Benchmarking Croatian airports: A data-driven approach through DEA window analysis

Damira Keček[1], **Katerina Fotova Čiković**[1,*] and **Violeta Cvetkoska**[2]

[1] *University North, Trg dr. Žarka Dolinara 1, 48000 Koprivnica, Croatia*
E-mail: ⟨{dkecek, kcikovic}@unin.hr⟩

[2] *Faculty of Economics – Skopje, University of St. Cyrill and Methodius, Boulevard Goce Delchev 9, Skopje 1000, North Macedonia*
E-mail: ⟨vcvetkoska@eccf.ukim.edu.mk⟩

Abstract. This study benchmarks the efficiency of seven certified international airports in Croatia using Data Envelopment Analysis (DEA) with a window framework under variable returns to scale, explicitly addressing the challenge of a small number of decision-making units through dynamic window specification. Efficiency scores were calculated across overlapping three-year periods from 2019-2023, allowing performance dynamics to be captured during both crisis and recovery phases. The results reveal substantial heterogeneity across airports. Osijek Airport emerged as the most consistently efficient, outperforming larger hubs such as Zagreb and Split, while Zadar and Rijeka demonstrated notable efficiency improvements over time. In contrast, Dubrovnik Airport recorded persistently low efficiency despite traffic recovery, suggesting structural cost rigidity and seasonal vulnerability. These findings highlight the operational resilience of smaller regional airports and signal performance constraints among major hubs. By integrating traffic trends with efficiency outcomes, the study shows that rising passenger volumes alone do not ensure improved economic performance. The results provide a timely, evidence-based framework for airport managers and policymakers to enhance strategic planning, improve resource allocation, and strengthen the financial sustainability and competitiveness of Croatia's air transport sector.

Keywords: airport efficiency, benchmarking, Croatian airports, data envelopment analysis, window analysis

Received: November 3, 2025; accepted: December 8, 2025; available online: February 9, 2026

DOI: 10.17535/crorr.2026.0017

Original scientific paper.

1. Introduction

Airports are not just transit hubs but also engines of economic growth, connectivity, and tourism development. They facilitate the transport of passengers and goods, stimulating trade, tourism, and investment. According to the report "The Economic and Social Impact of European Airports and Air Connectivity", European airports significantly impact regional economic development and social connectivity [25]. The report's key findings indicate that European airports positively impact the economy, contributing to the employment of approximately 6% of all jobs and generating 5% of European GDP. However, the report also emphasized striking a balance between the economic factors of air transport and its impact on the climate, all to reduce negative environmental impacts. Furthermore, research on the impact of airports on the environment is increasingly important in the context of the global goal of reducing CO emissions.

*Corresponding author.

[10] emphasized the need for sustainable operations, including the introduction of alternative energy sources to reduce the environmental footprint of airports.

Airport efficiency directly impacts the entire air transport system, including flight punctuality, resource utilization, and operating costs. According to [13], airports implementing advanced technologies, such as real-time traffic management systems and digital baggage handling, experience reduced delays and increased passenger satisfaction. Additionally, infrastructure optimization, such as terminal expansion or runway improvements, can significantly increase capacity and reduce congestion. [9] noted that operational efficiency increases airport capacity and enables better integration with other modes of transport, thereby improving the overall mobility of passengers and goods. Airport efficiency concerns not only operational aspects but also economic sustainability as increased productivity can reduce airline operating costs and passenger fees, increasing airport competitiveness.

Research in this area is crucial to improving airport performance while minimizing costs and environmental impact [19, 5]. Data envelopment analysis (DEA) allows accurate measurement of airport service quality and profitability [21, 12, 31]. Furthermore, airports with better operational management make greater economic contributions to the regions in which they operate, enabling greater connectivity, attracting investment, and supporting employment [25]. Given the increasing global demand for air transport and the need for sustainable solutions, research in this area is becoming essential for the future development of the aviation industry. Moreover, the digital transformation and digitalisation of airports globally is a topical and very contemporary subject. The digital transformation process of airports is still predominantly viewed from the aspect of technology application. At the same time, the organizational impact, environment and passenger experience are often neglected and insufficiently researched in the literature [26].

The efficiency of Croatian airports in the domestic literature has received insufficient attention. To the best of the authors' knowledge, the efficiency of Croatian airports via the DEA methodology was analyzed only in [3] for the period 2004-2008 and in [24] for the period 2009-2014. This paper aims to assess and compare the relative efficiency of certified international airports in Croatia via DEA for the more recent period (2019-2023), thereby filling a gap in the domestic literature and providing data-driven guidance for improving airport performance and competitiveness. The contribution of this research lies in presenting a comprehensive and updated assessment of airport efficiency in Croatia for the recent period, filling a significant empirical gap in the national literature. The study highlights current performance trends across airports by applying a dynamic benchmarking approach. It offers valuable, evidence-based guidance for enhancing operational efficiency, resource allocation, and strategic competitiveness in an increasingly demanding and globally interconnected air transport sector. The remainder of the paper is organized as follows: Section 2 reviews relevant literature on airport efficiency and DEA; Section 3 explains the methodology and data; Section 4 presents the results; and Section 5 discusses the findings and concludes the study.

2. Literature review

The aviation industry has flourished in recent years and airport management styles have evolved to apply various benchmarking techniques [20]. As critical infrastructure to the aviation industry, airports are essential for their success and overall performance [31].

Operational efficiency refers to an airport's ability to optimally utilize its resources to ensure a safe, fast, and reliable flow of passengers, cargo, and aircraft. Increasing airport operational efficiency reduces costs, improves the passenger experience and increases airports' competitiveness in the global marketplace. Analysis of the operational efficiency of airports uses different methods to identify opportunities for improvement and optimization of resources. According to [14] and [6], parametric and nonparametric methods are mainly applied, with an emphasis on the nonparametric method of data envelopment analysis (DEA).

DEA is a frequently applied methodology for assessing airport efficiency and can be used to improve airport efficiency [16]. The authors noted that there is no systematic approach to selecting input and output variables, but research depends on available data. A literature review is focused on relevant studies that use the DEA methodology. While DEA forms the core of this review, it is important to note that airports have also been benchmarked using alternative efficiency measurement techniques. Parametric approaches such as stochastic frontier analysis (SFA) have been applied to assess cost and technical efficiency and to compare results with nonparametric models, as shown in [20]. Earlier studies also used Free Disposal Hull (FDH) models alongside DEA, providing a useful comparison between deterministic and nonparametric frontiers. These alternative methods offer complementary insights and underscore the importance of methodological choice when interpreting airport efficiency outcomes. Against this broader methodological background, the present review focuses on DEA-based research, including different DEA model variants, the selection of input and output variables, and policy recommendations for improving airport efficiency proposed in previous empirical studies. Findings from previous studies help to formulate an appropriate DEA framework for assessing airport efficiency in Croatia, identify feasible input-output variables based on data availability, and derive policy recommendations tailored to national conditions.

Empirical studies based on the DEA methodology have been conducted in many countries. The findings of recent and relevant empirical studies emphasizing input and output variable selection are summarized in Table 1 and described in continuation. International studies provide useful benchmarks for Croatia, though their contexts differ. Research on large European hubs [14] highlights the role of user satisfaction, relevant for Zagreb as the main gateway airport. In contrast, analyses of Indian and Colombian regional airports [7, 22] emphasize how smaller airports can achieve high efficiency despite resource constraints, offering insights for Osijek or Rijeka. German airports [27], operating within the EU framework, provide the closest regulatory parallel to Croatia. These comparisons underscore that efficiency does not solely depend on size but on resource alignment, an especially critical factor for Croatia's tourism-driven airports with strong seasonal variation.

The evolution of the DEA methodology in analyzing airport efficiency, with methodological limitations and the complexities of airport operations included, is described in the following papers. [28] proposed a stepwise efficiency improvement DEA model incorporating fixed factors such as runways, addressing the need for objective efficiency analysis of Japanese airports. [29] presented an extended DEA model by combining the distance friction minimization (DFM) method to improve airport efficiency projections for both input reduction and output increase. [30] combined DFM with fixed factor analysis for a few airports in Europe, including the influence of commercial facilities.

By analyzing the operational efficiency of 37 Chinese airports for the period of 2016-2019 via a multi-input/output slack-based DEA model, [8] determined that all 37 airports have very low levels of operational efficiency. On the basis of these results, the authors concluded that airports are not self-sustaining and that more investment should be made in their infrastructure. The bound adjusted measurement (BAM)-DEA model with variable returns to scale [22] is considered the most suitable for measuring the efficiency of Colombian airports. The authors suggest introducing a larger number of variables to gain a more realistic insight into their effectiveness and enhance the competitiveness of the most important variables. The efficiency of Croatian airports was the subject of research by [3] and [24]. [3] reported that only Dubrovnik Airport was relatively efficient in 2008, whereas the average efficiency ratings of almost all Croatian airports increased during the five years analyzed. [24] identified Split, Pula, and Zadar as efficient airports over four years, and Zagreb and Osijek airports over one year. The research results indicate that the relative performance of airports in the analyzed period progressively declined.

Interestingly, even though the application of DEA in airport efficiency is increasing globally, its application in Croatia is quite modest. These two studies [3, 24] are the only studies in the Croatian scientific bibliography CROSBI. This was the main motivation for this study: to examine and assess the relative efficiency of Croatian airports in recent years. Owing to their vital role in traffic and tourism in Croatia, airport efficiency is extremely important to regulatory bodies, tourism offices, local governments, and scholars.

Author(s)	Period	Variables	Libraries and country	Methodology	DEA model orientation	Results
[7]	-	Inputs: average spending of the airport, the size, the number of parking bays, and the runways; Outputs: average passenger, average revenue, average aircraft movements, and freight	20 airports in India	DEA methodology	Output-oriented DEA model	Increasing returns to scale in 10 airports, decreasing in 2 airports, and constant in 8 airports
[22]	2018, 2019, 2020	Inputs: the length of the runway, the number of workers, the operational costs; Outputs: the number of passengers and tons of cargo.	26 airports in Colombia	Bounded Adjusted Measurement (BAM)-DEA method	Non-oriented DEA model	5 airports were detected as the most effective regional airports; variables runway length and number of employees noticed as the most important.
[14]	2018	Inputs: The number of runways at the airport and the total length of the airport runways; Outputs: the number of passengers	103 European airports	DEA CCR model	Output-oriented DEA model	9 airports detected as perfectly efficient
[15]	1992, 1993	Inputs: Employees, capital costs and other costs; Outputs: terminal passenger numbers and cargo	25 European and 12 Australian airports	DEA methodology and Free Disposal Hull Analysis (FDH)	n.a.	higher levels of efficiency detected in Australian airports
[27]	2016	Inputs: number of employees, number of runways, and airport area; Outputs: number of aircraft movements and the amount of cargo	27 airports in Germany	DEA methodology, CCR, and BCC models	Input-oriented DEA model	13 airports marked as efficient, 5 with an optimal and most productive size

[24]	2009-2014	Inputs: personnel costs, total expenditures excluding personnel costs, and total assets; Output: Total revenue/ATU.	7 airports in Croatia	DEA methodology, CCR and BCC window analysis	Input-oriented DEA model	relative performance of Croatian airports in the analyzed period is progressively declining
[30]	2003	Inputs: terminal space; the number of runways, the number of gates, the number of employees; Outputs: the number of passengers, aircraft movements	19 European airports	Extended DEA model by combining distance friction minimization (DFM)	The extended approach using DFM is non-radial	An extended DEA model is proposed to analyze and compare the efficiency of airports
[18]	2006-2010	Inputs: the airport size, the number of runways, the size of passenger terminals, and the size of cargo terminal; Outputs: the annual number of passengers and the annual cargo volume	20 major airports in East Asia, Europe, and North America	DEA-CCR, DEA-BCC, and DEA-Malmquist production index	Output-oriented DEA model	the most efficient were Gatwick, Zurich, Vienna, Leonardo da Vinci Fiumicino, Los Angeles International, Seattle-Tacoma, San Francisco, Hong Kong, Beijing Capital International, and Shanghai Pudong Airports
[3]	2004-2008	Inputs: expenditures and number of employees; Output: total number of passengers	7 Croatian airports	DEA CCR model, extended DEA method - window analysis	Input-oriented DEA model	The average efficiency ratings of almost all Croatian airports have increased over the observed period

Table 1: *Applications of the DEA methodology in airports' efficiency evaluation.*

Although many studies adopt input-oriented specifications, recent research increasingly supports output-oriented models when revenue generation is the primary performance objective.

3. Methodology and data

There are two basic approaches for assessing efficiency and performance in general, namely the parametric method (stochastic frontier) and the nonparametric method based on linear mathematical programming (which is most commonly the DEA methodology) [1]. The DEA approach is the leading nonparametric approach for the evaluation of airport efficiency, and compared with the stochastic frontier, the literature and the application of the DEA method in the hospitality and tourism sector are "significantly larger" [2].

DEA is one of the most prominent nonparametric methodologies in the field of operations research (OR) and is very popular among academic members, analysts, and consultants looking for ways to evaluate the efficiency of homogeneous units called decision-making units (DMU) [4]. This resulted in its continuous development and application in both theoretical and practical terms, as evidenced by numerous prestigious publications [11, 17].

The choice of DEA, rather than a parametric approach such as stochastic frontier analysis (SFA), is motivated by several methodological considerations. Airport operations involve complex and heterogeneous production processes for which specifying an explicit functional form is difficult and often restrictive; DEA avoids this by requiring no prior assumptions about the production technology. In addition, the relatively small number of Croatian airports makes nonparametric approaches more suitable, as DEA performs well with small samples where parametric estimations may lack statistical reliability. Although alternatives, such as the Malmquist productivity index, are frequently used for productivity analysis, they rely on stronger assumptions, including stable technology and consistent input-output structures across periods. Given the small number of airports and the structural break caused by COVID-19, Malmquist results would be unstable and potentially misleading. Window DEA is therefore more appropriate, as it avoids intertemporal frontier comparability and remains robust under crisis conditions.

Window DEA is a widely adopted mathematical programming extension that enhances discriminatory power and allows dynamic efficiency assessment in panel data settings [23] and treats each DMU as distinct across reporting periods, enabling dynamic efficiency assessments that better reflect reality than static DEA models do. Subdividing data into overlapping time windows analyzed separately addresses limitations tied to variable-DMU ratios and introduces a time dimension to efficiency tracking [24]. By treating the same airport in different years as distinct units, window analysis increases the number of observations, stabilizes efficiency estimates, and makes it possible to track performance dynamics. This is particularly useful in the Croatian context, where only seven certified airports exist, and where efficiency is strongly influenced by seasonal and cyclical fluctuations.

A standard DEA framework requires a sufficiently large number of decision-making units (DMUs) relative to the number of inputs and outputs to ensure reliable and discriminating efficiency results. One widely accepted condition is that the number of DMUs should satisfy:

$$N \geq 3(m+s) \tag{1}$$

where m is the number of input variables and s is the number of output variables. In the present study, three inputs and one output are used, implying a minimum requirement of $3(3+1) = 12$ DMUs. However, the Croatian airport system consists of only seven airports, which violates this criterion in a conventional DEA setting and would lead to inflated efficiency scores.

To overcome this limitation, a Window DEA framework is employed. Window DEA extends static DEA by converting panel data into overlapping sub-samples ("windows"), treating each DMU in each year as a separate unit. Let $i = 1, \dots, 7$ index airports, $t = 1, \dots, 5$ denote years (2019–2023), and $w = 1, \dots, 3$ represent analysis windows. Each window contains $7 \cdot 3 = 21$ DMUs, thus satisfying the required discrimination threshold:

$$N_w = 21 \geq 12 \tag{2}$$

The adopted windows are: (2019–2021), (2020–2022), and (2021–2023). Within each window, the output-oriented BCC model under variable returns to scale is solved.

For a given airport-year observation j in window w, the BCC model is defined as:

$$max_{\theta,\lambda}\theta \tag{3}$$

subject to:

$$\sum_{j=1}^{N_w} \lambda_j y_{rj} \geq \theta y_{rj_0}, r = 1, \dots, s \tag{4}$$

$$\sum_{j=1}^{N_w} \lambda_j x_{ij} \leq \ x_{ij_0}, i = 1, \dots, m \tag{5}$$

$$\sum_{j=1}^{N_w} \lambda_j = 1 \tag{6}$$

$$\lambda_j \geq 0, j = 1, \ldots, N_w \tag{7}$$

where x_{ij} and y_{rj} denote input and output values, respectively, and λ_j are intensity variables constructing the reference frontier. The convexity constraint ensures the variable returns to scale (BCC) specification, while the efficiency score θ represents the proportional expansion in outputs required for the evaluated airport to become efficient, given its current input levels.

In this formulation, θ is the scalar efficiency score of the evaluated airport-year observation (j_0). In the output-oriented model, $\theta \geq 1$ and $\theta = 1$ indicate full efficiency. The λ-weights represent intensity parameters that construct the reference (benchmark) frontier as a convex combination of observed DMUs. The constraint $\sum \lambda_j = 1$ imposes variable returns to scale, ensuring the BCC specification, where e denotes a row vector of ones. The BCC model requires two efficiency conditions: (1) $\theta = 1$ and (2) all constraints satisfied without excess input or output shortfalls.

Implementation Steps:

1. Form three-year moving windows,
2. Treat each airport-year as a DMU,
3. Apply BCC output-oriented DEA per window,
4. Aggregate efficiency results by airport and year,
5. Interpret trends across overlapping windows.

The model is specified under variable returns to scale (VRS), reflecting differences in airport size, capacity, and scale effects, large hubs such as Zagreb operate under fundamentally different conditions than small regional airports such as Osijek or Rijeka. VRS therefore provides a more realistic representation of the Croatian airport system than constant returns to scale. An output-oriented model was chosen because the primary managerial objective of airports is to maximise outputs (such as revenue generation) given largely fixed short-term inputs, especially infrastructure and labour. Other orientations are possible, but output orientation aligns best with both the operational reality of airports and the available dataset.

The main aim of this research is to measure and compare the relative efficiency of international airports in the Republic of Croatia by using the DEA window analysis technique for the period 2019-2023. Although the DEA model specification follows the structure used in [24], our choice of inputs and outputs is not based solely on that study. The broader literature review (shown in Table 1) reveals that financial variables, such as personnel costs, operating expenditures, assets, and revenues are among the most frequently used indicators in airport efficiency studies, particularly when the objective is to measure economic or financial performance (e.g., [3, 24, 7, 22, 8]). Airports differ substantially in size, traffic composition, seasonality, and commercial structure, which makes financial variables suitable since they capture resource utilization and performance in a way that is comparable across airports regardless of their operational mix.

Passenger traffic is indeed commonly used as an output variable in many DEA studies. However, its inclusion in our model was constrained by data consistency requirements. The annual passenger numbers presented in Table 7 originate from the Croatian Bureau of Statistics and represent realised traffic volumes. In contrast, the financial variables used in the DEA model were obtained directly from the annual financial statements of the airport operators. These two datasets are not fully synchronized: some airports classify transit passengers differently, some report combined domestic and international totals while others separate them, and cargo flows are inconsistently reported across years.

More importantly, the financial reporting framework remained consistent across all airports for the full 2019-2023 period, while the traffic dataset contains gaps in monthly and segment-level data for some airports during the COVID-19 years, making it unsuitable for constructing a uniform operational output across the entire sample. Another important methodological consideration is the ratio of sample size to the number of variables in DEA. With only seven airports in the sample (i.e. DMUs), expanding the model with several additional outputs (e.g., passenger volumes, aircraft movements, or cargo tonnage) would risk breaching established DEA guidelines that recommend maintaining a minimum of three times the total number of inputs and outputs to preserve discriminatory power and prevent an artificially high proportion of units from appearing fully efficient. Although the window analysis framework increases the total number of observations by treating each airport-year combination as a distinct unit, the effective number of DMUs within each window remains relatively small ($n = 21$), which constrains the feasible number of variables that can be included without compromising the robustness of the efficiency estimates.

To maintain discriminatory power and avoid model overspecification, we restricted the model to three inputs and one output. Given these constraints, total revenue was chosen as the output variable because it reflects the aggregate economic outcome of airport operations, encompassing both aeronautical and non-aeronautical activities. This aligns with the financial nature of the selected inputs (costs and assets), creating a coherent and internally consistent economic efficiency model. While passenger numbers could add a complementary operational dimension, the objective of this study is to assess economic efficiency rather than purely operational throughput. Future research may incorporate multiple operational outputs once fully harmonized traffic datasets become available.

Therefore, in this study, three input variables and one output variable are selected as follows: personnel costs, total expenditures excluding personnel costs and total assets as inputs and total revenue as output. The employed variables are presented in Table 2.

Character of variable	Variables
INPUTS	Personnel costs (I1) Total expenditures excluding personnel costs (I2) Total assets (I3)
OUTPUTS	Total revenue (O1)

Table 2: *Inputs and outputs of the DEA model.*

The empirical analysis was conducted using the dedicated window analysis module in MaxDEA 9, which automatically treats each airport-year observation as a separate DMU and ensures consistent window construction. The efficiency results for each airport help identify which Croatian airports are relatively efficient and which are not. Efficient airports are assigned a score of 1, i.e., 100%, whereas inefficient airports are assigned an efficiency score lower than 1.

We use a rolling window of three years, yielding three overlapping windows: 2019-2021, 2020-2022, and 2021-2023 (Table 3). Each airport appears in each window as a separate DMU for each year.

Window 1	2019	2020	2021		
Window 2		2020	2021	2022	
Window 3			2021	2022	2023

Table 3: *Length of the DEA windows used.*

The sample consists of 7 international airports that have been granted certificates in accordance with Commission Regulation no. 139/2014, i.e., Dubrovnik Airport (DU), Pula Airport (PU), Split Airport (ST), Zadar Airport (ZD), Franjo Tuđman Airport Zagreb (ZG), Osijek

Airport (OS), Rijeka Airport (RI). Brač Airport is excluded from the model since it is not an international airport. All the airports in the sample are "state or region/municipality owned with major state ownership" [24].

4. Results

The descriptive statistics offer critical insights into the operational diversity among Croatian international airports from 2019 to 2023 (Table 4). Across the dataset, variables such as personnel costs, other expenditures, total assets, and total revenues reveal wide dispersion and skewed distributions.

	Personnel costs	Total expenditures, excluding personnel costs	Total assets	Total revenue
Mean	5506917	16500335	129861906	24477038
Standard Error	878593	2848683	23355578	4339171
Median	3338275	6314172	24693255	11706093
Standard Deviation	5197826	16853036	138173464	25670879
Kurtosis	-0.3670	-0.7170	-1.1149	-0.8012
Skewness	0.9789	0.7960	0.7274	0.8714
Range	16491892	52485042	389650758	76381796
Minimum	477402	830050	13045695	1342196
Maximum	16969294	53315092	402696453	77723992
Sum	192742093	577511729	4545166709	856696346
Count	35	35	35	35

Table 4: *Descriptive statistics.*

For example, total assets ranged from approximately 13 million EUR to over 402 million EUR, with a standard deviation exceeding 138 million EUR. A similar pattern is evident in total revenue, which varies from just over 1.3 million EUR to more than 77 million EUR, emphasizing the heterogeneity of airport operations. All the variables exhibit positive skewness, with values ranging from 0.73 to 0.98, suggesting that most airports operate below the mean, but a few large airports (like Zagreb and Split) drive the upper end of the distribution. The kurtosis values are all negative, confirming flat, light-tailed distributions.

These observations justify the application of DEA, which remains robust in non-normal, high-variance datasets. Unlike traditional parametric methods, DEA handles this variability without imposing restrictive assumptions, ensuring fair and scale-independent efficiency comparisons.

Outlier detection was conducted over the full five-year period, with the results showing 2019 as an illustrative year (Figure 1). No outliers were identified in any of the years. The lack of extreme values strengthens the validity of the DEA results, as it indicates consistency in airport input-output behavior and confirms the reliability of the sample. It also eliminates concerns of frontier distortion, ensuring a more stable and interpretable efficiency frontier.

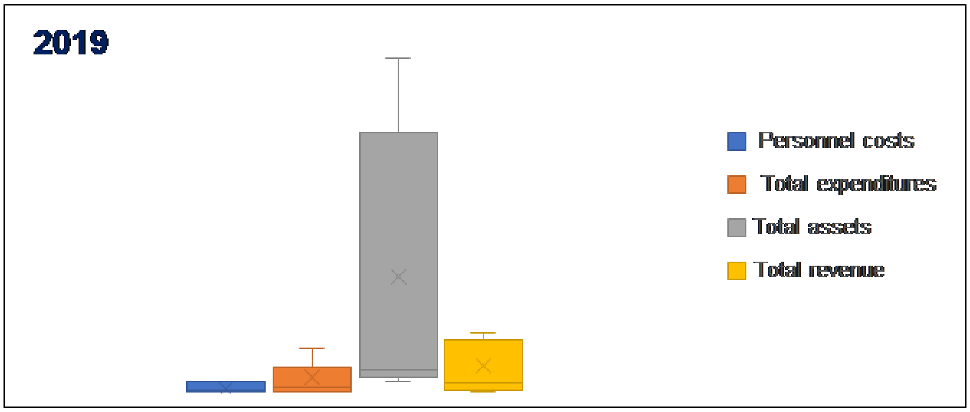

Figure 1: *Outlier diagnostics for input and output variables: evidence from the 2019 dataset.*

The output-oriented BCC DEA model, applied through window analysis with three-year overlapping windows, enabled a dynamic assessment of relative efficiency across the seven certified international airports in Croatia. Each airport was treated as a distinct decision-making unit in each window, allowing the model to capture both performance shifts over time and efficiency volatility. The analysis of the results is supported by efficiency scores across windows (Table 5) and average window DEA efficiency scores for each airport (Table 6), enabling a comprehensive interpretation of performance dynamics over time.

Osijek Airport (OS) demonstrated exceptional consistency and topped the efficiency rankings, with an average window DEA score of 0.9836. It maintained full efficiency in nearly all windows, showcasing highly effective resource management despite being one of the smaller airports in the system. Osijek's performance sets a benchmark for operational excellence and strategic agility in the sector.

Zadar Airport (ZD) ranked second, with an average score of 0.9008, indicating robust efficiency, particularly in the later windows. This indicates that Zadar has successfully adapted its operations over time, possibly benefiting from increased tourism flows and improved infrastructure.

Rijeka (RI) and Zagreb (ZG) followed closely, with average efficiency scores of 0.8627 and 0.8574, respectively. Rijeka achieved an efficiency score of 1.0000 in several later windows, suggesting improved cost control and better output generation. Zagreb, the capital airport and the country's largest airport, performed solidly overall, although not without fluctuations. Given its scale, a slightly lower average is not unexpected, as large airports often deal with more complex operational environments.

Split (ST), once reported as the most efficient airport in earlier studies [24], now ranks fifth, with an average efficiency of 0.7830. Although it reached full efficiency in later windows, its overall score reflects mid-range performance, which is likely affected by inconsistent cost efficiency or underutilization in certain years.

Pula Airport (PU) displayed moderate efficiency, with an average value of 0.6964. The gradual decline over successive windows points to either rising costs or stagnating revenues, which may require strategic investment and re-evaluation of service offerings.

Finally, Dubrovnik Airport (DU) recorded the lowest average score of 0.6695, despite the efficiency score of 1.0000 in the first year. Its persistent inefficiency across subsequent windows is concerning, especially considering Dubrovnik's prominent role in Croatian tourism. This drop might be attributed to seasonal imbalances, high fixed costs, or management challenges, and warrants a comprehensive performance review.

Window	Period	Dubrovnik (DU)	Osijek (OS)	Pula (PU)	Rijeka (RI)	Split (ST)	Zadar (ZD)	Zagreb (ZG)
1-3	1	1	1	0.9716	0.7783	1	1	1
1-3	2	0.3564	1	0.5162	0.5865	0.3577	0.63	0.5132
1-3	3	0.6043	1	0.7664	1	0.7238	1	0.6023
2-4	2	0.3706	1	0.5155	0.5264	0.3972	0.5809	0.7956
2-4	3	0.6033	1	0.7447	1	0.7841	0.9443	0.9357
2-4	4	0.8281	1	0.6795	1	1	1	1
3-5	3	0.6033	1	0.7447	1	0.7841	0.9517	0.9357
3-5	4	0.8145	1	0.6795	1	1	1	1
3-5	5	0.8454	0.8525	0.6497	0.8727	1	1	0.9337

Table 5: *Window DEA analysis score.*

DMU	Average Window DEA Efficiency Score
Osijek (OS)	0.9836
Zadar (ZD)	0.9008
Rijeka (RI)	0.8627
Zagreb (ZG)	0.8574
Split (ST)	0.7830
Pula (PU)	0.6964
Dubrovnik (DU)	0.6695

Table 6: *Average efficiency scores by airport (Window DEA).*

While Table 6 reports average efficiency scores aggregated across all windows, Table 6b presents year-specific averages, thereby restoring the dynamic dimension of airport performance.

Airport	2019	2020	2021	2022	2023
Dubrovnik (DU)	1.0000	0.3635	0.6036	0.8213	0.8454
Osijek (OS)	1.0000	1.0000	1.0000	1.0000	0.8525
Pula (PU)	0.9716	0.5159	0.7519	0.6795	0.6497
Rijeka (RI)	0.7783	0.5565	1.0000	1.0000	0.8727
Split (ST)	1.0000	0.3775	0.7640	1.0000	1.0000
Zadar (ZD)	1.0000	0.6055	0.9652	1.0000	1.0000
Zagreb (ZG)	1.0000	0.6544	0.8246	1.0000	0.9337

Table 6b: *Average efficiency scores by airport and year (Window DEA dynamic view).*

Dynamic efficiency trends become clearer when DEA scores are averaged by year. Table 6b reveals distinct efficiency trajectories across Croatian airports. Osijek displays exceptional consistency with near-perfect efficiency throughout the entire period, confirming superior resource optimization despite low traffic volumes. Zadar shows a strong upward trajectory, reaching full efficiency after 2021, which aligns with its expansion strategy and traffic growth. Rijeka exhibits significant improvement from inefficiency to sustained full efficiency in later years.

In contrast, Dubrovnik shows pronounced volatility. Despite full efficiency in 2019, it experienced a sharp drop during the COVID-19 period and recovered only partially by 2023, suggesting structural rigidity and high fixed costs. Pula similarly exhibits weakening economic performance. Zagreb and Split, while large hubs, display unstable patterns caused by scale complexity and recovery frictions. These year-wise averages confirm that airport efficiency is dynamic rather than static and strongly influenced by crisis resilience, structural flexibility, and business model adaptation.

A comparative review with earlier studies offers a meaningful perspective. The current ranking diverges from the findings of [24], who identified Split as the top performer from 2009 to 2014. Moreover, the results contradict those of [3], who found Dubrovnik to be among the most efficient between 2004 and 2008. These discrepancies suggest that airport efficiency is not static but rather subject to shifts in policy, investment, demand dynamics, and managerial adaptation.

Window analysis proves invaluable in this context, allowing decision-makers to track performance trajectories rather than static snapshots. For example, Zadar, Rijeka, and Split all show increasing trends, whereas Pula and Dubrovnik reflect stagnation or decline. These patterns can inform resource allocation, strategic planning, and policy interventions at both the airport and national aviation levels.

According to data from the Croatian Bureau of Statistics (DZS), in terms of actual passenger traffic, Croatian airports experienced significant fluctuations during the 2019-2023 period, largely due to the COVID-19 pandemic and the uneven pace of recovery, as shown in Table 7. Zagreb (ZAG), the country's main hub, handled around 3.4 million passengers in 2019, saw traffic fall to only 0.9 million in 2020, and then gradually recovered to over 3.7 million by 2023. Split (SPU) followed a similar pattern, dropping from approximately 3.3 million passengers in 2019 to just 0.6 million in 2020, before rebounding to more than 3.0 million by 2023. Dubrovnik (DBV), heavily dependent on international tourism, was hit particularly hard: from nearly 2.9 million passengers in 2019, traffic collapsed to 0.3 million in 2020 and recovered more slowly compared to Split or Zagreb, reaching only 2.4 million by 2023. Regional airports reflected different dynamics. Zadar (ZD) grew from nearly 800,000 passengers in 2019 to more than 1.2 million in 2023, boosted by the expansion of Ryanair's base. Rijeka (RI), while smaller with around 150,000-200,000 passengers annually, remained stable with moderate growth in seasonal routes. Pula (PU), with approximately 770,000 passengers in 2019, showed a slower recovery to around 600,000 by 2023 due to its reliance on seasonal tourism flows. Finally, Osijek (OS) remained the smallest international airport, handling only 40,000-50,000 passengers annually, yet its DEA efficiency scores suggest that lean operations allowed it to perform relatively well despite limited traffic.

To examine the relationship between operational activity and economic efficiency, passenger traffic trends were compared with DEA efficiency trajectories. A clear association is observed for several airports: Zadar and Rijeka exhibit simultaneous growth in passenger volumes and efficiency scores, suggesting that rising traffic translated effectively into revenue generation and operational scale benefits. Osijek represents a distinctive case of lean efficiency, maintaining high DEA performance despite consistently low passenger numbers, which reflects strict cost control and flexible operations rather than volume-driven efficiency. In contrast, Dubrovnik demonstrates a mismatch between traffic recovery and efficiency outcomes. Although passenger volumes rebounded strongly after 2021, its DEA scores remained persistently low, implying that increased traffic did not proportionally convert into economic performance. This pattern indicates structural cost rigidity, seasonal dependence, and possibly inefficiencies in capacity utilization. Similarly, Pula's stagnant efficiency despite modest traffic recovery reflects vulnerability to seasonal operations and weak revenue diversification. Zagreb and Split, as dominant hubs, display greater efficiency volatility, consistent with scale complexity and delayed cost adjustment during post-pandemic recovery. Although formal statistical correlation is not the primary focus of DEA, the consistency of directional patterns across efficiency scores and traffic volumes supports the robustness of the benchmarking results.

Passenger flows at Croatian airports	2019	2020	2021	2022	2023
Osijek (OS)	45697	6382	10905	15174	36062
Zadar (ZD)	782574	111179	500286	1082672	1213247
Rijeka (RI)	197151	25460	52773	161873	152053
Zagreb (ZG)	3409977	913703	1388736	3102485	3696371
Split (ST)	3271045	659350	1559178	2885863	3336119
Pula (PU)	765508	78832	261647	383477	413439
Dubrovnik (DU)	2877801	322601	917666	2139382	2406674

Table 7: *Passenger flows at Croatian airports (2019-2023).*
Source: *Croatian Bureau of Statistics, TRAFFIC IN AIRPORTS.*

5. Discussion and conclusion

This study benchmarks the efficiency of Croatian international airports in 2019-2023, a period shaped by post-COVID recovery and rapid digital transformation in global aviation. While earlier research evaluated Croatian airports' efficiency from 2004-2014, this paper offers a much-needed update by capturing how airport performance has evolved. The DEA results reveal notable variations across airports, yet efficiency scores alone cannot explain performance gaps. Placing these findings in context highlights structural and managerial factors behind the results.

The applied methodology, incorporating overlapping time windows, allowed for a dynamic understanding of efficiency rather than a static snapshot. The results clearly reveal variations in airport performance. Osijek Airport consistently demonstrated the highest levels of efficiency, indicating that even smaller airports can lead to operational effectiveness when resources are well managed. On the other hand, Dubrovnik Airport, despite its prominent role in Croatian tourism, recorded the lowest average efficiency. This indicates the potential need for deeper strategic and operational adjustments. Zadar, Rijeka, and Split showed increasing trends, reflecting improvements in their efficiency over the observed period. Zagreb, though the largest hub, faces efficiency constraints due to complex operations and infrastructure bottlenecks.

This research offers several important contributions. First, it extensively reviews the global and European literature on airport efficiency, highlighting the strengths of nonparametric methods such as DEA. Second, it fills a significant empirical gap by evaluating the recent performance of Croatian airports, which have not been studied for nearly a decade. Third, and most importantly, the results have direct relevance for a wide range of stakeholders. Regulators, airport operators, and policymakers can use these insights to identify areas for improvement, develop tailored strategies, and inform investment and infrastructure decisions. From a managerial point of view, the study supports data-informed decision-making. Airports can benchmark their performance against that of their national peers and adjust their operations to improve output and cost efficiency. For policymakers, these findings can contribute to broader transport planning, regional development goals, and the design of performance-based support mechanisms.

This study advances the work of [24], in several important ways. While the earlier study focused on a stable pre-pandemic period (2009-2014), our research examines airport efficiency during a period characterized by unprecedented volatility, allowing us to observe how Croatian airports respond to external shocks and recovery trajectories. Moreover, this paper expands the methodological rigor by providing a more comprehensive explanation of the window DEA framework, its assumptions, suitability for small DMU sets, and advantages over static DEA and Malmquist indices under conditions of structural disruption. The study also incorporates a refined financial dataset that enables a cleaner comparison of economic efficiency, avoiding inconsistencies in traffic reporting observed in earlier work. Consequently, the findings contribute new empirical evidence on how Croatian airports adjust their resource utilization during periods of crisis and thereafter, normalization, offering insights that were not available in the previous literature.

Despite offering valuable insights, this study has certain limitations that should be acknowledged. First, the analysis is limited to seven certified international airports in Croatia, excluding smaller regional or seasonal airports, which may also play important roles in local connectivity and tourism. Second, the choice of input and output variables and the use of only one output variable (total revenue) in the DEA model was guided by data availability and comparability across airports in the 2019-2023 period, which may not capture the full complexity of airport operations, particularly nonfinancial dimensions such as passenger satisfaction or environmental performance. While additional outputs such as passenger traffic or cargo volumes could provide a broader picture of business efficiency, comparable and complete datasets for all airports were not available for the entire period. Previous DEA studies in the aviation sector have demonstrated that financial outputs alone can yield meaningful and robust results when the selected inputs are also financial in nature. Third, the analysis covers the period 2019–2023, which includes the COVID-19 crisis. We recognize that the pandemic caused abnormal distortions in air traffic and efficiency scores. However, the inclusion of this period also represents a strength, as it provides insight into how airports managed efficiency during both crisis and recovery. This perspective is particularly relevant for policymakers and managers seeking to improve resilience against future demand shocks. Third, while window analysis adds a dynamic perspective, it still assumes consistent behavior of decision-making units within each window, which may overlook short-term shocks or rapid operational changes. Finally, the study is based on financial and operational data without integrating qualitative insights from airport management or governance structures, which could provide a deeper context behind efficiency scores. Future research could employ a multi-output DEA framework that incorporates operational measures such as passenger flows or cargo volumes, as well as by conducting sensitivity analyses that exclude the COVID-19 years. Such studies would allow a clearer distinction between structural efficiency patterns in normal conditions and performance under crisis circumstances.

For airport CEOs and policymakers, the results suggest several concrete actions: diversify revenues beyond seasonal passenger flows, expand digital solutions for cost and flow management, and invest in resilience against demand shocks. CFOs should use DEA benchmarking to refine cost efficiency strategies, while operations managers can adopt predictive analytics and automation to optimize resource allocation. Coordinated planning with national tourism authorities can further mitigate seasonal inefficiencies.

By combining DEA insights with traffic and operational realities, this study provides actionable guidance. Croatian airports can enhance competitiveness and sustainability by embracing digital transformation, strengthening cost discipline, and addressing seasonal imbalances, aligning local performance with global trends shaping the future of air transport.

Building on the findings of this study, future research should consider expanding the scope to include a broader set of airports, both within Croatia and across the region, to enable cross-country benchmarking and comparative policy analysis. Integrating parametric approaches such as stochastic frontier analysis (SFA) alongside DEA could offer complementary perspectives and strengthen the robustness of efficiency evaluations. Researchers may also explore multistage models that incorporate environmental and service quality indicators, aligning the assessment with sustainability and customer-centric goals in aviation. Additionally, extending the analysis period to include pre- and post-pandemic data would provide critical insights into how external shocks affect airport efficiency over time. Finally, future studies could incorporate qualitative methods, such as interviews with airport managers and stakeholders, to better understand the strategic and operational factors driving performance outcomes.

References

[1] Arbula Blecich, A. (2024). The performance of Croatian hotel companies–DEA window and Malmquist productivity index approach. Zbornik radova Ekonomskog fakulteta u Rijeci: časopis za ekonomsku teoriju i praksu, 42(1), 9-38. doi: 10.18045/zbefri.2024.1.9

[2] Assaf, A. and Cvelbar, K. L. (2011). Privatization, market competition, international attractiveness, management tenure and hotel performance: Evidence from Slovenia. International Journal of Hospitality Management, 30(2), 391-397. doi: 10.1016/j.ijhm.2010.03.012

[3] Bezić, H., Šegota, A. and Vojvodić, K. (2010). Measuring the efficiency of Croatian airports. In: Trivun, V., Djonlagic, Dz. and Mehic, E. (Eds.) *Economic Development Perspectives of SEE Region in the Global Recession Context – ICES 2010*. Sarajevo: University of Sarajevo, School of Economics and Business, 110–112.

[4] Braimllari, A. and Benga, A. (2019). Cost efficiency of banks in Albania: A Data Envelopment Analysis for the period 2015–2017. In: *Proceedings from the International Conference on Applied Analysis and Mathematical Modelling – ICAAMM19*, 10–13.

[5] Budd, T., Budd, L. and Ison, S. (2015). Environmentally sustainable practices at UK airports. Proceedings of the Institution of Civil Engineers: Transport, 168(2), 116–123. doi: 10.1680/tran.13.00076

[6] Cifuentes-Faura, J. and Faura-Martínez, U. (2021). Twenty Years of Airport Efficiency – A Bibliometric Analysis. Promet - TrafficTransportation, 33(4), 479-490. doi: 10.7307/ptt.v33i4.3790

[7] Chand, G., Mohapatra, D. R. and Jena, P. R. (2024). A DEA Approach to Efficiency Analysis of Major Indian Airports. Vision, 0(0). doi: 10.1177/09722629241255741

[8] Choi, Y., Wen, H., Lee, H. and Yang, H. (2020). Measuring operational performance of major Chinese airports based on SBM-DEA. Sustainability, 12(19), 8234. doi: 10.3390/su12198234

[9] Doganis, R. (2005). *Airline business in the 21st century*. Routledge.

[10] European Union Aviation Safety Agency (EASA) (2005). European aviation environmental report. doi: 10.2822/1537033

[11] Emrouznejad, A. and Yang, G. L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. Socio-economic planning sciences, 61, 4-8. doi: 10.1016/j.seps.2017.01.008

[12] Fasone, V. and Zapata-Aguirre, S. (2016). Measuring business performance in the airport context: a critical review of literature. International Journal of Productivity and Performance Management, 65(8), 1137-1158. doi: 10.1108/IJPPM-06-2015-0090

[13] Graham, A. (2018). *Managing Airports: An International Perspective*. Routledge.

[14] Henke, I., Esposito, M., della Corte, V., del Gaudio, G. and Pagliara, F. (2021). Airport efficiency analysis in Europe including user satisfaction: A non-parametric analysis with DEA approach. Sustainability, 14(1), 283. doi: 10.3390/su14010283

[15] Holvad, T. and Graham, A. (2000). Efficiency measurement for airports. Proceedings from the Annual Transport Conference at Aalborg University, 7(1). doi: 10.5278/ojs.td.v7i1.4834

[16] Iyer, K. C. and Jain, S. (2019). Performance measurement of airports using data envelopment analysis: A review of methods and findings. Journal of Air Transport Management, 81, 101707. doi: 10.1016/j.jairtraman.2019.101707

[17] Jablonský, J., Emrouznejad, A. and Toloo, M. (2018). Special issue on data envelopment analysis. Central European Journal of Operations Research, 26, 809-812. doi: 10.1007/s10100-018-0584-1

[18] Kim, H-S and Park, J-R. (2013). An analysis of the operational efficiency of the major airports worldwide using DEA and Malmquist productivity indices. Journal of Distribution Science 11(8), 5-14. doi: 10.15722/jds.11.8.201308.5

[19] Lau, C. R., Stromgren, J. T. and Green, D. J. (2010). Airport energy efficiency and cost reduction. Airport Cooperative Research Program (ACRP) Synthesis 21. Transportation Research Board, Washington, DC. url: http://onlinepubs.trb.org/onlinepubs/acrp/acrp_syn_021.pdf [Accessed 19/07/2025]

[20] Matulová, M. and Rejentová, J. (2021). Efficiency of European airports: Parametric versus non-parametric approach. Croatian Operational Research Review, 12(1) 1-14. doi: 10.17535/crorr.2021.0001

[21] Merkert, R. and Assaf, A.G. (2015). Using DEA models to jointly estimate service quality per-

ception and profitability – Evidence from international airports. Transportation Research Part A: Policy and Practice, 75, 42-50. doi: 10.1016/j.tra.2015.03.008

[22] Montoya-Quintero, D. M., Larrea-Serna, O. L. and Jiménez-Builes, J. A. (2022). Evaluation of the efficiency of regional airports using data envelopment analysis. Informatics, 9(4), 90. doi: 10.3390/informatics9040090

[23] Peykani, P., Farzipoor Saen, R., Seyed Esmaeili, F. S. and Gheidar-Kheljani, J. (2021). Window data envelopment analysis approach: A review and bibliometric analysis. Expert Systems, 38(7), e12721. doi: 10.1111/exsy.12721

[24] Rabar, D., Zenzerović, R. and Šajrih, J. (2017). An empirical analysis of airport efficiency: the Croatian case. Croatian Operational Research Review, 8(2), 471–487. doi: 10.17535/crorr.2017.0030

[25] SEO Amsterdam Economics (2024). The Economic and social Impact of European Airports and Air Connectivity. url: aci-europe.org/downloads/resources/SEO [Accessed 19/07/2025]

[26] Spremić, H. (2025). Digitalna transformacija zračnih luka. Ekonomska misao i praksa, 34(2), 599-620. doi: 10.17818/EMIP/2025/30

[27] Stichhauerova, E. and Pelloneova, N. (2019). An Efficiency Assessment of Selected German Airports Using the DEA Model. Journal of Competitiveness, 11(1), 135–151. doi: 10.7441/joc.2019.01.09

[28] Suzuki, S. and Nijkamp, P. (2011). A stepwise efficiency improvement DEA model for airport operations with fixed production factors. European Regional Science Association Conference Paper, 1–18. url: hdl.handle.net/10419/120169 [Accessed 19/07/2025]

[29] Suzuki, S., Nijkamp, P., Rietveld, P. and Pels, E. (2010). A distance friction minimization approach in data envelopment analysis: A comparative study on airport efficiency. European Journal of Operational Research, 207(2), 1104-1115, doi: 10.1016/j.ejor.2010.05.049

[30] Suzuki, S., Nijkamp, P., Pels, E. and Rietveld, P. (2014). Comparative performance analysis of European airports by means of extended data envelopment analysis. Journal of Advanced Transportation, 48, 185-202. doi: 10.1002/atr.204

[31] Yu, C. (2023). Airport Performance-a multifarious review of literature. Journal of the Air Transport Research Society, 1(1), 22-39. doi: 10.59521/E7E8098D7A835864