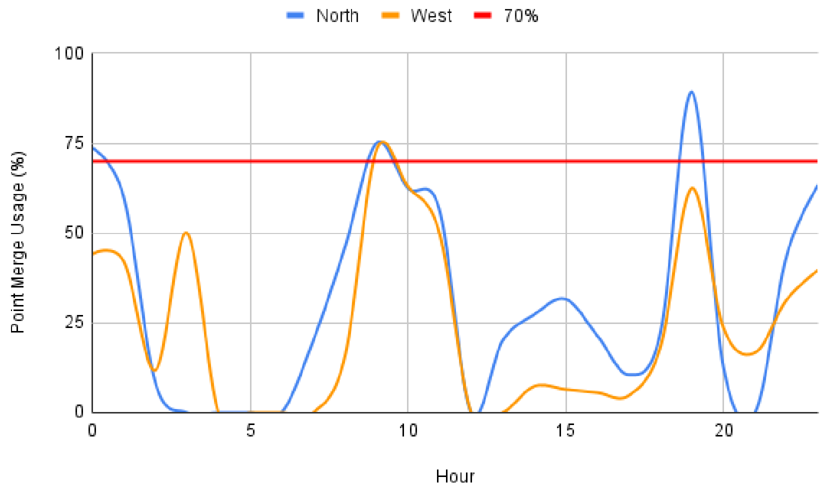
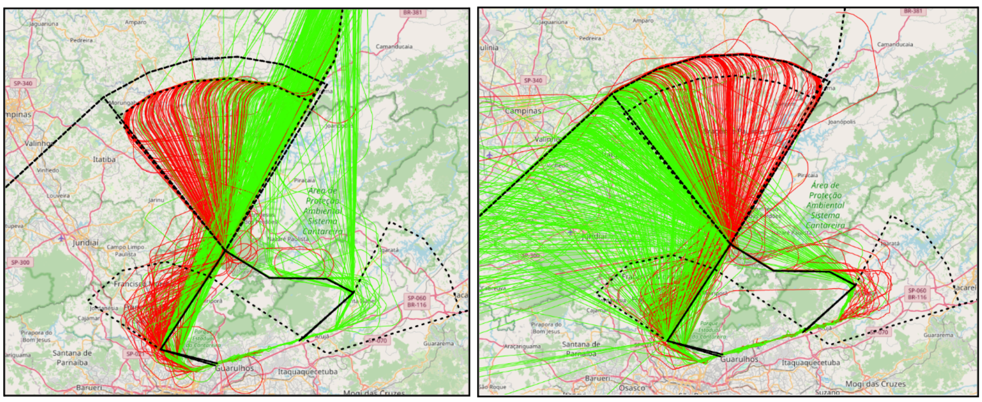


Figure 9 Average percentage of Point Merge Utilization in the Northern and Western sector from April 15, 2023, to April 20, 2023, by hour (UTC) of the day, according to the clustering method.

3.2.2. September 15-20, 2023

Similarly, this subsection details the classification of flights based on the cluster analysis carried out from September 15 to 20, 2023. Figure 10 presents the classification of flights in the (a) North and (b) West sectors. A total of 1,164 flights were observed in the 5-day sample of September 2023. Of these, 27.84% (n=324) performed the point merge, while 72.16% (n=840) did not perform a point merge in the analyzed sectors.

We can observe that the results found for both tested time periods using the clustering method are in agreement with those obtained by the terminal phase time metric presented in section 4.1. There is a higher presence of misclassifications, considering flights that adhered to the Point Merge with shorter sequencing leg trajectories as not adherent. However, overall, the result found is valid.



(a) **(b)**

Figure 10 Clusters of flights (a) in the Northern sector and (b) in the Western sector from September 15, 2023, to September 20, 2023.

Figure 11 shows the average point merge utilization curves by time of day, based on cluster analysis. The results indicate that, in the North sector, no time slot had 70% of flights executing the point merge. The time slot with the highest number of flights executing the point merge was from 8h to 9h, with 67.16% (n=45). On the other hand, the time slots from 2h-4h, 5h-6h, 11h-12h, 16h-17h, and 20h-21h did not register any flights executing the point merge. In the West sector, the time slots from 9h-10h and 19h-20h had more than 70% (n=19) of flights using the point merge. On the other hand, the time slots from 2h-3h, 6h-7h, 11h-12h, 17h-18h and 20h-22h did not register flights using point merge.

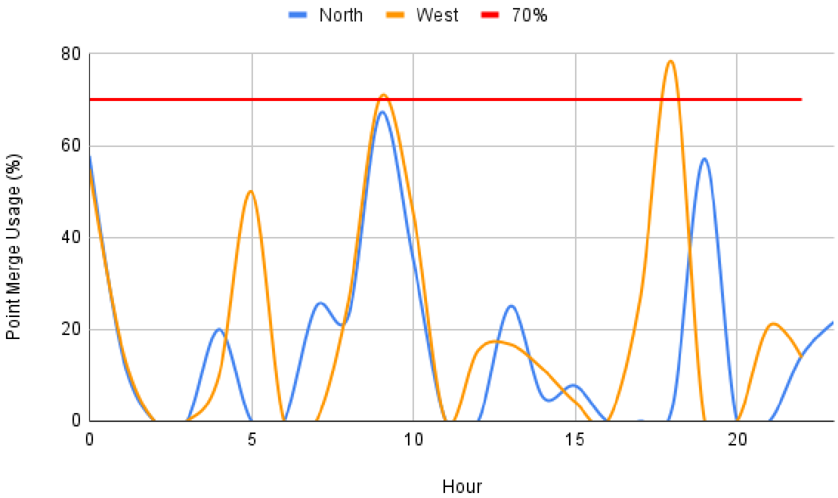


Figure 11 Average percentage of Point Merge Utilization in the Northern and Western sector from September 15, 2023, to September 20, 2023, by hour (UTC) of the day, according to the clustering method.

4. DISCUSSIONS

After presenting the results, it is possible to obtain a behavioral profile of landing movements at GRU regarding adherence to Point Merge. The curves, whose main characteristics are the peak and off-peak intervals highlighted in Section 3, exhibit similar behavior, even though they occur at different periods. This indicates that the analysis can be generalized to other periods of the year. The main difference between the presented curves lies in the amplitude of the peaks. It is observed that the curves obtained using the KPI08-based method are more binarizable for the empirical threshold of 70%. Therefore, it can be determined that the KPI08-based method is more appropriate for the task.

Evaluating the North and West sectors, it was possible to show that some time slots exhibited similar behaviors when using the KPI08-based method. For example, the 8h-9h and 18h-19h time slots stand out, as they show that more than 70% of flights execute the Point Merge. These findings suggest that demand and route planning could be strategically adjusted to better utilize off-peak hours, optimizing airspace use. Extra fuel planning can be fine-tuned to enhance operational efficiency, reducing waste and improving resource management. Conversely, the moderate adherence observed between 20h and 22h indicates potential for revising procedures and adjusting operations to enhance efficiency and lower costs, both economically and environmentally.

The results obtained were competitive with those found in the literature. The KPI08-based method represents an improvement in the interpretability of the problem, as it can be represented one-dimensionally, in contrast to solutions like those of Basora et al. (2017), which represent the trajectory in four dimensions and across various spectra, such as in the distance domain, for example. Murça et al. (2016) and Basora et al. (2017) use methods based on DBSCAN, which, in its classical implementation, has a high computational cost due to repeated comparisons using all trajectory points. Given that trajectory data is massive, as radar data is generated every 4 seconds, a costly algorithm can cause significant challenges in production environments. The use of the KPI08-based method also suggests a computational advantage, as the determination of the KPI08 class, according to Table 2, is done by applying rules, while the KPI08 calculation is based on time calculations involving only two points of the trajectory, which is significantly advantageous compared to the methods of Murça et al. (2016) and Basora et al. (2017), which use the complete trajectory.

5. CONCLUSIONS

This work allowed us to observe that the execution of the merge point in the analyzed periods can be extracted from both developed classifiers. However, the method based on KPI08 allowed a more precise and defined identification of flights that performed the point merge, although cluster analysis also allows this identification, but to a lesser extent. Additionally, this study may indicate an improvement in the arrival flow management at GRU airport, due to demand predictability achieved through an hour-by-hour description of adherence patterns to Point Merge in arrival movements. This predictability also enables better route planning, which may result in additional fuel reduction and other positive environmental and economic impacts.

As a proposal for future work, we highlight the need to analyze the influence of flight level during point merge execution, in addition to verifying the impact of the runway in use on the point merge adherence pattern. Another possible analysis would be to verify the correlation between point merge adherence and arrival capacity, in order to analyze whether the implementation of the double point merge system would bring any operational gain.

6. References

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