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Causal analysis of vertical flight inefficiency during descents

Análise causal da ineficiência vertical dos voos durante descidas

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ABSTRACT
Continuous Descent Operations (CDOs) have proven to deliver significant economic and environmental benefits. Yet, flight trajectories are often observed to deviate from optimal procedures during actual operations. Better assessing and understanding the level of trajectory adherence to reference ideal procedures is a key step towards identifying opportunities for system performance improvement. To this end, this paper presents a statistical model of flight trajectory performance and investigates causal factors for vertical inefficiency during descents. Based on historical flight tracking data, a trajectory clustering analysis is performed to learn the airspace structure and identify the trajectory pattern followed by each aircraft. Vertical inefficiency is quantified in terms of the amount of level flight during descent. A regression model is then developed to map structural and operational factors into vertical efficiency. Our case study consists of 26,040 arrival flights for the two major airports in the Sao Paulo metroplex, Congonhas (CGH) and Guarulhos (GRU). The results reveal that airspace structure and convective weather are the most important factors affecting vertical performance in the airspace analyzed.

RESUMO
As Operações de Descida Contínua (CDOs) provaram entregar benefícios econômicos e ambientais significativos. No entanto, em operações reais, as trajetórias de voo são frequentemente desviadas em relação aos procedimentos ideais. Avaliar e compreender melhor o nível de aderência da trajetória aos procedimentos ideais de referência é uma etapa fundamental para a identificação de oportunidades de melhoria de desempenho do sistema. Para tanto, este trabalho apresenta um modelo estatístico de desempenho de trajetórias de voo e investiga fatores causais de ineficiência vertical durante descidas. Com base em dados históricos de rastreamento de voo, uma análise de agrupamento de trajetórias é realizada para aprender a estrutura do espaço aéreo e identificar o padrão de trajetória seguido por cada aeronave. A ineficiência vertical é quantificada em termos da quantidade de voo nivelado durante a descida. Um modelo de regressão é então desenvolvido para mapear fatores estruturais e operacionais que influenciam a eficiência vertical. Nosso estudo de caso consiste em 26.040 voos de chegada para os dois principais aeroportos da região metropolitana de São Paulo, Congonhas (CGH) e Guarulhos (GRU). Os resultados revelam que a estrutura do espaço aéreo e tempo convectivo são os fatores mais importantes que afetam a eficiência vertical no espaço aéreo analisado.

1. INTRODUCTION

A modern Air Traffic Management (ATM) system is recognized as a critical step for enhancing

the safety, efficiency, and environmental performance of the aviation sector. One of the top priorities of the International Civil Aviation Organization's Global Air Navigation Plan for ATM systems modernization is the implementation of innovative and optimized operational procedures (ICAO, 2019a). Continuous Descent Operations (CDOs), also referred to as Continuous Descent Approaches (CDAs) or Optimized Profile Descents (OPDs), are among these operational solutions and have already been implemented in many parts of the world, coordinated by Air Navigation Service Providers (ANSPs) under their ATM modernization programs, such as SESAR in Europe, NextGen in the U.S. and SIRIUS in Brazil.

In a conventional, or non-CDO approach, the aircraft performs a step-down descent, i.e. with descent segments and level flight segments interspersed from the top of descent to the final approach path. CDOs allow the arriving aircraft to remain higher for longer and descend from cruise flight to final approach continuously, with less engine thrust and a minimum of level flight segments that occur only if required to configure the aircraft for landing or to establish on a landing guidance system (e.g. ILS – Instrument Landing System). Thus, CDOs allow aircraft to stay longer at cruise altitude, where jet engines burn less fuel per distance flown, and to spend less time flying with high engine thrust at lower altitudes, where there is greater fuel consumption.

The benefits of CDOs and the feasibility of practical implementations have been extensively investigated and demonstrated under the Partnership for Air Transportation Noise and Emissions Reduction (PARTNER), coordinated by the Federal Aviation Administration (Alcabin *et al.*, 2009; Clarke, 2006; Clarke *et al.*, 2004; Sun and Post, 2011). In Europe, the Eurocontrol, the International Air Transport Association (IATA), and the Civil Air Navigation Services Organization (CANSO) signed a joint industry CDO Action Plan in 2009 that defined commitments and specific actions to be undertaken by the European Aviation Industry to ensure the fast deployment of CDOs for as many flights as possible. In Brazil, the implementation of Performance Based Navigation (PBN) procedures, under the SIRIUS program, are expected to enable CDOs, as described in the National ATM Implementation Plan (DECEA, 2012).

Despite the economic and environmental benefits of CDOs, a significant proportion of flights perform non-continuous descents during actual operations. Even in regions where CDO procedures are already implemented, flight trajectories are often observed to deviate from optimal procedures. The ability to quantify the level of flight trajectory adherence to reference ideal procedures and assess the causes for inefficiencies is key to expand the CDO practice by allowing for the identification of potential improvements in airspace design and traffic flow management. Fortunately, novel opportunities have arisen to characterize and understand flight trajectory performance through the application of data analytics techniques on increasingly available operational data. Indeed, recent studies have leveraged aircraft tracking data to gain insights about trajectory performance, particularly focused on the horizontal flight profiles (Liu *et al.*, 2017; Marcos *et al.*, 2018; Murça *et al.*, 2018).

This paper presents a statistical model of flight trajectory vertical performance and empirically investigates the causes of non-continuous descents in the Sao Paulo Terminal Maneuvering Area (TMA). Based on historical aircraft tracking data of 26,040 arrival flights for the two major airports in the Sao Paulo metroplex, Congonhas (CGH) and Guarulhos (GRU), the structure and the use of the terminal airspace is learned with a trajectory clustering analysis, and vertical inefficiency is quantified in terms of the amount of level flight during descent.

A regression model is then learned to map structural and operational factors into trajectory performance, allowing for the identification of the most important causal factors for vertical inefficiency.

The remainder of this paper is organized as follows. Section 2 presents the literature review on CDOs and on trajectory data analytics for air traffic performance assessment and discusses the contributions of this work. Section 3 presents the methodology, describing the datasets used, the trajectory data analytics methods, and the statistical model of vertical performance. Section 4 presents the data analysis, model estimation results, and discussions, which are followed by the conclusions.

2. LITERATURE REVIEW

2.1. Benefits of continuous descent operations

Many studies have estimated the potential benefits of CDOs in terms of fuel consumption. In this stream of literature, the fuel consumption of ideal flight tracks are typically compared with actual ones through an aircraft performance model (e.g. Base of Aircraft Data – BADA). Melby e Mayer (2008) analyzed the potential benefits of CDOs and CCOs using flight data for one day of operation at 34 major airports in the U.S. Their results suggest that flight operators could save about US$ 380 million per year with more efficient climbs and descents, considering fuel and time costs. Robinson and Kamgarpour (2010) estimated the potential benefits of CDOs in congested airspace. Flight trajectories were built from flight plans in eight U.S. airports. Their results indicate that potential savings vary substantially according to the type of traffic analyzed. Scenarios with low and moderate demand showed more potential for fuel consumption reduction. Knorr et al. (2011) analyzed the potential benefits of CDOs along with speed reductions during cruise flight and highlighted the ATM's role in managing delay along the trajectory in a time-constrained environment. Their results indicate that potential reductions are in the order of 100 kg of fuel and 3 minutes per flight, on average. In Brazil, Pamplona et al. (2015) evaluated the benefits of CDOs and PBN procedures in the Guarulhos (GRU) – Galeão (GIG) route using fast-time simulations with TAAM software. Their results indicated that fuel savings due to CDOs could be in the order of 30%.

The studies described above concern pre-implementation analysis. Howell and Dean (2017) on the other hand, assessed the impact of new flight procedures, implemented in 30 airports in the U.S., on the efficiency of descents. Using flight tracks of representative days, they observed that fuel and time reductions in the order of 30-40% were achieved where time-based separation and optimized descents were implemented.

2.2. Trajectory data analytics for air traffic performance assessment

While CDOs have proven to deliver significant benefits, flight trajectories are often observed to deviate from optimal procedures during actual operations. The lack of adherence to reference ideal procedures is observed not only at the vertical but also at the horizontal dimension (Reynolds, 2014). Recent studies have focused on better assessing and understanding trajectory performance as a first step towards operational improvements.

A stream of literature has been dedicated to applying data analytics methods to exploiting flight tracking data to identify air traffic patterns and characterize their performance at both spatial and temporal dimensions. Murça et al., (2018) applied clustering methods to learn both trajectory patterns and traffic flow patterns in the terminal airspace of the New York, Hong

Kong, and Sao Paulo metroplex systems towards identifying structural and operational performance differences between them. Their analysis included an assessment of horizontal and temporal traffic efficiencies. Carmona et al. (2020) evaluated the horizontal adherence of actual flight trajectories to standard routes and planned trajectories for the London TMA and observed that the trajectory adherence varies significantly by route. Pasutto et al. (2019) assessed the vertical inefficiency at four major European airports, using the deviation from best local practice for each flow as an inefficiency metric. They considered the 50 NM (nautical miles) area around each airport and six months of data from 2018 during daytime operations for more than 200,000 flights in total. Their results indicated that: descent profile's efficiencies are significantly lower than best practices; there is a degradation of the descent profile's efficiency with the level of congestion, but it varies for one same level of congestion.

Building upon the ability to identify and characterize air traffic patterns, another set of studies have developed statistical models of flight trajectory performance to investigate the causes for air traffic inefficiencies observed. These studies on causal analysis of flight inefficiency have focused only on the horizontal profile. Liu et al. (2017) applied clustering techniques and developed a linear regression model to analyze flight trajectories arriving at or departing from 34 major U.S. airports. They investigated contributions of wind, convective weather, and Miles-in-Trail (MIT) restrictions to en route horizontal flight inefficiency. Results varied across city-pairs, but in general convective weather showed the greatest contribution, followed by winds and MIT restrictions. Marcos et al. (2018) also investigated the causes of en route horizontal flight inefficiency for the Bordeaux Control Center using a Random Forests regressor. They found that the route structure was the most important factor, followed by the direction of the flight.

Our work contributes to this literature by developing a statistical model to investigate causal factors of vertical inefficiency in the Sao Paulo metroplex. Historical flight tracking data for the two major airports, Congonhas (CGH) and Guarulhos (GRU), is leveraged to learn the structure and the use of the airspace and to quantify vertical inefficiency in terms of the amount of level flight during descent. A regression model is then created to map structural and operational factors, including airspace structure, weather conditions, and traffic flow management restrictions, into vertical performance.

3. METHODOLOGY

3.1. Data description

We analyzed 26,040 arrival flights at GRU and CGH, within the period of September 5th – December 12th of 2019. The flight tracking data was obtained from FlightRadar24 and consists of one-minute reports with temporal and spatial position (time, latitude, longitude, altitude) and flight information (aircraft type, call sign, origin, and destination).

Two complementary datasets were used to learn the statistical model. Historical weather conditions for the period analyzed were collected from the Meteorological Aerodrome Reports - METARs (ASOS Network, 2019) of both airports. Historical Air Traffic Flow Management (ATFM) restrictions were obtained from the Brazilian Air Navigation Management Centre (CGNA, 2019).

3.2. Vertical Inefficiency of Descents (VID)

To measure the vertical inefficiency of a flight trajectory, a quantitative metric is needed.

The methodology adopted to measure VID follows ICAO's Key Performance Indicator (KPI) 19 (ICAO, 2019b). This KPI is intended to indicate the amount of level flight during the descent phase. There are two variants. The first considers the average distance flown in level flight, while the second uses the average time flown in level flight during descent. We use the distance variant, but the same method could also be applied with the time variant. Equation (1) defines the VID metric.

$$VID = \frac{total\ distance\ in\ level\ flight\ during\ descent}{total\ descent\ distance} \times 100 \quad (1)$$

This analysis considers a radius of 40 NM around each airport. Henceforth, for practical purposes, the airspace contained within the radius of 40 NM from the destination airport will be referred to as terminal airspace. Level flight segments in descent trajectories are detected using a vertical speed limit or an altitude limit. The vertical speed limit considered is 300 feet per minute and the altitude limit is 150 feet below or above the previous data point. Thus, a data point is the start of a flight segment in constant altitude if the vertical speed towards the next data point is less than or equal to the vertical speed limit (300 feet per minute), or if the altitude difference to the next data point is less than or equal to the module of the altitude limit (150 feet). An exclusion box of 90% is also adopted, which means that we exclude from the analysis data points at which the altitude is higher than 90% of the maximum altitude of each flight within the 40 NM airspace.

3.3. Identification of Arrival Trajectory Patterns

The airspace surrounding an airport is typically structured with several arrival and departure procedures that allow aircraft to transition between the en route airspace and the airport. This highly structured airspace is one of the main factors that are expected to drive the VID, especially in busy metroplex airspace where procedures from closely located airports have to be de-conflicted. To account for this factor, we perform a trajectory clustering analysis to learn the route structure actually flown in the airspace analyzed and identify the arrival trajectory patterns followed by each aircraft.

The trajectory clustering process was performed with the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm (Ester *et al.*, 1996). The choice for this algorithm is based on the following reasons: it can automatically handle noise observations, enabling the identification of the trajectory patterns in the presence of abnormal trajectories; it allows for the correct identification of non-convex clusters; and it does not require the number of clusters as an input. Moreover, the DBSCAN algorithm has been extensively used for clustering flight trajectory datasets in previous studies (Gariel et al., 2011; Liu et al., 2017; Murça et al., 2018).

3.4. Statistical Modeling

The statistical model seeks to map structural and operational factors into vertical performance. A linear regression model, shown in Equation (2), was learned from the data collected from each airport. The VID metric of flight k in hour t is the dependent variable and each flight is considered as a unique observation. The hour t corresponds to the time of the last data point, before landing, of each flight. The regressors fall into one of the following five categories: demand, weather conditions, ATFM restrictions, airspace structure, and aircraft type, as shown in Table 1.

$$VID(\%) = \beta_0 + \beta_1\ ARR\_CGH_t + \beta_2\ DEP\_CGH_t + \beta_3\ ARR\_GRU_t + \beta_4\ DEP\_GRU_t + \beta_5\ WX_t + \beta_6\ IMC_t + \beta_7\ MIT_t + \beta_8\ CLUSTER_* + \beta_9\ ACFT.MODEL_k + \mu \quad (2)$$

Table 1 – Description of model input variables

Category	Variable Label	Description
Demand	ARR_CGHt	number of flights arriving at CGH at hour t
	DEP_CGHt	number of flights departing from CGH at hour t
	ARR_GRUt	number of flights arriving at GRU at hour t
	DEP_GRUt	number of flights departing from GRU at hour t
ATFM restrictions	$MITt$	dummy variable that indicates whether a flight was performed during a period in which an ATFM restriction (MIT) was in place.
Weather Conditions	WXt	dummy variable indicating the presence of convective weather. It is 1 when the METAR of hour t reports rain, thunderstorm, or cumulonimbus clouds.
	$IMCt$	dummy variable that indicates instrument meteorological conditions. It is 1 when the METAR of hour t reports visibility below 3 NM or ceiling below 1000 ft.
Trajectory Pattern	$CLUSTER\_*$	dummy variables indicating which nominal route was used by the flight. The baseline is the group of non-conforming trajectories, i.e., that do not fall into any of the identified trajectory patterns.
Aircraft Type	$ACFT.MODELk$	dummy variables for each aircraft type.

The demand and weather variables are intended to capture the possible effect of increased traffic complexity on vertical performance. Congested periods, convective weather activity, and low visibility and ceiling conditions may cause additional holdings and rerouting, which can be performed in level flight, potentially increasing the VID. To capture the possible effect of traffic interference between the two airports in the metroplex system, the demand variables of both airports are used in the model of each of them. The ATFM variable is intended to capture potential impacts of tactical MIT restrictions on vertical efficiency. MIT restrictions are the most common ATFM strategy used by the Brazilian Air Navigation Management Center to regulate the traffic and handle demand-capacity imbalances. As vectoring may be used by air traffic controllers to provide the MIT separations, these restrictions might affect the VID. The trajectory pattern variables seek to account for the impacts of the airspace structure on the VID. Finally, the aircraft model variables are intended to capture the effects of performance differences among aircraft models.

4. RESULTS AND DISCUSSION

4.1. Quantification of vertical performance

The VID metric was calculated for each flight in the period analyzed using Equation (1). We observed that 13% of the descents were CDOs (VID = 0) in CGH and 3% in GRU. Figure 1 displays the frequency histograms of VID for CGH and GRU, where each bar represents the flight count in each 5% VID interval. For example, 4,592 flights showed up to 5% of VID in CGH, and 6,554 in GRU. The airports exhibit similar vertical performance: the mean VID was found to be 8.86% for CGH and 8.67% for GRU (dashed lines); 89% of the flights showed up to 20% of inefficiency in both airports.

With the trajectory clustering analysis performed with DBSCAN, six arrival trajectory patterns were identified for CGH, and nine were identified for GRU. Figure 2 shows the nominal routes (centroids of the trajectory clusters) learned for each airport.

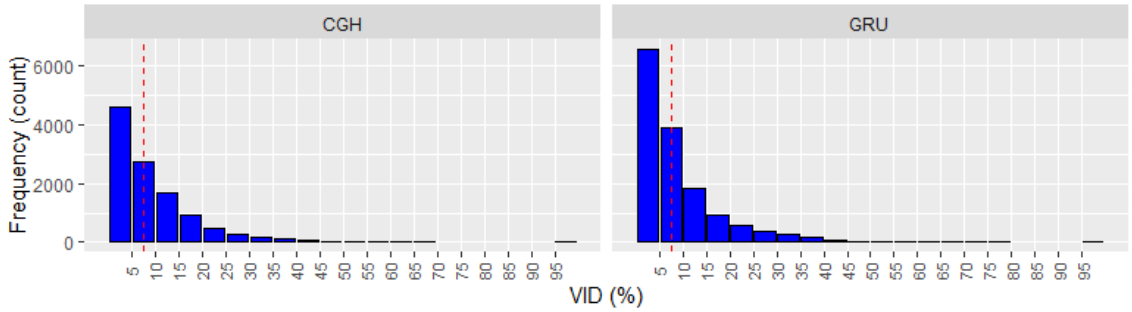

Figure 1. Distribution of VID at GRU and CGH

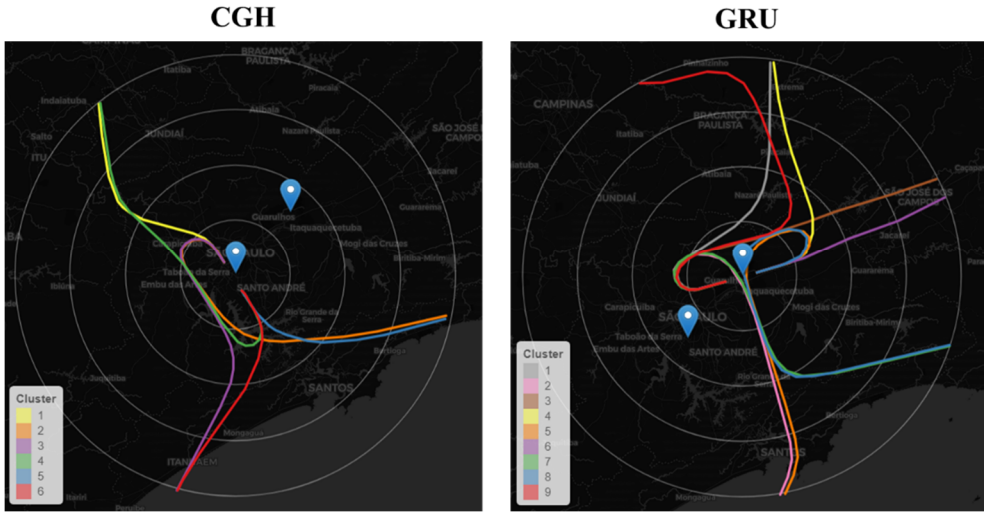

Figure 2. Nominal routes learned for GRU and CGH

Figures 3 and 4 show the clusters of flight trajectories for CGH and GRU, respectively, represented in different colors. The non-conforming trajectories automatically identified with the clustering algorithm employed are also shown in the bottom row. They are colored according to the nearest cluster. It is observed that most of them are a result of tactical air traffic control instructions such as airborne holding, excessive vectoring, or rerouting. The complete trajectories in the terminal airspace are displayed on the left of Figures 3 and 4 whereas only flight segments at constant altitude are shown on the right. The white circles drawn have radii of 10, 20, 30, and 40 NM. For both airports, most level flight segments were observed to occur within 20 NM from the airport for flights conforming to a particular trajectory pattern, whereas holdings, vectoring, and rerouting segments of non-conforming trajectories were observed to occur throughout the terminal airspace, usually more than 20 NM away from the airport. Figure 3 shows that a significant portion of the level flight segments was observed to occur within around 10 NM from CGH in trajectory patterns that circulate the aerodrome for landing at the opposite runway threshold (clusters 2, 3, and 4). Figure 4 shows a similar behavior for cluster 2 at GRU.

Figure 5 shows the frequency of each cluster and the group of non-conforming trajectories, labeled as NC. The non-conforming trajectories represent 7.3% of the flights in CGH and 8.3% in GRU. The top-three most flown trajectory patterns for CGH are associated with landings on runway 17R. For GRU, the top-three trajectory patterns are associated with landings on runway 09R. Together, they represent over 70% of the operations at each airport, revealing a dominant runway configuration.

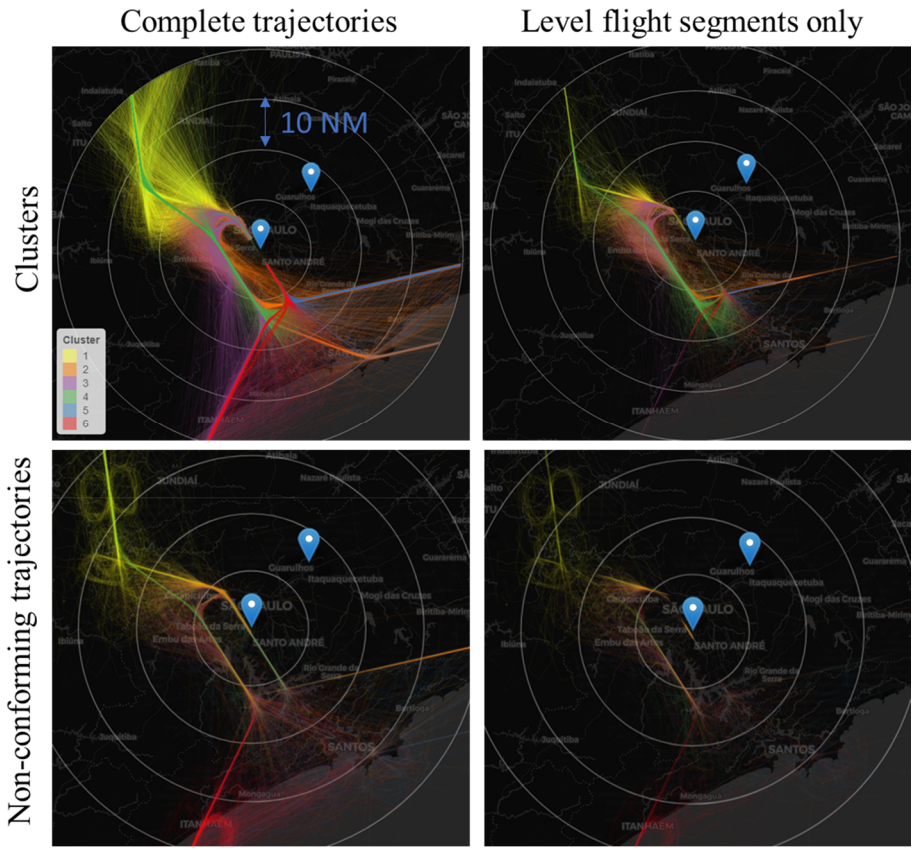

Figure 3. Arrival trajectories in CGH

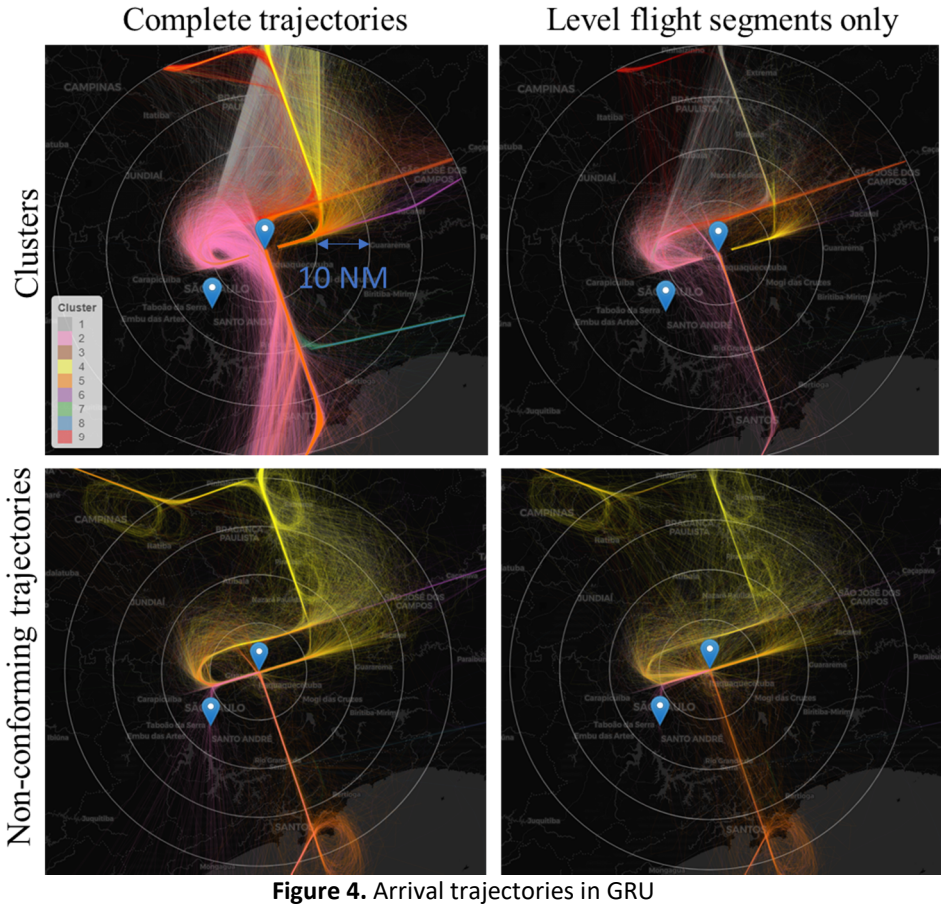

Figure 4. Arrival trajectories in GRU

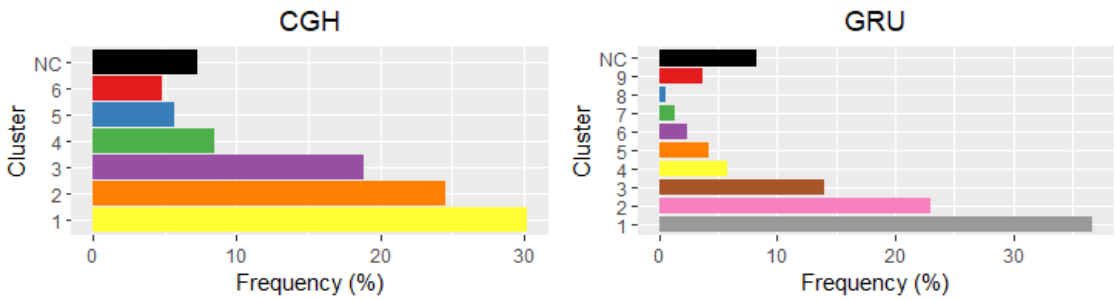

Figure 5. Distribution of trajectories by cluster (non-conforming trajectories labeled as NC)

Figure 6 shows the amount of non-conforming trajectories that are associated with each cluster, as a percentage of the cluster size (number of flights). It suggests that non-conforming trajectories due to holding, vectoring, and rerouting are more likely to be observed for flights that would have ideally followed trajectory pattern 6 at CGH and trajectory pattern 4 at GRU. Besides, the non-conforming trajectories whose nearest cluster is one of the top-three most flown in each airport represent less than 10% of the size of the respective clusters.

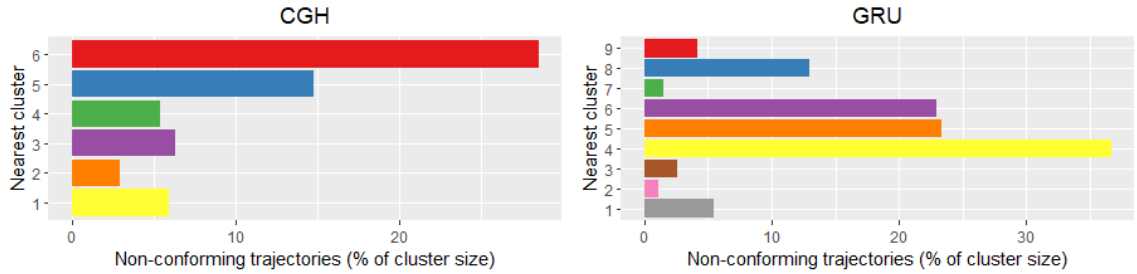

Figure 6. Amount of non-conforming trajectories as a percentage of the nearest cluster's size (number of flights)

Figures 7 and 8 illustrate the vertical trajectory profile for flights arriving at CGH and GRU, respectively, by cluster. Each line, colored based on the calculated VID, represents a trajectory. It is possible to note that many trajectories classified as non-conforming showed flying times of more than 30 minutes within the terminal airspace at relatively low altitudes for both airports. For arriving flights at CGH, most of them enter the airspace contained within the radius of 40 NM considered in this analysis at an altitude lower than 20,000 feet. The flights associated with trajectory patterns 1, 5, and 6 enter the terminal airspace usually at a lower altitude than the others and also spend less time inside the terminal area. The flights associated with trajectory patterns 2, 3, and 4, that circulate the aerodrome for landing on the runway threshold of opposite direction to the terminal arrival gate, enter the terminal airspace at higher altitudes, and usually fly for over 20 minutes until landing. For arriving flights at GRU, most of them enter the terminal airspace at an altitude higher than 20,000 feet, except for trajectory patterns 3 and 6, which are associated with flights that come from Rio de Janeiro.

Figure 9 displays the boxplot of VID for each trajectory pattern and the group of non-conforming trajectories. For CGH, arrival pattern 4, that corresponds to flights descending through the north gate to land on runway 35L, and the group of non-conforming trajectories stand out with the highest mean vertical inefficiency. For GRU, arrival pattern 9, which corresponds to flights descending through the northwest arrival gate to land on runway 09R, and the group of non-conforming trajectories stand out with higher VIDs.

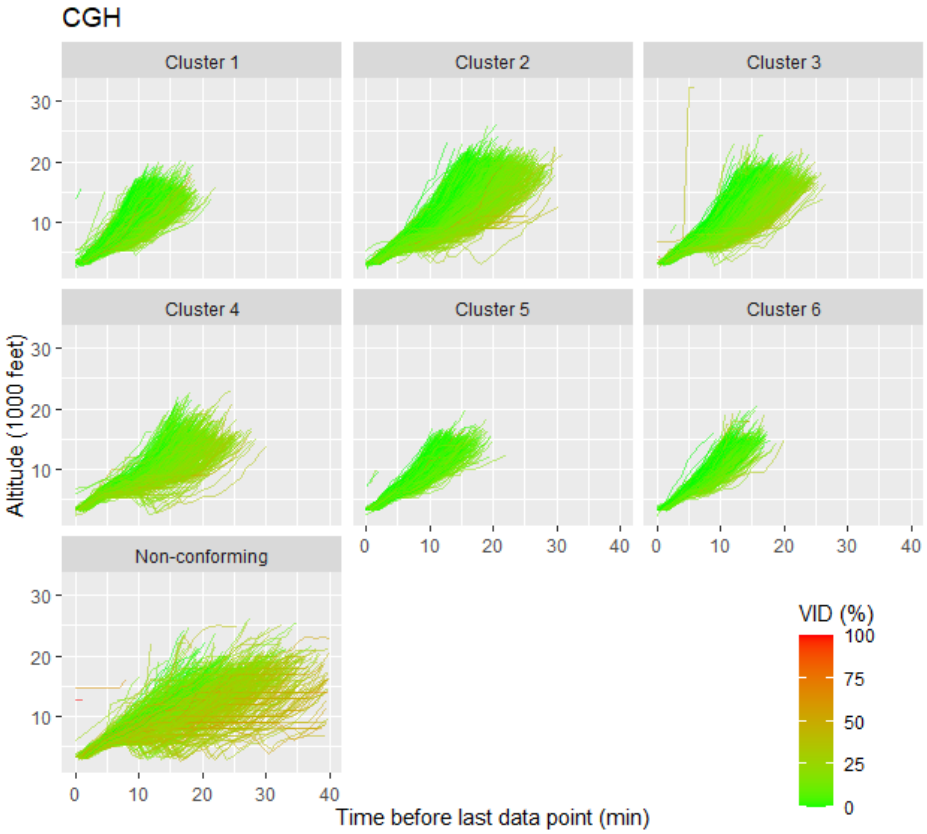

Figure 7. Vertical profile of actual flight trajectories by cluster for CGH

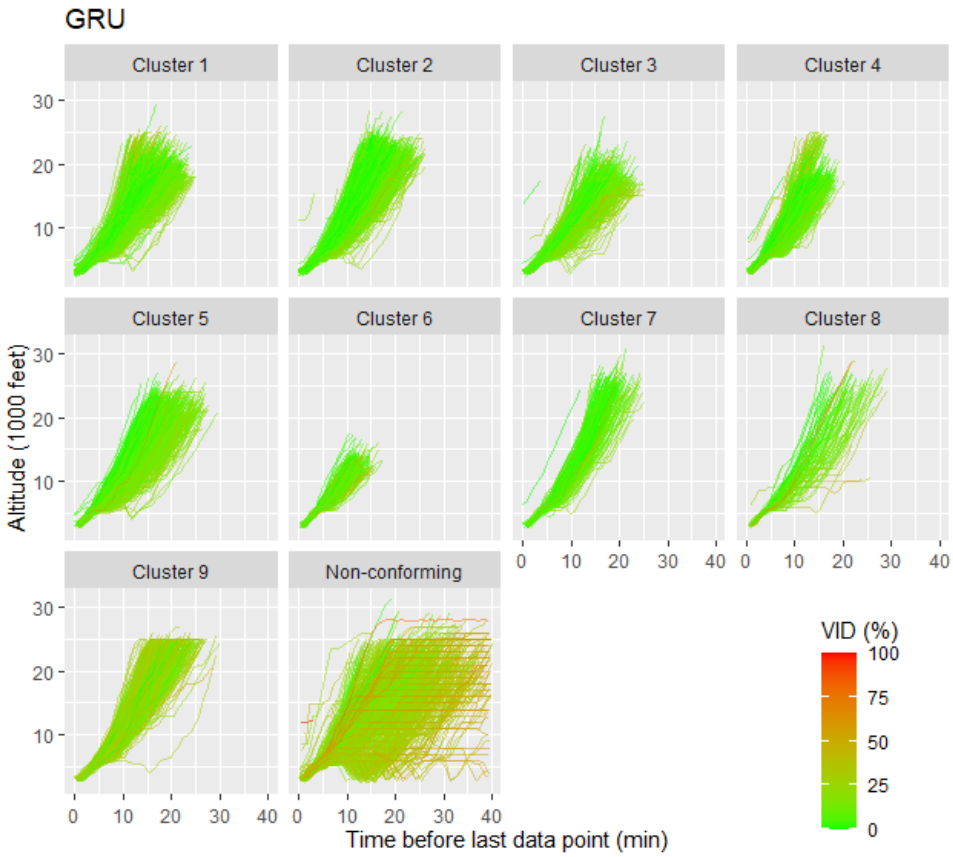

Figure 8. Vertical profile of actual flight trajectories by cluster for GRU

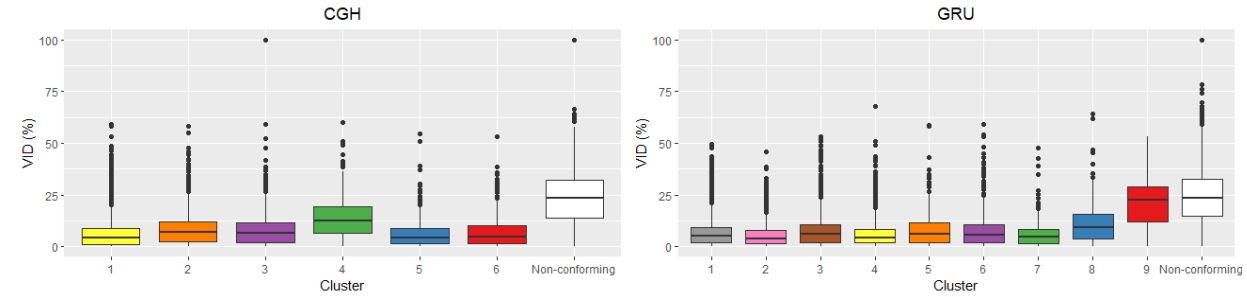

Figure 9. VID by arrival cluster for CGH and GRU

Figure 10 shows the mean altitude of level segments by trajectory pattern for flights with VID higher than zero, weighted by the distance flown at each altitude. The altitude at which level flights occur is an important factor in the VID analysis since level-offs in low altitudes are more critical in terms of fuel consumption and noise. In general, the trajectory patterns with the highest VIDs also presented the highest altitude of level segments. This may indicate an initiative of the Brazilian ANSP to reduce fuel consumption and noise through the airspace design. For CGH, trajectory pattern 4 and the group of non-conforming trajectories presented mean altitude of level segments of 8,448.4 ft and 9,625.2 ft, respectively. For GRU, the mean altitude of level segments was found to be 18,722.9 ft for trajectory pattern 9 and 12,077.6 ft for the group of non-conforming trajectories.

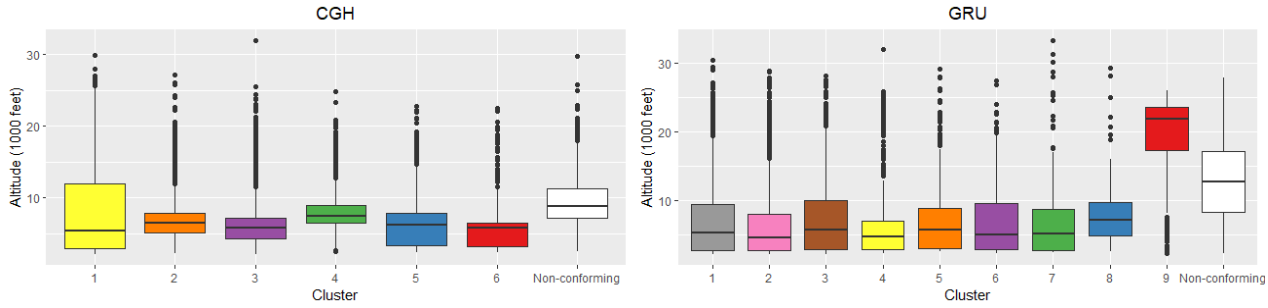

Figure 10. Mean altitude of level segments during descents by cluster at CGH and GRU

For a better understanding of vertical inefficiencies, Figure 11 shows the level flight segments of the most inefficient clusters and the group of non-conforming trajectories. For both airports, the level flight segments of the non-conforming trajectories are observed to occur at different altitudes, especially in holding patterns that happen within specific areas of the terminal airspace. For CGH, the most inefficient trajectory pattern (4) shows level flight segments at an altitude between 5,000 ft and 10,000 ft, when aircraft fly parallel to the runway for landing at the runway threshold of opposite direction relative to the terminal arrival gate. For GRU, the most inefficient trajectory pattern (9) shows a significant amount of level flight segments near the terminal airspace entrance at altitudes close to 25,000 ft. It also shows a concentration of flight segments at a constant altitude between 5,000 ft and 7,000 ft in the last turn.

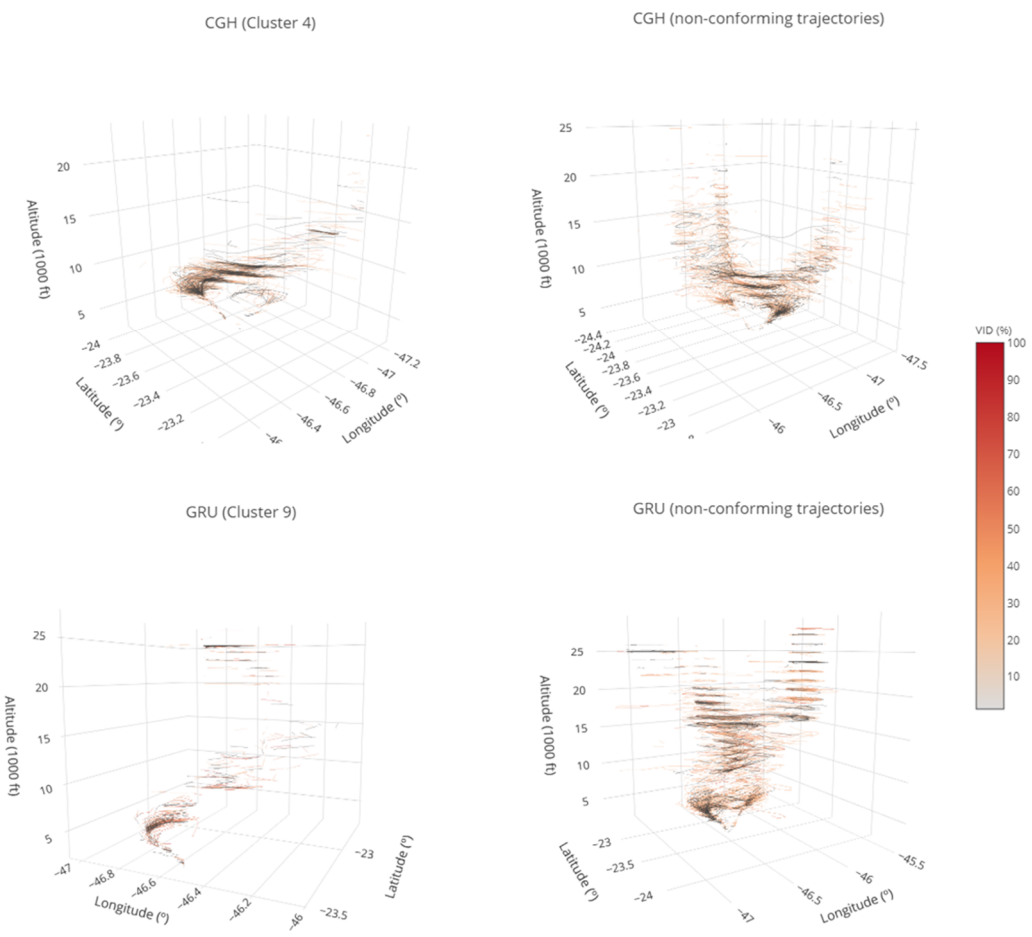

Figure 11. 3D visualization of level flight segments for the most inefficient clusters

4.2. Model Estimation Results

A linear regression model was learned from the data of each airport to analyze the causal factors for vertical inefficiency. The model estimation results are summarized in Table 2. Most coefficients resulted statistically significant, and their signs generally match the theoretical expectations. An important factor explaining VID variability was found to be the airspace structure, as expected, due to the different intrinsic characteristics of flight procedures published in the aeronautical charts. The coefficients of all the trajectory pattern variables resulted significant with negative signs, indicating lower vertical performance for flight trajectories of the baseline group, that did not follow any of the trajectory patterns. Indeed, most non-conforming trajectories were observed to be a result of holding instructions and vectoring in the terminal area, as Figure 3 suggests, indicating that some amount of time is spent in level flight due to tactical air traffic control. Among the trajectory patterns, cluster 4 for CGH and cluster 9 for GRU stood out as the least efficient, as expected. These results match the statistics presented in Figure 4.

The positive and statistically significant coefficients of the arrival demand variables indicate that the number of arriving aircraft increases the VID, i.e., vertical performance tends to degrade with higher levels of congestion. Yet, the neighboring airport arrival demand was not found to be statistically significant, potentially indicating that the Sao Paulo metroplex operations have a low level of interdependency. This agrees with the observations made by Murça et al. (2018).

The coefficient of the variable WX resulted statistically significant at 1%, with a positive sign for both airports, revealing that convective weather tends to increase the VID, probably because of time spent in level flight during holdings and rerouting. The positive coefficient of the variable IMC also suggests an impact of low ceiling and visibility conditions on vertical performance, although low statistical significance was observed. Finally, the coefficient of the MIT variable was found to be positive and statistically significant at the 1% level, revealing that tactical traffic flow management restrictions also contribute to degrading trajectory performance in the Sao Paulo TMA.

Table 2 – Model estimation results

	CGH	GRU
Intercept	21.1765***	22.5838***
ARR_CGH	0.1368***	0.0292
ARR_GRU	0.0034	0.0890***
DEP_CGH	-0.0498	-0.0015
DEP_GRU	0.0633*	-0.0512*
WX	6.3494***	3.9406***
IMC	0.0218	0.1275
MIT	1.6705***	1.5604***
CLUSTER_1	-17.0745***	-17.4840***
CLUSTER_2	-14.5444***	-18.8360***
CLUSTER_3	-15.0241***	-16.3570***
CLUSTER_4	-9.3908***	-17.5369***
CLUSTER_5	-17.0653***	-16.4698***
CLUSTER_6	-16.2905***	-15.6019***
CLUSTER_7		-17.9197***
CLUSTER_8		-13.0882***
CLUSTER_9		-1.0738**
Adjusted R2	0.275	0.379
RMSE	7.906	7.695
N_obs	11144	14848

p-value representations: * p<0.10, ** p<0.05, *** p<0.01

4.3. Relative Importance of Causal Factors

The statistical models were further used to estimate the relative importance of each causal factor on VID, based on the decomposition of the model R^2. The relative importance metric adopted (LMG) uses sequential sums of squares from the linear model and an overall assessment is obtained by averaging over all orderings of regressors (Grömping, 2007). For p regressors added to the model, the LMG of each regressor is given by Equations (3)-(5). The order in which regressors are added to the model is denoted as $r = (r_1, ..., r_p)$, which is a permutation of the regressors' indices $\{1, ..., p\}$, and the set of regressors appearing before X_1 in the order r is denoted as $S_1(r)$.

$$LMG(1) = \frac{1}{p!}\sum_{r\ permutation} svar(\{1\}|S_1(r)) \quad (3)$$

$$svar(M|S) = evar(M \cup S) - evar(S) \quad (4)$$

$$evar(S) = var(Y) - var\left(Y\middle|X_j, j \in S\right) \quad (5)$$

Equation (5) defines the explained variance based on regressors with indices from S and Equation (4) defines the sequentially added explained variance when adding the regressors with indices in M to a model that already contains the regressors with indices in S.

Figure 6 shows the relative importance based on the LMG metric for the regressors in Equation 2. To assess the stability of the ranking, bootstrap confidence intervals are provided.

The results indicate that the trajectory patterns (clusters) explained most of the variance in VID, accounting for over 75% of the R^2 in Table 2. The second most important causal factor for vertical inefficiency in the Sao Paulo TMA was found to be convective weather.

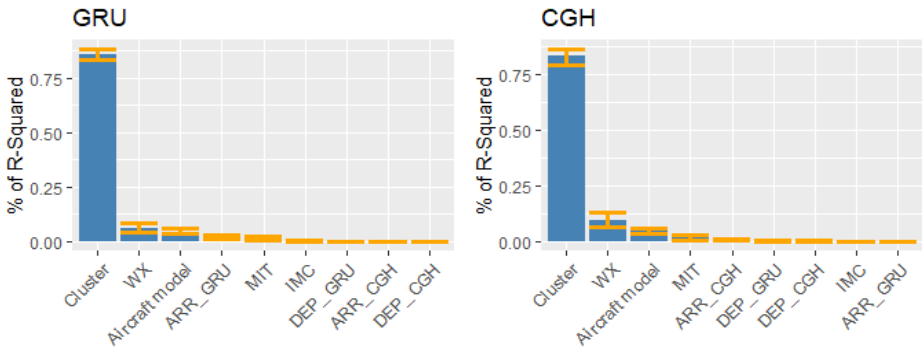

Figure 12. Relative importance of causal factors for VID

5. CONCLUSIONS

Assessing the level of flight trajectory adherence to reference ideal procedures is key to identify structural and operational improvements that can increase air traffic efficiency. Fortunately, recent opportunities have arisen to characterize and understand trajectory performance through data analytics techniques applied on increasingly available operational data.

This paper presented a statistical model of flight trajectory performance and investigated causal factors for vertical inefficiency during descents in the Sao Paulo metroplex. Historical flight tracking data for the two major airports, Congonhas (CGH) and Guarulhos (GRU), was leveraged to learn the structure and the use of the metroplex terminal airspace, with a trajectory clustering analysis, and to quantify vertical inefficiency in terms of the amount of level flight during descents. A regression model was then developed to map structural and operational factors into vertical performance.

We found that the airspace structure was the most important factor explaining the variability in vertical performance and that some trajectory patterns consistently showed lower efficiency. We also obtained statistical evidence for the negative impacts of arrival demand, adverse weather conditions, and traffic flow management restrictions on vertical efficiency. Among these, convective weather was found to be the most important causal factor for the inefficiencies observed. The results suggest that local improvements in airspace design, as well as the implementation of strategic traffic flow management measures, might be pursued to increase the vertical performance of air traffic operations in the Sao Paulo TMA. For example, the TMA-SP Neo project, which will redesign the Sao Paulo TMA in 2021, can contribute to mitigating the inefficiencies pointed out in this study.

The methodology presented in this paper can help targeting interventions to reduce vertical inefficiencies by identifying the causes that are most important for different airports. It also indicates how much inefficiency cannot be attributed to any of the observable factors considered. Extensions of this work may assess the fuel consumption and extra flight time associated with each cause of inefficiency. In addition, a more in-depth analysis of flights that occurred during convective weather can be useful to assess the impacts of ATFM measures taken in these circumstances.

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