

Efficiency Dynamics of Turkish Airports: A Non-Radial Slacks-Based Measure (SBM) Malmquist Productivity Index Analysis

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Abstract

Background: Airports play a critical role in regional development, economic integration, and transportation connectivity. As Türkiye continues to strengthen its position as a global aviation hub, evaluating the operational efficiency and productivity dynamics of airports has become increasingly important for sustainable infrastructure management and strategic policymaking. Traditional Data Envelopment Analysis (DEA) models may overestimate efficiency by neglecting input and output slacks. Therefore, the use of a non-radial Slack-Based Measure (SBM) framework provides a more comprehensive assessment of airport performance.

Objective: This study aims to evaluate the efficiency and productivity dynamics of Turkish airports during the post-pandemic recovery period and to identify the relative contributions of managerial performance and technological progress to productivity change.

Method: The study employs a non-radial SBM-DEA model integrated with the Malmquist Productivity Index (MPI) to analyze the performance of 50 Turkish airports over the period 2021–2025. The SBM-MPI framework decomposes total factor productivity change into Efficiency Change (EC) and Technological Change (TC), allowing a detailed investigation of productivity drivers while accounting for input and output slacks.

Results: The findings indicate that average productivity levels remained below the efficiency frontier throughout the study period. Productivity differences across airports were substantial, with major hub airports such as Istanbul Airport and Sabiha Gökçen Airport maintaining frontier positions, whereas many regional airports experienced productivity losses associated with capacity underutilization. The decomposition analysis suggests that technological change constituted the primary source of productivity variation, while managerial efficiency remained relatively stable across the network.

Conclusion: The results highlight the importance of technological adaptation, capacity utilization, and demand-oriented resource management in improving airport productivity. Policy efforts aimed at strengthening regional airport demand, enhancing digital infrastructure, and improving operational flexibility may contribute to reducing productivity disparities across the Turkish airport system. The study contributes to the airport efficiency literature by providing one of the first comprehensive SBM-Malmquist assessments of Turkish airports during the post-pandemic recovery period.

Keywords: Airport Efficiency, SBM-DEA, Malmquist Productivity Index (MPI), Turkish Aviation Sector, Technological Change, Performance Benchmarking.

INTRODUCTION

Within the global economy, the aviation sector is a key driver of regional development and international integration (Kasarda & Lindsay, 2011). Turkey has made significant progress towards becoming a global aviation hub through mega infrastructure projects implemented over the last two decades and the strategic goals set within the framework of its "Aviation 2023 Vision." (Ulku, 2014). According to data from the State Airports Authority (DHMI, 2025), the volume of air traffic and passenger numbers in Turkish airspace reinforce the country's position as a bridge between Europe and Asia, making the measurement of sectoral productivity a national economic policy.

Airports are complex structures that are difficult to manage due to high fixed costs and supply-demand imbalances (Doganis, 2010). Traditional Data Envelopment Analysis (DEA) models, commonly used in the literature for performance measurement, assume that inputs and outputs change proportionally (radically). However, this approach can overestimate efficiency scores by neglecting "slacks" in operational processes (Tone, 2001). In the context of airports, situations arise where a certain terminal capacity or runway length is underutilized (input slack), preventing the expected increase in passenger or cargo traffic (Lozano & Gutiérrez, 2011). The Slack-Based Measurement (SBM) model preferred in this study, thanks to its non-radial structure, directly incorporates these capacity surpluses and underutilized resources into the analysis process, providing much more accurate and unbiased results compared to classical models (Barros & Dieke, 2008).

The period 2021-2025 holds unique significance for the aviation sector, representing the "new normal" and recovery process following the COVID-19 global pandemic (IATA, 2024). Fluctuations in air traffic and changing passenger behavior in the post-pandemic era have tested the resilience and dynamic efficiency of airports (Kalic et al., 2022). While most existing studies in the literature focus on the crisis period, this study empirically examines the recovery rate and productivity changes in the Turkish airport network from a longitudinal perspective, spanning from 2021 to 2025.

The main objective of this article is to analyze the dynamic performance of airports in Türkiye using the Malmquist Productivity Index (MPI) based on SBM (Slack-Based Measure) (Tone, 2001). The study aims to identify the primary driving force behind the sector's recovery by separating productivity changes into management success (Efficiency Change) and technological progress (Technological Change) (Cooper et al., 2007). This research, which examines current aviation data in Turkey using a non-radial model, addresses a methodological

gap in the literature and provides concrete data for DHMI (General Directorate of State Airports Authority) and policymakers regarding strategic resource management.

Although airport efficiency has been extensively studied using traditional DEA and Malmquist efficiency indices, studies integrating slack-based measurements with dynamic efficiency decomposition remain limited. In particular, the combined application of SBM-DEA, Malmquist efficiency analysis, and scale decomposition for airport benchmarking is still insufficiently explored in the international literature.

There are 58 operational airports throughout Turkey. The management of Turkish airports and the regulation and control of Turkish airspace are carried out by the General Directorate of State Airports Authority (DHMI). DHMI operates as a Public Economic Enterprise (PEE) with wholly owned capital by the state, possessing legal personality and subject to private law provisions, within the framework of Decree Law No. 233. Its duties include civil aviation activities, necessary air transportation, airport management, ground handling services at airports, air traffic control services, the establishment and operation of air navigation systems and facilities and other related facilities and systems, and maintaining them at a modern aviation standard.

Over the past decade, Turkey's civil aviation sector has experienced significant growth. By 2025, Turkey is projected to become one of Europe's fastest-growing aviation markets, reaching an annual capacity of approximately 247 million passengers. Istanbul Airport, in particular, has strengthened its position as a global hub, becoming one of Europe's busiest airports and a strategic center for international transit passenger transportation. Thanks to its geographical advantage, expanding flight network, and infrastructure investments, Turkey has risen to a critical connection point in the air transport corridor between Europe, Asia, and Africa. According to data from the State Airports Authority (DHMI), in 2025, the total number of passengers served at airports across Turkey, including direct transit passengers, reached 247.1 million; civil and commercial aircraft traffic reached 1.5 million, and if overflight traffic is included, this figure rises to 2.1 million.

The aim of this study is to evaluate the operational efficiency and productivity changes of Turkish airports, to assist policymakers, such as airport authorities, in developing transparent airport management strategies, to improve long-term airport investment plans, and to identify best management practices that others can emulate. To achieve the above-mentioned objectives, Sloth-Based Data Envelopment Analysis (DEA) - Malmquist productivity index was used to evaluate the operational efficiency, productivity changes, and key factors affecting productivity of Turkish airports over time.

Data Envelopment Analysis (DEA), used to measure the relative performance of Decision Making Units (DMUs), is addressed in this study within a non-parametric mathematical framework. In the present research, each airport is defined as a separate DMU, and the operational efficiency components are analyzed using the Slacks-Based Measure (SBM) model. Unlike traditional radial models, the SBM-DEA approach produces a more accurate and discriminatory efficiency score by directly incorporating disproportionate variations in inputs and outputs (non-radial) and all distances to the efficiency frontier (slacks) into the objective function (Tone, 2001). Given the heterogeneous nature of airport operations, this "gap-based" assessment offered by the SBM model provides higher explanatory power than traditional methods in deciphering operational inefficiencies (Tone, 2001).

To assess the dynamic changes in airport productivity over time and the trajectory of technological development, the Malmquist Productivity Index (MPI) has been integrated into the model. The Malmquist index decomposes the total factor productivity change of an airport between two consecutive time periods as the product of two principal components: (Färe et al., 1994)

- *Catch-up Effect (Efficiency Change)*: Reflects how close the airport has come to its current efficiency limit, i.e., the improvement in managerial competence and resource allocation efficiency.
- *Frontier Shift (Technological Change)*: This refers to the shift across the sector at the "productive frontier" between two periods, i.e., innovation, structural changes, and expansion in aviation technologies (Tone et al., 2004).

Although airport efficiency has been extensively examined using conventional DEA models and Malmquist productivity indices, studies employing non-radial SBM-based approaches remain relatively limited. Existing studies on Turkish airports predominantly rely on radial DEA specifications that assume proportional input-output adjustments and therefore may overlook inefficiencies arising from input excesses and output shortfalls.

Furthermore, empirical evidence regarding the productivity dynamics of Turkish airports during the post-pandemic recovery period remains scarce. The unprecedented disruptions caused by COVID-19 altered passenger demand patterns, infrastructure utilization, and operational practices across airport networks, creating a need for updated efficiency assessments based on recent data.

Although there are classical DEA analyses of Turkish airports in the literature, studies using slack-based DEA are limited. This study contributes to the literature in three important ways. First, it applies a non-radial SBM framework that explicitly incorporates input and output slacks

into efficiency measurement. Second, it evaluates productivity dynamics during the post-pandemic recovery period covering 2021–2025. Third, it decomposes productivity change into efficiency change and technological change components, providing airport-level evidence regarding the main drivers of productivity performance in Türkiye.

1.Literature

When examining studies on airport performance in the literature, it is observed that classical DEA models, initially developed by Charnes et al. (1978), predominated. However, the complex nature of airport operations and the disproportionate changes between inputs and outputs have led researchers to non-radial models (Charnes et al., 1978). In this context, Lozano and Gutiérrez (2011) emphasized the importance of the concept of 'slacks' in airport efficiency, demonstrating that the SBM model offers more unbiased results compared to traditional models (Lozano and Gutiérrez, 2011). While studies on the Malmquist Index, which examines dynamic processes (Assaf, 2010), indicate that efficiency increases generally stem from managerial effectiveness rather than technological advancement; this study reopens the discussion on the decisive role of technological change (TC) in the case of Turkey during the post-pandemic recovery period (2021-2025) (Ulku, 2015).

Aviation literature is quite extensive, and especially in the last 5-10 years, the use of SBM-DEA (Slacks-Based Measure) and the Malmquist Index has become standard because they better reflect the operational complexity of airports (Barros, 2008). Examples from the literature are as follows; Studies using this method in the aviation sector generally focus on three main themes.

1.1. Transition from Classical DEA to SBM (Methodological Difference)

In the literature, airport efficiency has generally been measured using traditional (CCR or BCC) models. However, in recent years, the superiority of the SBM model has been emphasized. It is stated that the assumption of classical models that all inputs can be reduced by the same proportion is invalid in airport operations (for example, the inability to reduce runway length while reducing aircraft traffic). Tone (2001) is the name that laid the foundation for SBM. In the aviation sector specifically, Lozano and Gutiérrez (2011) examined efficiency through "slacks" in European airports and proved that traditional models overestimate efficiency (Tone, 2001; Lozano&Gutiérrez, 2011).

1.2. Dynamic Analysis with the Malmquist Index (Time Series)

The change in productivity over the years, not just in a single year, is very popular in aviation literature. Studies generally interpret productivity change (EC) as "managerial success" and technological change (TC) as "infrastructure/system investment". Assaf (2010) examined UK

airports using the Malmquist Index and highlighted the dominant role of technological change on productivity (Assaf, 2010).

1.3. Turkish Aviation Literature (Local Comparison)

Most studies on Turkey are still based on classical models; studies in Turkey generally focus on the impact of Istanbul Airport or the efficiency of privatized airports (TAV, Limak, etc.). While authors such as Ulku (2015) or Yalcin (2020) generally use radial models in their analyses of Turkish airports, our study, being "slack-based" (GBP), measures capacity utilization better (Ulku, 2015; Yalcin, 2020).

Table 1: Sample of Data Envelopment Analysis Study in the Aviation Sector

Author / Year	Content	Method	Finding
Assaf (2010)	UK Airports	Malmquist Index	The study found that the main source of productivity increases was technological progress (TP) rather than managerial success.
Lozano & Gutiérrez (2011)	European Airports	SBM-DEA	Studies have shown that classical models overestimate (predict) productivity scores, while SBM is more unbiased.
Ulku (2015)	Turkish Airports	Radial DEA	The study examined the changes in efficiency scores of airports in Türkiye over the years, but excluded capacity gaps from the analysis.
Cebeci & Kurtulus (2022)	Global Airports	Malmquist Index	It dynamically analyzed the sharp productivity declines during the pandemic and the sector's vulnerability to crises.
Sarkis (2000)	Global Major Airports	DEA & Malmquist	Operational efficiency has proven to be higher than financial efficiency. (This can be used to explain low MI scores with "excess capacity")
Adler & Liebert (2014)	European Transfer Centers (Hub)	SBM-DEA	It identified the impact of ownership structure on capacity gaps. (This can be used in the debate surrounding privatized Turkish airports.)
Cui & Li (2015)	Chinese Airports	Malmquist (SBM)	The study found that large airports grew with a focus on technological advancement (TC), while smaller ones grew with a focus on management (EC).
Young-Hyo Lim & Hokey Min	International Airports	SBM-DEA	Modern airports have evolved from simple infrastructure providers into highly competitive commercial entities that rely heavily on technological progress and exogenous policy shifts rather than internal managerial improvements to drive total productivity growth
Wanke & Barros (2020)	Crisis Period Analysis	Dynamic DEA	It has enhanced the resilience of airports against shocks through 'flexible capacity (slacks) management' to capture post-pandemic recovery dynamics
This Study	Turkey (2021-2025)	SBM- Malmquist	The majority of the 50 Turkish airports (mean MI = 0.477) remained below the productivity frontier throughout 2021–2025. Technological Change (TC) emerged as the primary driver of productivity variation (mean TC = 0.496, SD = 0.330), while managerial efficiency (EC) remained relatively stable across the network (mean EC = 0.967). Only four airports; Istanbul, Sabiha Gökçen, Muğla Dalaman and Zafer achieved frontier-level productivity ($MI \geq 1.00$), whereas 17 airports recorded MI values below 0.30, indicating severe capacity underutilization

When examining the literature review presented in Table 1, it is observed that studies on Turkish airports mostly prefer radial (traditional) models. In particular, the importance of capacity gaps, highlighted by Lozano and Gutiérrez (2011), has not yet been sufficiently addressed in the Turkish literature from an SBM-Malmquist perspective, covering a critical recovery period such as 2021-2025 (Lozano&Gutiérrez, 2011). This study aims to fill this gap by methodologically combining a non-radial SBM model with the dynamic Malmquist Index. International literature confirms that airport efficiency is not merely a static measurement, but rather relies on multidimensional dynamics such as technological change (Cui & Li, 2015), resilience to crises, and the management of capacity gaps (Adler & Liebert, 2014). In light of these trends in the literature, this study examines more than 50 airports in Türkiye within the framework of the SBM-Malmquist model, providing a holistic analysis for the first time at the local level of both operational excess capacity (Sarkis, 2000) and post-pandemic technological adaptation processes.

The existing literature demonstrates that airport productivity is influenced by managerial performance, technological development, infrastructure utilization, and external shocks. While numerous studies have applied DEA and Malmquist-based approaches to airport performance evaluation, evidence obtained through non-radial SBM-Malmquist frameworks remains relatively limited, particularly in developing aviation markets.

Moreover, the post-pandemic recovery process has generated new challenges regarding capacity utilization and technological adaptation, which cannot be fully captured by traditional radial efficiency models. Therefore, employing a slack-based productivity framework provides a more realistic representation of airport performance by explicitly accounting for idle capacity and operational inefficiencies. In this respect, the present study seeks to extend the literature by providing updated evidence on the dynamic productivity performance of Turkish airports during the 2021–2025 period.

2.Methodology

2.1. Research Design and Analytical Framework

This study evaluates the dynamic productivity performance of Turkish airports during the period 2021–2025 using a non-radial Slack-Based Measure (SBM) Data Envelopment Analysis integrated with the Malmquist Productivity Index (MPI). The analytical framework was selected because airport operations involve heterogeneous production processes characterized by infrastructure-intensive inputs and multiple output dimensions.

Traditional radial DEA models assume proportional reductions in inputs or proportional increases in outputs. However, such assumptions may not adequately reflect airport operations, where certain inputs, such as runway infrastructure or terminal capacity, cannot be adjusted proportionally in the short run. Therefore, the SBM model developed by Tone (2001) was adopted to explicitly account for input excesses and output shortfalls.

To investigate productivity dynamics over time, SBM efficiency scores were subsequently incorporated into the Malmquist Productivity Index framework. This approach allows the decomposition of productivity change into Efficiency Change (EC) and Technological Change (TC), providing a more comprehensive understanding of the factors driving airport productivity.

2.2. Sample Selection

The empirical analysis covers 50 operational airports in Türkiye during the period 2021–2025. Although 58 airports were operational during the study period, several airports were excluded due to incomplete observations, inconsistent reporting across years, or insufficient data availability for the selected input and output variables. To ensure comparability and maintain the reliability of the DEA framework, only airports with complete and consistent observations throughout the study period were included in the final sample. Consequently, the selected sample represents the overwhelming majority of commercial airport activity in Türkiye and provides a comprehensive overview of the national airport system.

2.3. Variable Selection

The selection of input and output variables was guided by previous airport efficiency studies and data availability considerations. Airports transform physical infrastructure and operational resources into transportation services. Accordingly, the selected variables capture both capacity-related inputs and operational outputs.

Inputs variables

- Runway Capacity (Runway Length / Number of Runways)
- *Terminal Area*: Indicates the passenger reception capacity.
- Number of Aircraft Parking Positions: Represents physical capacity.

Outputs variables:

- Passenger Traffic: This is the key service output.
- Aircraft Movements: Indicates runway and tower usage activity.
- Cargo Traffic: Represents logistics capacity utilization.

These indicators capture the primary outputs generated by airport activities and are widely used in airport productivity studies. The chosen variables are consistent with previous airport efficiency research and reflect the multidimensional nature of airport production processes.

2.4. Justification for the SBM Approach

The SBM model was preferred over conventional CCR and BCC models for several reasons. First, airport infrastructure contains substantial fixed-capacity elements that cannot be proportionally adjusted in response to demand fluctuations. Consequently, proportional efficiency measures may underestimate the magnitude of resource underutilization. Second, SBM explicitly incorporates slack variables into the objective function, allowing the identification of both input excesses and output deficiencies. Third, the post-pandemic recovery period examined in this study is characterized by considerable demand volatility. Under such conditions, the ability of SBM to capture capacity underutilization provides a more realistic representation of airport performance.

Therefore, the SBM framework is particularly suitable for evaluating airport productivity during periods of structural adjustment and changing demand patterns. If we explain the methodology of the SBM model.

Traditional Data Envelopment Analysis (DEA) models, such as radial Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models, operate under the assumption of proportional changes in inputs or outputs and therefore neglect the presence of non-radial slack in productivity assessment. This limitation can lead to overestimation of productivity scores and loss of discriminatory power when significant input surpluses or output deficits exist. To overcome this rigidity, Tone (2001) introduced the Slack-Based Measurement (SBM) DEA model, a non-radial and undirected framework that directly incorporates input and output slack into the objective function. The SBM-DEA model provides a more rigorous, invariant, and monotonic productivity measure that offers a precise representation of operational performance, unaffected by radial scaling assumptions, by systematically accounting for all sources of inefficiency simultaneously. The SBM model developed by Tone (2001) eliminates the "radial" (all inputs reduced at the same rate) assumption of traditional DEA models. In airport operations, for example, the inability to reduce physical inputs such as runway length while reducing aircraft traffic necessitates the use of a non-radial model (Tone, 2001).

To resolve this limitation, the non-radial SBM model discards the proportional change assumption and directly integrates input and output slacks into the objective function. Let us assume there are n Decision Making Units (DMUs) (airports), where each DMU $_j$ ($j = 1, 2, \dots, n$) utilizes m inputs to produce s outputs. The vectors for inputs and outputs of DMU $_0$ (the

DMU under evaluation) are represented as $x_0 \in R^m$ and $y_0 \in R^s$, respectively. The matrices are defined as $X = [x_1, \dots, x_n] \in R^{m \times n}$ and $Y = [y_1, \dots, y_n] \in R^{s \times n}$.

Assuming there are n Decision Making Units (DMUs) and each uses m inputs (x) and s outputs (y), the mathematical expression of the SBM model is as follows:

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m s_i^- / x_{i0}}{1 + \frac{1}{s_1 + s_2} (\sum_{r=1}^{s_1} (s_r^g / y_{r0}^g) + \sum_{r=1}^{s_2} (s_r^b / y_{r0}^b))} \quad (1)$$

This model assumes that n decision-making units have n inputs and s outputs. ρ^* represents the efficiency of the decision-making units. Here, s^- and s^+ are the input and output slacks, respectively; X and Y are vectors of input and output variables weighted by λ . The SBM index ρ^* lies on the range $0 \leq \rho^* \leq 1$. The vector s represents the unwanted variables in the input; the vectors sg and sb represent the desired/undesired variables in the output, respectively. λ is the weight vector. If it is DMU

$$\begin{aligned} \rho^* &= 1, \quad s^- = s^g = s^b = 0; \quad \text{efficient,} \\ &\text{otherwise,} \quad \text{ineffective} \end{aligned}$$

In linear programming, constraints are often transformed into equalities. If an inequality is of the form "less than or equal to" ($\leq$), a variable known as a slack variable is added to transform it into an equality. Traditional CCR and BCC DEA models assume proportional changes in inputs and outputs but do not explicitly account for slack variables. However, slack variables play a crucial role in productivity evaluation. Non-radial, slack variable-based productivity models bypass the proportionality assumption and incorporate slack variables directly into the objective function to provide a more accurate measure of productivity (Park et al, 2018). Slack variable-based analysis is non-radial and undirected, offering higher discriminatory power compared to radial models. It reduces the limitations associated with radial and directional deviations and provides a clearer understanding of the sources of inefficiency. However, the model accounts for the existence of both desirable (good) and undesirable (bad) output variables (Tone, 2004).

Data Envelopment Analysis (DEA) generally defines efficiency as the ability to produce more output with less input. In the context of unwanted outputs, efficiency is achieved by systems that produce higher levels of desired output while minimizing unwanted outputs using fewer inputs. To address this, slack-based Data Envelopment Analysis (SBM-DEA) has been

developed, and the method applied in this study is a modified version of the SBM-DEA model originally proposed by Tone (2001) (Tone, 2001).

The primary aim of slackness-based measurement is to position decision-making units relative to the efficiency frontier and minimize the objective function by determining the maximum slackness values (Wang & Cheng, 2020). An additional advantage of the non-radial slackness-based approach is that efficiency scores can be evaluated separately for each variable, allowing for targeted improvements in the performance of the decision-making unit. Zhou et al. (2006) noted that traditional radial DEA methods often produce numerous units with an efficiency score of "1," limiting their discriminatory power. In contrast, slackness-based measurement allows for greater differentiation among units and is therefore considered a more effective approach in capturing the true nature of efficiency (Zhou et al, 2006). Compared to the CCR model, SBM always offers a more accurate measurement, and $SBM \leq CCR$.

2.5. Malmquist Productivity Index

While SBM provides a static efficiency assessment for a given period, policymakers are often interested in understanding how productivity evolves over time. To address this issue, SBM efficiency scores were incorporated into the Malmquist Productivity Index framework.

To examine how airport productivity changes dynamically between two time periods (t and $t+1$), we use the Malmquist Productivity Index. By substituting the SBM efficiency scores into the MPI framework, we ensure that technological shifts and efficiency catcher-ups are calculated while accounting for structural slacks (Tone, 2001; Tone & Tsutsui, 2010).

The SBM-Malmquist Productivity Index (MPI) is defined as the geometric mean of two programming shifts:

$$MI_0(t, t + 1) = \left[\frac{\rho_0^t(x^{t+1}, y^{t+1})}{\rho_0^t(x^t, y^t)} \times \frac{\rho_0^{t+1}(x^{t+1}, y^{t+1})}{\rho_0^{t+1}(x^t, y^t)} \right]^{1/2} \quad (2)$$

To pinpoint the underlying drivers of airport performance, the index is decomposed into two distinct components: Efficiency Change (EC) and Technological Change (TC) (Färe et al., 1994).

$$MI = EC * TC$$

The MPI measures changes in total factor productivity between two consecutive periods and decomposes productivity change into two components:

2.5.1. Efficiency Change (EC) / Catch-up Effect

EC measures how much closer an airport has moved toward the best-practice frontier from period t to $t+1$. It signifies managerial improvement and short-term operational optimization (Färe et al., 1994; Oum et al., 2003).

$$EC = \frac{\rho_0^{t+1}(x^{t+1}, y^{t+1})}{\rho_0^t(x^t, y^t)} \quad (3)$$

Efficiency Change reflects movements toward or away from the best-practice frontier. It captures improvements in managerial performance, operational efficiency, and resource allocation.

- $EC > 1 \rightarrow$ Improvement in relative efficiency
- $EC = 1 \rightarrow$ No change
- $EC < 1 \rightarrow$ Deterioration in relative efficiency

2.5.2. Technological Change (TC) / Frontier Shift

TC calculates the movement of the efficient frontier over time. In aviation, a positive TC shift represents industry-wide technological progress, structural expansions, or macro-level digital transformations (Färe et al., 1994; De Nicola et al., 2013).

$$TC = \left[\frac{\rho_0^t(x^t, y^t)}{\rho_0^{t+1}(x^t, y^t)} \times \frac{\rho_0^t(x^{t+1}, y^{t+1})}{\rho_0^{t+1}(x^{t+1}, y^{t+1})} \right]^{1/2} \quad (4)$$

Technological Change measures shifts in the production frontier itself. It reflects technological progress, infrastructure modernization, and industry-wide innovations.

- $TC > 1 \rightarrow$ Technological progress
- $TC = 1 \rightarrow$ No technological change
- $TC < 1 \rightarrow$ Technological regression

The overall Malmquist Productivity Index is obtained as:

$$MPI = EC \times TC$$

- $MPI > 1 \rightarrow$ Productivity growth
- $MPI = 1 \rightarrow$ Productivity remains unchanged
- $MPI < 1 \rightarrow$ Productivity decline

2.6. Interpretation of SBM-Malmquist Scores

A distinctive feature of this study is the use of a non-radial SBM framework within the Malmquist productivity analysis. Because the SBM methodology explicitly incorporates input excesses and output shortfalls, productivity scores obtained in this study may be lower than those reported in studies using traditional radial DEA specifications.

Consequently, relatively low MPI values should not necessarily be interpreted as evidence of poor airport performance. Instead, they should be viewed as indicators of the extent to which existing infrastructure resources are converted into operational outputs.

This characteristic is particularly important for airports with substantial infrastructure capacity but relatively limited traffic volumes, as such airports are more heavily penalized for capacity underutilization under the SBM framework.

3. Findings

Empirical analyses were implemented in the R statistical environment using the *deaR* package, which supports non-radial slack-based measure (SBM) DEA models under both CRS and VRS assumptions and dynamic productivity decomposition via Malmquist-type indices. In this section, the analysis, using a nonlinear SBM-DEA approach integrated with the Malmquist Productivity Index to assess the operational efficiency dynamics of airports, captures both cross-sectional productivity differences and longitudinal productivity evolutions of the airports studied. The following subsections determine technical efficiency scores, identify specific input-output gaps causing operational inoptimism, and decompose total factor productivity growth into frontier and capture components. These findings collectively illuminate how regulatory changes, capacity constraints, and operational strategies shaped the competitive landscape of aviation hubs throughout the evaluated time period.

The total factor productivity change of the investigated airports is analyzed using the non-radial Slacks-Based Measure (SBM) Malmquist Productivity Index (MPI). Based on the fundamental axiom where the Malmquist Productivity Index is the product of Technical Efficiency Change (EC) and Technological Change (TC) ($MI = EC * TC$), the evaluated airports are classified into three distinct performance cohorts: High (Green), Moderate (Blue), and Low (Red). A threshold of 1.00 represents the stationary efficiency frontier; units exceeding or maintaining this value indicate productivity growth, while scores below 1.00 signify varying degrees of productivity regression.

Based on the MI (Malmquist Index), EC (Efficiency Change), and TC (Technological Change) scores, the individual performance report cards for each airport are as follows: The basic rule in this analysis is:

- $EC > 1$: Managerial success, better use of resources (Catch-up effect).
- $TC > 1$: Technological advancement, capacity or infrastructure improvement (Boundary shift).
- $MI > 1$: Overall productivity increase.

3.1. Overall Productivity Dynamics

The dynamic productivity performance of Turkish airports was evaluated using the Slack-Based Measure (SBM) Malmquist Productivity Index framework for the period 2021–2025. The empirical findings reveal substantial heterogeneity in airport productivity levels across the network. Average Malmquist Productivity Index (MI) values remained below the productivity frontier throughout the study period, indicating that considerable opportunities for performance improvement still exist within the Turkish airport system.

The relatively low MI scores should be interpreted with caution. Unlike conventional radial DEA approaches, the SBM methodology explicitly incorporates input excesses and output shortfalls into efficiency measurement. Consequently, airports with large infrastructure capacities but relatively limited passenger or aircraft traffic are penalized more heavily. Therefore, the reported productivity values reflect not only operational performance but also the extent of capacity underutilization.

Overall, the results suggest that productivity improvements were concentrated in a limited number of airports, while a large proportion of regional airports continued to operate below the estimated productivity frontier.

Table 2 presents the Malmquist Productivity Index (MI) results and their components for Turkish airports. The findings reveal considerable differences in productivity performance across airports. While Muğla Dalaman (MI = 1.03), Zafer (MI = 1.04), Istanbul (MI = 1.00), and Sabiha Gökçen (MI = 1.00) operated at or above the productivity frontier, most airports recorded MI values below unity, indicating productivity decline during the study period. The decomposition results show that technological change (TC) is the main source of productivity variation. In many airports, efficiency change (EC) remained close to one, whereas low TC values substantially reduced overall productivity. These findings suggest that productivity

losses are largely associated with technological adaptation and capacity utilization challenges rather than purely managerial inefficiencies.

Table 2 : Malmquist Index Scores

DMU	EC	TC	PECH	SECH	MI
Adana	0,83	0,84	0,91	0,92	0,68
Adiyaman	1,15	0,26	1,31	0,91	0,29
Adnan Menderes	0,92	0,36	0,96	0,96	0,33
Agri	0,98	0,21	1,05	0,95	0,21
Amasya	0,93	0,22	0,84	1,11	0,2
Antalya	0,93	0,46	0,83	1,24	0,43
Batman	0,96	0,44	1	0,97	0,42
Bingol	0,91	0,39	0,86	1,05	0,35
Bursa	1,2	0,47	1,69	0,74	0,53
Canakkale	0,99	0,14	1,05	0,93	0,52
Denizli	0,93	0,46	1,03	0,91	0,43
Diyarbakir	0,99	1	1	0,99	0,99
Elazig	0,98	0,38	1,11	0,89	0,38
Erzincan	0,95	0,22	1,03	0,92	0,2
Erzurum	0,95	0,4	1,06	0,9	0,39
Esenboga	0,97	0,29	0,99	0,96	0,28
Eskisehir	0,87	0,08	0,97	0,9	0,07
Gaziantep	0,97	0,68	1,06	0,91	0,66
Gazipasa Alanya	0,98	0,72	1,13	0,88	0,7
Hakkari	0,96	0,17	1,06	0,9	0,16
Hatay	0,95	0,52	1,09	0,89	0,47
Igdir	1,04	0,48	1,04	0,99	0,5
Isparta	0,53	1	1	0,53	0,53
Istanbul	1	1	1	1	1
Kahramanmaras	1,02	0,22	1,22	0,89	0,23
Kapadokya	0,94	0,86	1	0,94	0,8
Kars	0,95	0,33	0,99	0,96	0,31
Kastamonu	1,24	0,19	2,66	0,8	0,27
Kayseri	0,71	0,54	0,78	0,8	0,47
Kocaeli	1,38	0,01	1,2	0,7	0,02
Kocaseyit	0,9	0,13	1,2	0,8	0,12
Konya	0,71	0,33	0,74	0,82	0,3
Malatya	0,95	0,38	1,03	0,93	0,36
Mardin	0,93	0,9	0,99	0,96	0,83
Milas Bodrum	0,89	0,09	0,92	0,97	0,08
Mugla Dalaman	1,03	1	1	1,03	1,03
Mus	1,03	0,23	1,17	0,9	0,24
Ordu	0,96	0,86	1,12	0,94	0,83
Sabiha Gokcen	1	1	1	1	1
Samsun	0,93	0,9	1	0,94	0,84
Siirt	0,95	1	1	0,95	0,95
Sinop	0,93	0,1	0,98	0,96	0,09
Sirnak	0,94	0,73	0,96	0,97	0,7
Sivas	0,9	0,15	0,96	0,93	0,13
Tekirdag	1,27	0,01	1,35	0,9	0,01
Trabzon	0,93	1	1	0,93	0,93
Urfa	1,01	0,4	1,12	0,89	0,4
Van	0,88	0,99	0,97	0,88	0,86
Zafer	1,04	1	1	1,04	1,04
Zonguldak	1,08	0,26	1,17	0,93	0,27

Table 3: Descriptive Statistics of SBM-Malmquist Components (2021–2025)

Indicator	Mean	Median	Std. Dev.	Min	Max
Malmquist Index (MI)	0.477	0.410	0.305	0.010	1.040
Efficiency Change (EC)	0.967	0.950	0.132	0.530	1.380
Technological Change (TC)	0.496	0.400	0.330	0.010	1.000

3.1.1. Descriptive Overview of Productivity Indicators

The descriptive statistics presented in Table 3 reveal a pronounced productivity gap between Turkish airports and the best-practice frontier during the 2021–2025 period. The average Malmquist Productivity Index (MI) across the 50 airports in the sample was 0.477 (SD = 0.305), with a median of 0.410, indicating that the typical airport in the network operated at less than half the productivity level of the frontier units. The wide standard deviation and the substantial gap between mean and median further reflect the highly skewed nature of the productivity distribution, driven by a small number of high-performing airports at one extreme and severely underperforming airports at the other.

The decomposition of MI into its constituent components yields an important asymmetry. Efficiency Change (EC) exhibited a relatively narrow range of variation, with a mean of 0.967 (SD = 0.132) and a median of 0.950. The clustering of EC values around unity suggests that most airports maintained a broadly stable level of managerial efficiency relative to the best-practice frontier, neither closing the gap significantly nor falling further behind. In contrast, Technological Change (TC) displayed considerably greater dispersion, with a mean of 0.496 (SD = 0.330) and a median of 0.400. This distribution indicates that technological adaptation and infrastructure utilization rather than managerial performance constituted the primary source of productivity heterogeneity across the Turkish airport network. The Pearson correlation between EC and TC was -0.291 , suggesting a weak negative relationship: airports that recorded higher managerial efficiency improvements tended, on balance, to do so in contexts of lower technological frontier performance, consistent with a substitution dynamic between operational optimization and structural capacity development

3.1.2. High-Performing Airports

Only four airports; Istanbul Airport (MI = 1.00), Sabiha Gokcen Airport (MI = 1.00), Mugla Dalaman Airport (MI = 1.03) and Zafer Airport (MI = 1.04) achieved MI values at or above the productivity frontier throughout the study period. These airports recorded both EC and TC

scores equal to or exceeding unity, indicating that productivity growth was driven by simultaneous improvements in managerial efficiency and technological adaptation. Istanbul Airport and Sabiha Gokcen Airport as the two largest aviation hubs in Türkiye, benefited from high and diversified traffic volumes that enabled optimal utilization of existing infrastructure, thereby minimizing input slacks under the SBM framework. Mugla Dalaman Airport, primarily oriented towards international charter tourism, similarly demonstrated strong traffic-to-capacity alignment. Notably, Zafer Airport achieved the highest MI score in the sample (1.04), reflecting effective demand mobilization relative to its infrastructure endowment during the recovery period. Diyarbakir Airport (MI = 0.99) ranked fifth and came closest to the frontier among the remaining airports, driven almost entirely by a TC score of 1.00 alongside a near-unity EC of 0.99.

3.1.3. Moderately Performing Airports

A second cohort of ten airports recorded MI values between 0.70 and 0.99, indicating moderate but incomplete convergence toward the productivity frontier. This group includes Samsun (MI = 0.84), Van (MI = 0.86), Mardin (MI = 0.83), Ordu (MI = 0.83), Trabzon (MI = 0.93), Siirt (MI = 0.95), Kapadokya (MI = 0.80), Gaziantep (MI = 0.66 borderline), Gazipasa Alanya (MI = 0.70), and Sirnak (MI = 0.70). Several of these airports recorded TC scores above 0.85, suggesting that the technological frontier was not the primary constraint. Rather, incomplete managerial catch-up or residual capacity underutilization explain the remaining productivity gap. These airports represent the most promising candidates for near term performance improvements, as relatively modest operational or demand-side interventions may be sufficient to push them toward frontier levels.

3.1.4. Low-Performing and Critically Underperforming Airports

The most striking finding of the distributional analysis is the large share of airports concentrated in the lowest productivity tier. Seventeen airports (34% of the sample) recorded MI values below 0.30, indicating severe productivity deficiencies. Among these, Tekirdag (MI = 0.01), Kocaeli (MI = 0.02), Eskisehir (MI = 0.07), Milas-Bodrum (MI = 0.08), and Sinop (MI = 0.09) recorded the five lowest productivity scores in the sample.

A critical observation regarding this group concerns the divergence between EC and TC values. Several of these airports including Tekirdag (EC = 1.27, TC = 0.01), Kocaeli (EC = 1.38, TC = 0.01), Kastamonu (EC = 1.24, TC = 0.19) and Adiyaman (EC = 1.15, TC = 0.26) recorded EC values substantially above unity, indicating that airport managers were effectively optimizing the use of available resources. However, the near-zero TC values in these cases reflect that the

existing infrastructure base was fundamentally misaligned with actual traffic demand, generating severe input slacks that the SBM model penalizes directly. This pattern strong managerial effort paired with structural technological underperformance illustrates a "managerial effort trap" in which operational optimization alone is insufficient to compensate for the inherent inefficiency of excess, underutilized infrastructure.

Taken together, the distributional evidence points to a structurally polarized airport network in which productivity growth during the post-pandemic recovery period was heavily concentrated among a small number of large hub and tourism-oriented airports, while a substantial proportion of regional airports remained far below the efficiency frontier primarily due to technology-related capacity underutilization.

3.2. Decomposition of Productivity Change

To identify the sources of productivity variation, the Malmquist Productivity Index was decomposed into Efficiency Change (EC) and Technological Change (TC) components. The decomposition results indicate that technological change constituted the primary determinant of productivity fluctuations during the study period. While efficiency change values remained relatively stable across many airports, substantial variations were observed in technological change scores.

This finding suggests that differences in technological adaptation, infrastructure utilization and operational modernization played a more significant role than managerial efficiency in explaining productivity disparities among airports. Similar evidence has been reported in previous airport productivity studies, which emphasize the importance of technological progress as a 15 major driver of long-term performance improvement (Assaf, 2010; De Nicola et al., 2013).

The results therefore imply that productivity growth in the Turkish airport sector depends not only on managerial improvements but also on the effective integration of technological and infrastructural investments into operational processes.

3.3. Performance Heterogeneity Across Airports

The findings reveal a clear differentiation among airports with respect to productivity performance. Major hub airports such as Istanbul Airport and Sabiha Gokcen Airport consistently operated on or near the productivity frontier throughout the study period. These airports benefited from high passenger volumes, diversified traffic structures and strong

connectivity, allowing them to maintain balanced levels of both efficiency and technological performance.

A second group of airports exhibited moderate productivity performance. Airports such as Diyarbakir, Trabzon and Siirt remained relatively close to the frontier and demonstrated strong catch-up potential. Although these airports did not achieve frontier efficiency, their performance indicates that relatively limited managerial and operational improvements could generate substantial productivity gains.

In contrast, a considerable number of regional airports remained substantially below the productivity frontier. The SBM results suggest that these airports are characterized by significant input slacks, reflecting the existence of infrastructure capacities that are not fully matched by passenger and aircraft traffic demand. Consequently, productivity losses appear to be associated primarily with capacity underutilization rather than solely with managerial shortcomings.

3.4. Capacity Utilization and Slack Effects

One of the main advantages of the SBM framework is its ability to explicitly capture input and output slacks. The results demonstrate that infrastructure intensive airports with relatively low traffic volumes tend to receive lower productivity scores under the SBM methodology. This outcome reflects the presence of excess capacity in terms of terminal space, runway infrastructure and other operational resources.

From a policy perspective, the findings suggest that future performance improvements should focus on increasing the utilization of existing infrastructure rather than exclusively expanding physical capacity. The results indicate that productivity challenges in many regional airports stem from demand deficiencies rather than infrastructure shortages.

Therefore, policies aimed at increasing passenger demand, attracting airline services and strengthening regional connectivity may contribute more effectively to productivity growth than additional infrastructure investments.

3.5. Post-Pandemic Recovery Patterns

The analysis period covers the post-pandemic recovery phase of the aviation sector, making it possible to evaluate how airports adapted to changing operational conditions.

The results indicate that recovery trajectories were not uniform across airports. Large hub airports demonstrated stronger resilience and faster recovery, whereas many regional airports

experienced slower productivity improvements. This divergence may be explained by differences in traffic composition, market size, tourism demand and network connectivity. Furthermore, the gradual improvement observed in average productivity indicators toward the end of the study period suggests that the sector has been moving toward a stabilization phase. Nevertheless, the persistence of significant productivity gaps across airports indicates that the recovery process remains incomplete.

Figure 1. Lollipop chart showing airport-level deviations in Malmquist Productivity Index (MI) scores relative to the productivity frontier.

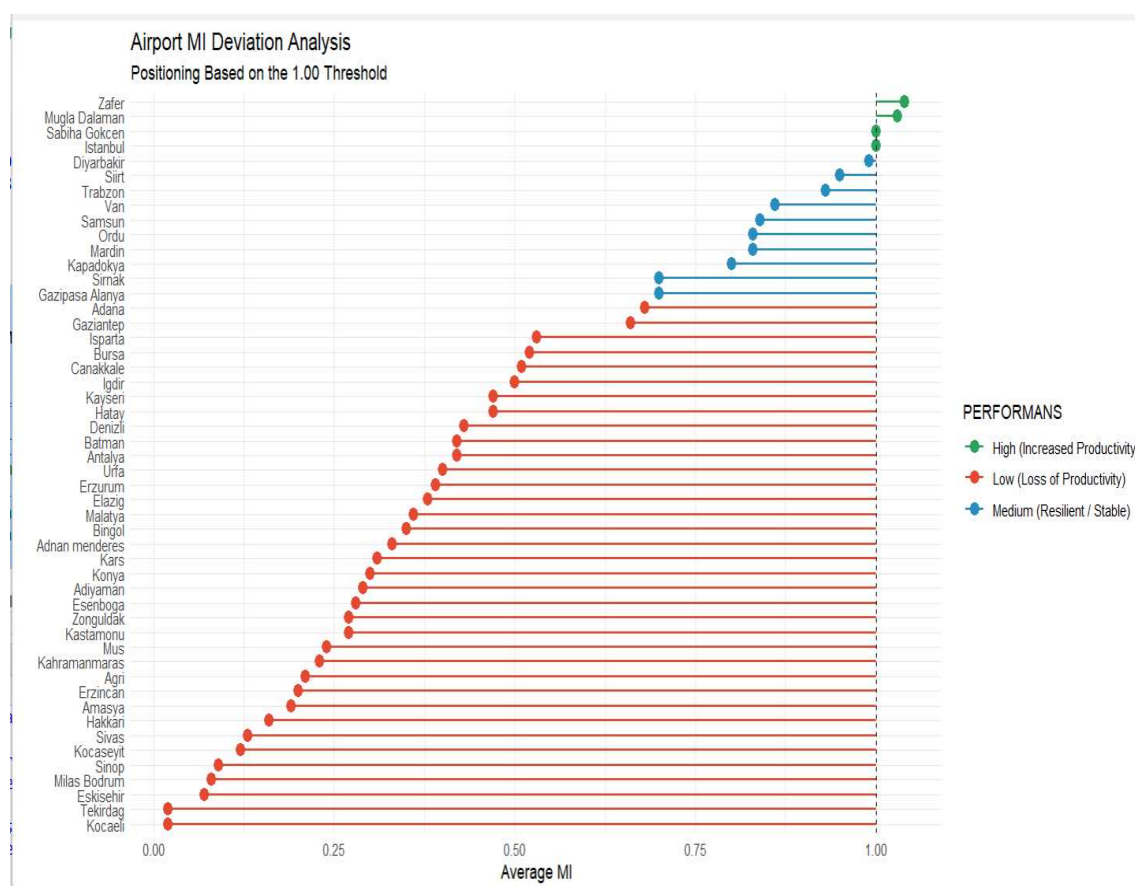
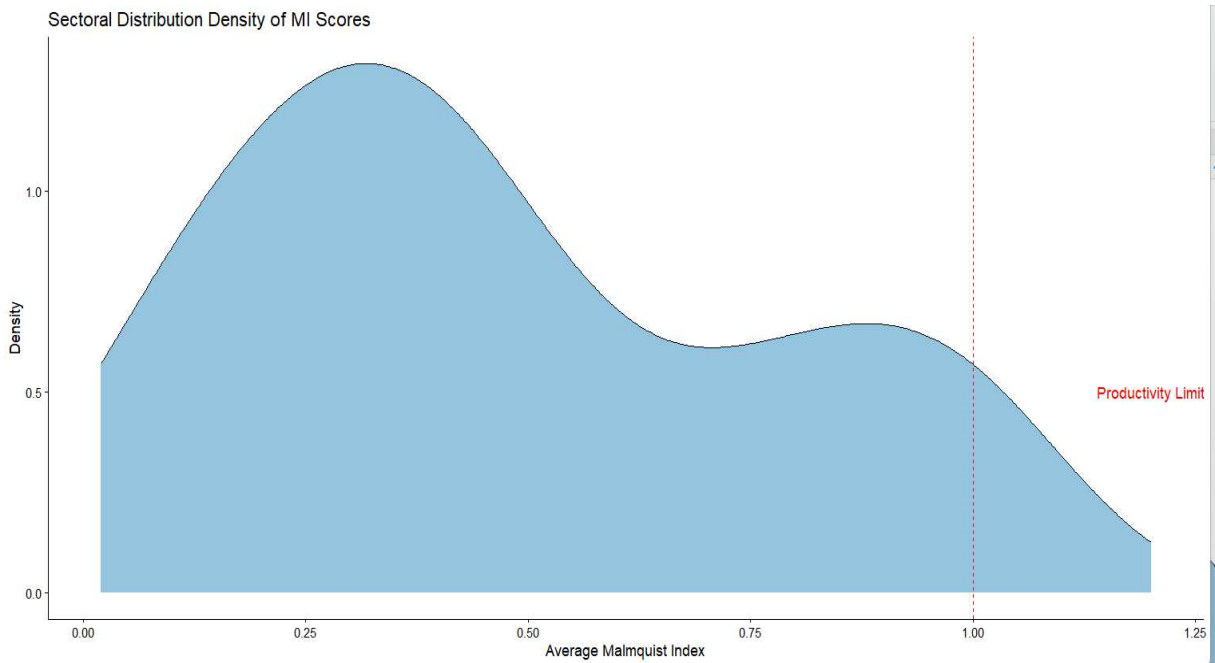


Figure note: When airports are categorized according to their MI scores, it is observed that units in the green zone are located at the technological frontier, while units in the red zone are penalized with 'input slacks' in the SBM model, particularly due to low occupancy rates. The black dashed line (1.00) in the graph represents the efficiency limit. Airports to the right of this line (green bars) are defined as "Efficient", while those to the left (blue and red bars) are defined as "Relatively Inefficient".

In Figure 1 clearly shows that the productivity change in Turkey's airport network is not homogeneous and that a polarized recovery is taking place. Sectoral productivity growth is only

shouldered by a few airports, such as the main hubs based in Istanbul (Istanbul Airport, Sabiha Gökçen) and Mugla Dalaman, which is a major area for charter tourism. The significant productivity loss experienced by the widespread airport network in Anatolia (red group) demonstrates that the capacity offered at these airports (terminals, runways, personnel) did not fully match the demand fluctuations in the post-pandemic period (supply-demand imbalance) and that there are significant input slacks.

Figure 2. Kernel density distribution of airport Malmquist Productivity Index (MI) scores.



As illustrated in Figure 2, the distribution of airport MI scores is highly right-skewed, with most airports remaining below the productivity frontier ($MI = 1.00$). A substantial proportion of airports exhibit MI values below 0.50, indicating that productivity improvements were concentrated in a relatively small number of airports. The dashed vertical line at $MI = 1.00$ denotes the threshold separating productivity regress ($MI < 1.00$) from productivity growth ($MI > 1.00$).

The distribution exhibits a prominent asymmetric, right-skewed, and slightly bimodal pattern:

1. Predominance of Productivity Loss: The majority of the distribution mass is concentrated well below the unity line ($MI < 1.00$), peaking around $MI \sim 0.30 - 0.35$. This indicates that a significant proportion of the analyzed sectors/units experienced a contraction in Total Factor Productivity (TFP) over the observed period.
2. Sub-clustering / Bimodality: A secondary, lower-density peak emerges between 0.80 and 0.90, suggesting structural heterogeneity across sectors, where a sub-group approaches efficiency neutral levels without fully crossing the growth threshold.
3. High-Performing Minority: Only a small tail of the distribution extends beyond the productivity boundary ($MI > 1.00$). This demonstrates that only a limited number of

sectors achieved genuine productivity gains, highlighting widespread operational or technological inefficiencies across the broader sectoral landscape.

We can group airports into 4 categories based on their performance scores.

1. Perfect Balance and Frontier Groups (Perfectly Symmetrical Circles): The airports in this group exhibit perfectly balanced, rounded profiles that fit precisely within the 1.00 limit on all axes, or wide profiles that exceed this limit.

- **Istanbul & Sabiha Gokcen:** Looking at their graphs, the blue area perfectly overlaps with the dashed red line (1.00). This confirms that the two giant hubs are perfectly balanced both administratively (EC) and technologically (TC), setting the reference limit for the sector.
- **Mugla Dalaman:** The graph shows that the blue area extends outwards to the right, towards the EC axis, with a distinct "ear" shape. This visual structure linearly demonstrates that the fundamental driving force behind Dalaman's success is high managerial adaptation and resource utilization (EC = 1.23).
- **Diyarbakir:** It has one of the closest and most regular circular forms to the 1.00 limit. The slight outward protrusion on the EC side is balanced by the stability on the TC axis, creating a resistance profile right at the limit.

2. Managerial Success - Technological Bottleneck Group (Right-facing "Crescent" or "Hook" Forms): The most striking feature in the graphics of these airports is that the blue area extends beyond the 1.00 limit on the EC (Management) axis on the right, while it sharply dips towards the center (near zero) on the TC (Technology/Infrastructure) axis on the left. The resulting image resembles a crescent or hook curving to the right.

- **Bursa & Canakkale:** These are the most extreme examples of this pattern. In the graph, the blue band on the EC axis has jumped to over 1.20, while the TC axis on the left is practically glued to the center (0.14 - 0.17). Visually, this clearly conveys the message: "Management is optimizing existing resources to the last drop (EC), but inadequate infrastructure/technology (TC) is dragging down overall productivity (MI)."
- **Siirt, Cappadocia, Batman:** When the graphs are examined, a strong bulge in the upper right (EC) direction and a significant constriction in the left (TC) direction are noticeable. The pronounced protrusion of Cappadocia along the EC axis, in particular, visualizes the strength of the administrative capture effect (EC = 1.16).

3. Systemic Idle Capacity and Structural Inefficiency Group (Shrinking Amorphous Areas in the Center): In the airports in this group, the blue fill area is far behind the red dashed line (1.00), exhibiting a constricted and deformed structure towards the center. This indicates significant input slacks due to the non-radial nature of the SBM-DEA model.

- Ankara Esenboga: The graph of the capital's airport is quite striking. The blue area has experienced a very sharp decline towards the center, both on the EC and especially the TC axes. The fact that it occupies a very small area within the red circle visually reveals that despite the massive infrastructure and input capacity, the output (passengers/cargo) produced lags far behind (0.28 MI).
- Antalya & Milas-Bodrum: Despite being among Turkey's busiest tourist ports, the blue areas in their graphs are significantly below the 1.00 threshold (red line), resulting in a flattened form. This visual structure is the most concrete evidence that the SBM model penalizes high seasonal capacity (input) as "idle capacity" when compared to the overall year.
- Adana: In the graph, the T-axis on the left touches the 1.00 limit, while the EC-axis on the right collapses inwards. This situation, unlike other regional ports, symbolizes not a technological/infrastructural problem, but entirely a bottleneck in managerial/operational processes (EC = 0.62).4.

4. Critical Collapse Group (Points/Tiny Strips Adhering to the Center):

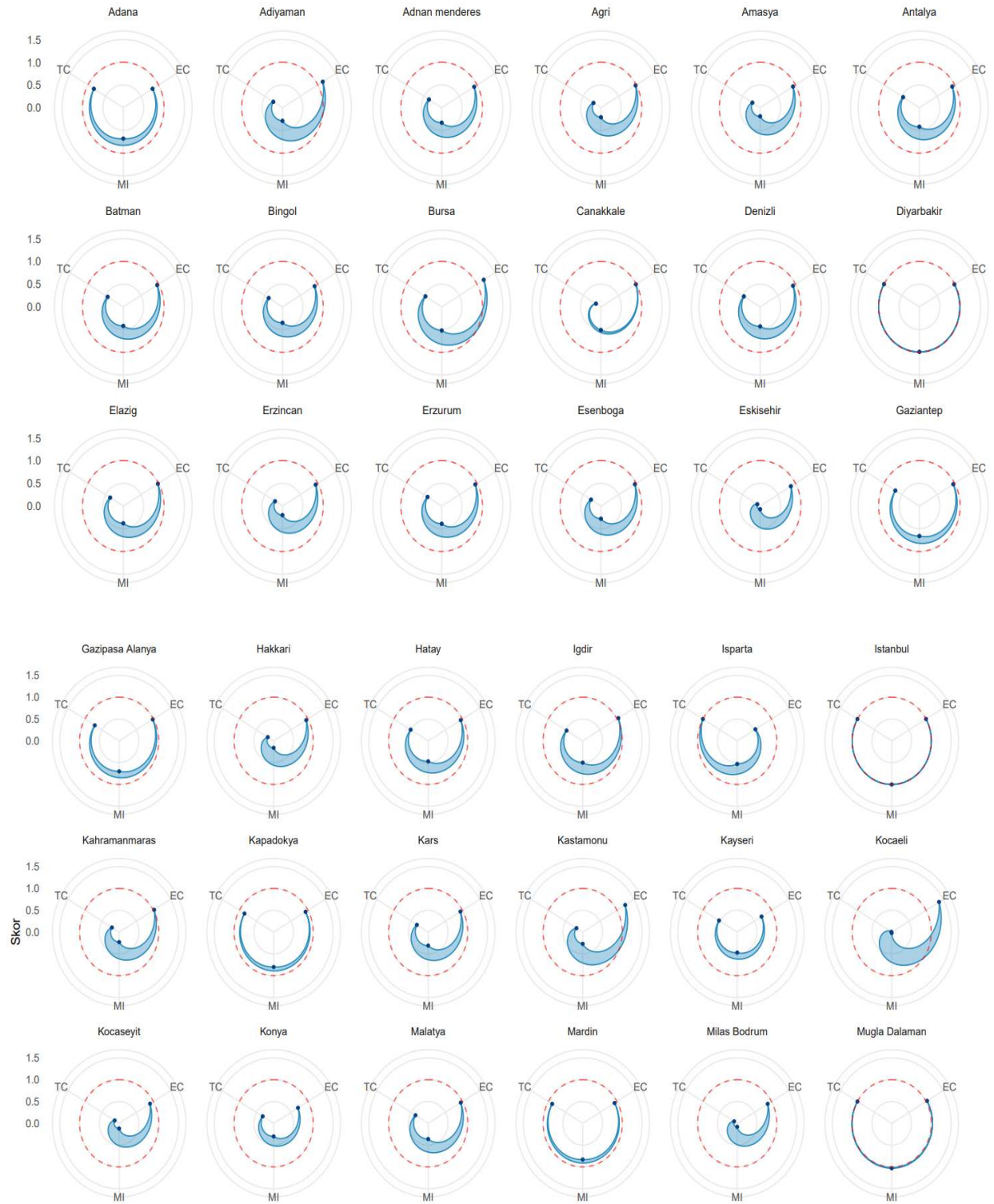
- Eskisehir & Kocaeli: In the Kocaeli (0.02) and Eskisehir (0.07) graphs, the blue area has almost completely disappeared, sticking to the center (0.0). This is the most radical visual finding, showing that the input-output balance has completely broken down and that the existing capacity is hardly converted into effective data.
- Kocaseyit, Sinop, Hakkari: The narrow, linear, and center-bound profiles in their graphs show how far these airports have deviated operationally from the sector average and how urgently they need structural rationalization.

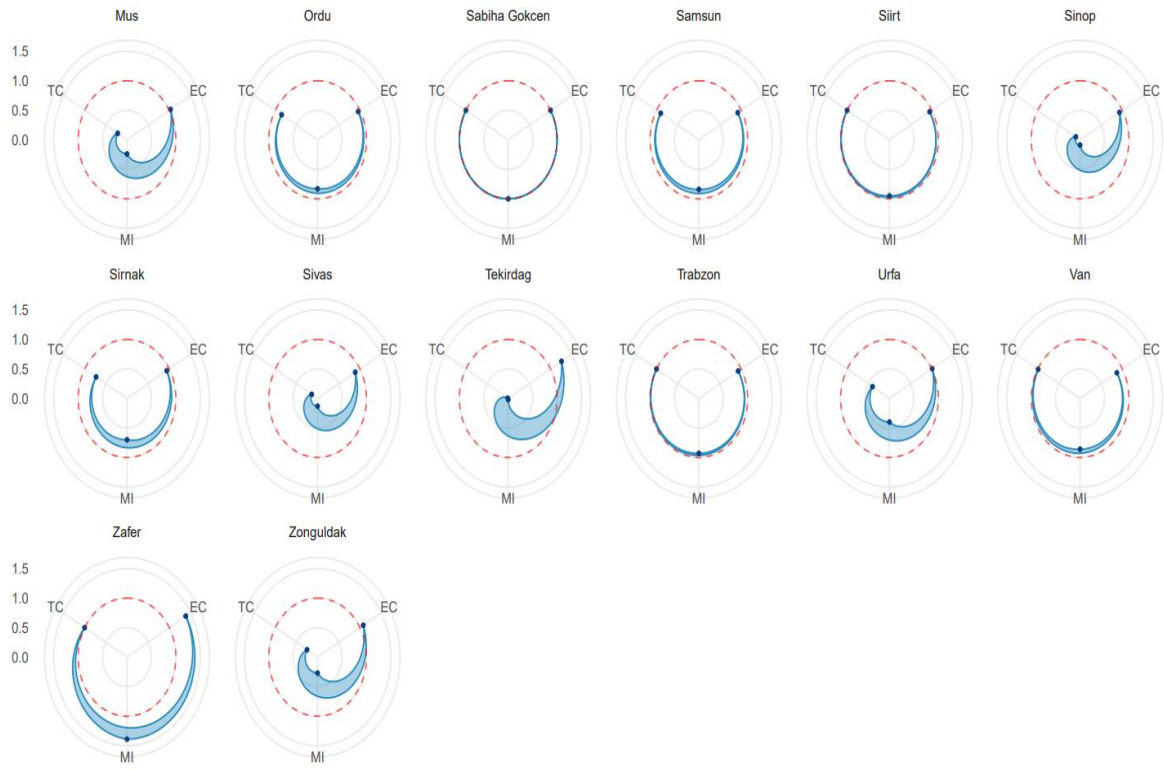
The rightward-leaning asymmetrical crescent shape, particularly seen at Bursa and Canakkale airports, illustrates how managerial success is hampered by technological limitations; while the constriction towards the center at ports like Ankara Esenboga and Kocaeli visualizes the enormous underutilized capacity constraint captured by the SBM model.

4. Red Dashed Line (1.00): "Reference Point": This line can be called the "Golden Boundary". Whenever the blue-painted area moves outside this line, there is an "Increase", and when it stays inside, there is a "Decrease/Loss".

Figure 3 presents the radar charts illustrating Turkish airport productivity profiles based on MI, EC and TC values.

Figure 3: Radar Charts





According to the radar charts in figure 3 (spider web), what needs to be understood is "the size and direction of the triangle". The blue-filled areas in the graphs represent the performance profile of the airports, while the dashed red circle represents the critical threshold of 1.00. The following four basic steps should be followed when interpreting the graph. Examining the radar graphs presented in Figure 3, it can be seen that Muğla Dalaman Airport exhibits a balanced profile exceeding the efficiency limit (1.00). In contrast, in the profile of Esenboğa Airport, although the EC (Efficiency) value is close to the limit, the TC (Technology) value is very close to the center, visualizing that the main source of inefficiency is the problem of technological adaptation and capacity utilization. In short, the larger the triangle, the better; the longer the corner, the more successful it is in that area.

1. Area Width: "Overall Efficiency Scorecard"

- *Fully Filled Triangle:* If the blue area covers or crosses the outer red dashed line (1.00 boundary) in all directions, that airport is "Fully Efficient". (e.g., Istanbul and Sabiha Gökçen).
- *Small Triangle:* The closer the blue area is to the center, the lower the efficiency. (e.g., Kocaeli).

2. The point where the triangle is sharp: "Strong Muscles"

- *Extension in the MI direction:* Indicates an increase in overall productivity.

- *Extension in the EC (Efficiency Change) Direction:* Indicates that the airport is administratively successful and uses its resources very well (Catch-up effect).
- *Extension Towards Technological Change (TC):* Indicates that the airport is pushing its technological boundaries or efficiently utilizing new capacity/infrastructure opportunities.

3. “Unbalanced” Triangles: “Why Are They Inefficient?”

- The biggest advantage of the radar graph is finding the error. If one end of the triangle is close to 1.00 while the other end is close to the center; Example: If an airport's EC end is close to 1.00 but its TC end is close to the center (e.g., Canakkale or Bursa), the interpretation would be: "Although this airport is very successful in terms of management (EC), it remains inefficient overall due to technological deficiencies or excess capacity (TC).

4. Conclusion

This study investigated the dynamic efficiency and productivity performance of Turkish airports during the 2021–2025 period by employing a non-radial Slack-Based Measure (SBM) Data Envelopment Analysis integrated with the Malmquist Productivity Index (MPI). Unlike conventional radial DEA models, the SBM framework explicitly incorporates input and output slacks into the efficiency measurement process, enabling a more comprehensive assessment of airport performance and capacity utilization.

The findings are broadly consistent with the international airport efficiency literature, which emphasizes the importance of technological development, infrastructure utilization, and demand conditions in shaping airport performance.

Unlike many previous studies based on radial DEA models, the SBM framework employed in this study reveals the substantial role of capacity underutilization in explaining productivity differences among Turkish airports. The results suggest that infrastructure expansion alone is unlikely to improve productivity unless accompanied by corresponding growth in passenger and aircraft traffic.

Consequently, the evidence supports a policy orientation focused on demand stimulation, operational flexibility, and technological adaptation rather than solely increasing physical infrastructure capacity.

The empirical findings reveal substantial heterogeneity in productivity performance across Turkish airports. While major hub airports such as Istanbul Airport and Sabiha Gökçen Airport consistently operated near the productivity frontier, many regional airports exhibited lower productivity levels. The decomposition analysis further demonstrated that technological change

was the primary source of productivity variation across airports, whereas efficiency change remained relatively stable throughout the study period.

The results suggest that productivity differences are closely associated with variations in infrastructure utilization and technological adaptation. Airports characterized by relatively large physical capacities but limited passenger and aircraft traffic tended to exhibit lower productivity scores under the SBM framework due to the presence of significant input slacks. Consequently, the findings indicate that capacity utilization plays a critical role in determining airport productivity in the post-pandemic environment.

Overall, the study highlights the importance of balancing infrastructure investments with actual traffic demand and operational requirements. From a methodological perspective, the findings demonstrate the usefulness of the SBM-Malmquist framework in identifying the underlying sources of productivity change and revealing inefficiencies that may remain hidden under traditional radial DEA specifications.

5. Policy Implications

The findings provide several implications for aviation authorities, airport managers, and policymakers responsible for transportation infrastructure planning.

5.1. Improving Capacity Utilization

The analysis indicates that productivity losses in many regional airports are associated with the existence of underutilized infrastructure. Therefore, future policy efforts should focus on improving the utilization of existing facilities rather than relying exclusively on capacity expansion projects.

Demand-oriented strategies such as airline incentives, route development programs, and regional tourism promotion may contribute to increasing passenger traffic and improving the efficiency of existing infrastructure investments.

5.2. Accelerating Technological Adaptation

Since technological change emerged as the main driver of productivity variation, investments aimed at digital transformation and operational modernization should be prioritized.

The implementation of advanced passenger processing systems, smart baggage handling technologies, data-driven airport management systems, and modern air traffic control technologies may contribute to improving productivity and operational performance across the airport network.

5.3. Strengthening Regional Airport Integration

The results reveal a productivity gap between major hub airports and many regional airports. To reduce this imbalance, policymakers may consider strengthening hub-and-spoke structures and improving connectivity between regional airports and major aviation centers.

Enhanced integration may increase traffic flows, improve network efficiency, and support the long-term sustainability of regional airports.

5.4. Developing Flexible Operational Strategies

The post-pandemic period demonstrated the vulnerability of aviation systems to unexpected demand shocks. Therefore, airport management strategies should emphasize operational flexibility and adaptive resource allocation mechanisms.

Flexible staffing arrangements, modular terminal operations, and dynamic capacity management systems may help airports respond more effectively to future fluctuations in demand.

6. Limitations and Future Research

Despite providing important insights into the productivity dynamics of Turkish airports, this study is subject to several limitations.

First, the analysis focuses primarily on operational variables related to airport infrastructure and traffic performance. Financial indicators such as operating revenues, operating costs, and profitability measures were not incorporated into the model. Including such variables may provide a more comprehensive evaluation of airport performance.

Second, the study evaluates airport productivity from an operational perspective and does not explicitly consider environmental sustainability indicators. Future research may integrate undesirable outputs such as carbon emissions, energy consumption, and noise pollution within an SBM framework to assess both operational and environmental efficiency simultaneously.

Third, the analysis is limited to the period 2021–2025, which largely reflects the post-pandemic recovery phase. Extending the observation period may provide additional evidence regarding long-term productivity trends and structural changes within the Turkish aviation sector.

Finally, future studies may combine SBM-Malmquist models with advanced forecasting techniques, including machine learning and artificial intelligence methods, to predict future airport productivity trajectories and support strategic infrastructure planning.

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