



An Intelligent Evaluation and Optimization System for Integrating Efficiency and Sustainability in Aviation Operations

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Abstract

Enhancing operational efficiency while promoting sustainability remains a key challenge in aviation systems. This study proposes an intelligent evaluation and optimization system (IEOS) integrating multidimensional efficiency assessment with sustainability-oriented optimization. Using airport-level data from China, the system evaluates operational inputs, desirable outputs, and undesirable outcomes. Results show that most airports operate at moderate efficiency levels (0.60–0.80), with undesirable outputs accounting for 46% of total inefficiency, followed by desirable output shortfalls (32%) and input redundancy (22%). The proposed optimization reduces taxi-out time by 18.6 min, delays by 22.3 min, and CO₂-related emission proxies by 17.4 units without infrastructure expansion. Robustness tests confirm stable efficiency rankings across alternative specifications ($r=0.88$). The proposed evaluation-diagnosis-optimization framework provides practical decision support for improving aviation efficiency and sustainability.

1. Introduction

Aviation systems support large-scale mobility and economic activity, yet they operate under stringent constraints related to safety, energy consumption, and environmental impact (Tafur et al., 2025). In this context, operational efficiency refers to the ability to deliver planned capacity while minimizing unnecessary expenditure of fuel, time, labor, and infrastructure resources. A central challenge arises from the inherently interconnected nature of aviation operations: activities are distributed across multiple stages and organizations, and local disruptions can quickly propagate across the network. Even minor delays caused by weather, congestion, or resource mismatches can trigger system-wide inefficiencies and elevate emissions (Xu, 2025).

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Sustainability adds an additional layer of complexity to aviation operations. In practice, environmental performance is driven primarily by daily operational decisions rather than long-term technological changes alone. Choices related to scheduling, ground operations, and disruption recovery directly influence fuel consumption and environmental outcomes, while remaining constrained by infrastructure capacity and airspace regulation (Elbir et al., 2026). As a result, the relationship between operational efficiency and sustainability is often nonlinear, with improvements in one dimension potentially imposing trade-offs on the other (Lingrui & Xin, 2024). In such complex contexts, existing evaluation approaches frequently struggle to integrate diverse performance indicators, capture nonlinear interactions, and effectively support decision-making aligned with sustainability objectives (Wen et al., 2025).

Despite the widespread use of performance analytics, evaluation and decision making in aviation remain weakly connected. Operational indicators are typically assessed in isolation, while sustainability measures are treated as reporting outcomes rather than decision objectives. This limits the ability of managers to distinguish managerial performance from structural conditions and to translate evaluation results into effective improvement actions (Liu & Wen, 2024). This study proposes an intelligent evaluation and optimization system (IEOS) that integrates operational and sustainability indicators within a unified decision framework. The approach aims to produce interpretable efficiency assessments across heterogeneous operational units and to support feasible improvement strategies under real world constraints. The framework is illustrated using data from China's aviation system, where scale, network diversity, and regulatory complexity provide a relevant context for management and policy analysis. By linking efficiency evaluation directly to operational optimization, this study contributes to more actionable analytics for aviation management. It embeds sustainability within operational efficiency and offers insights applicable to large aviation systems facing increasing performance and environmental pressures.

2. Literature Review

This review examines studies on aviation operational efficiency, the use of intelligent analytics, and the integration of sustainability. It highlights what has been addressed, the remaining limitations, and the resulting research gap. The discussion is organized around three themes that directly inform the design of the proposed IEOS.

2.1 Measurement of Aviation Operational Efficiency

Early studies on aviation operational efficiency relied primarily on productivity and performance analysis frameworks, in which resource inputs such as labor, runways, gates, and capital were compared against outputs including aircraft movements, passenger volumes, and cargo throughput. Simple ratio indicators, such as flights per runway or passengers per employee, were widely used due to their transparency. However, these measures treat efficiency as a largely one-dimensional concept and fail to account for substitution effects and interactions among multiple inputs and outputs (Wang et al., 2025).

To address these limitations, data envelopment analysis (DEA) became a dominant approach in aviation efficiency research. DEA has been extensively applied to evaluate airport performance, airline productivity, and air navigation service efficiency. Its appeal lies in the ability to handle multiple inputs and outputs without imposing a predefined functional form.

Recent studies have further extended DEA frameworks to capture the complexity of airport operations and sustainability considerations. For instance, Ngo et al. (2026) developed a two-stage slack-based measure DEA (SBM-DEA) model to evaluate airport efficiency by jointly examining infrastructure performance and environmental impacts, incorporating undesirable outputs such as fuel consumption and emissions. Voltes-Dorta et al. (2024) applied an advanced DEA framework to investigate airport efficiency under sustainability-oriented operational conditions, demonstrating how environmental and operational dimensions can be assessed simultaneously within an efficiency analysis framework. Similarly, Yang et al. (2024) proposed a fuzzy common-weight additive network DEA model that incorporates shared resources, undesirable outputs, and negative data, while using Z-number representations to account for data uncertainty. DEA-based studies have also examined efficiency differences across hub and non-hub airports, ownership structures, and regional aviation systems (Gao & He, 2025). Despite its popularity, the literature has consistently highlighted several weaknesses of DEA. Efficiency rankings can be sensitive to variable selection and outliers, particularly in heterogeneous systems. More importantly, DEA primarily offers relative efficiency scores and limited guidance on how identified inefficiencies can be addressed through concrete operational actions.

In addition to DEA-based approaches, stochastic frontier analysis (SFA) has been proposed as an alternative that distinguishes inefficiency from random noise. Empirical studies have applied SFA to various aviation contexts. For instance, Karanki and Yu (2025) employed a two-tier stochastic frontier model to analyse bargaining power and pricing dynamics between airlines and airports in the United States. Expanding the scope to airline strategic management, Bourjade and Muller-Vibes (2023) utilized SFA on a global dataset of 134 airlines to investigate the impact of aircraft leasing on cost efficiency, identifying optimal leasing levels across different business models. In addition, Bergantino et al. (2021) incorporated spatial dependence into stochastic frontier modelling to examine how competition and geographic proximity influence airport efficiency across 206 airports worldwide. While SFA offers a stronger statistical foundation, it requires restrictive assumptions regarding functional forms and error distributions (Karanki & Yu 2026). Such assumptions are often difficult to justify in aviation operations characterized by nonlinear dynamics, regime shifts, and exogenous shocks such as weather conditions and airspace constraints. As a result, SFA has seen more limited adoption in applied aviation studies. Overall, existing efficiency measurement approaches have made substantial progress in comparative assessment but remain limited in their ability to support operational decision making under uncertainty and sustainability-oriented objectives (Nazeer et al., 2024).

2.2 Smart and Data-Driven Aviation Operations

With the rapid expansion of digitalization, artificial intelligence (AI) and machine learning (ML) have become increasingly prominent in aviation research. These methods have been applied to demand forecasting, crew scheduling, gate assignment, trajectory planning, and disruption management. Compared with traditional optimization models, AI and ML are particularly effective at capturing nonlinear patterns and extracting actionable insights from large historical datasets. For example, Ogunsina & DeLaurentis (2022) developed a multi-agent system capable of concurrently managing aircraft, crew, and passenger scheduling, addressing operational challenges that often exceed human planning capacity during major disruptions. Beyond operational efficiency, the integration of AI-driven services has also been shown to

enhance customer service performance in major airport hubs (Ku, 2024). Collectively, these applications reflect the transition from static evaluation toward adaptive operational intelligence (Fondevila-Gascón, 2025).

Despite their predictive power, AI-driven models face two critical limitations. Many are opaque, offering little interpretability for managers or regulators, which restricts their practical use in safety-critical operations. In addition, prediction-focused models rarely link directly to efficiency or sustainability objectives. A model that forecasts delays does not automatically indicate how to adjust operations to improve system-wide or environmental performance. Some hybrid approaches, such as combining ML with DEA or clustering similar operational patterns, have been proposed to mitigate these issues. While promising, they often stop short of integrating optimization and sustainability comprehensively (Cui et al., 2024). In summary, smart methods have advanced operational awareness in aviation but remain only loosely connected to formal efficiency assessment and sustainability-driven decision making.

2.3 Sustainability During Aviation Operations

Traditional sustainability research in aviation has focused on emissions reduction, fuel efficiency, and long-term decarbonization strategies. Policy-oriented studies emphasize technological innovation, fleet modernization, and market-based solutions, often framed within global guidelines such as those of the international civil aviation organization (ICAO) (Guo et al., 2025). These contributions are essential but largely macro-focused and long-term.

Operational efficiency is increasingly recognized as a lever for immediate sustainability gains. Reducing taxi times, streamlining turnarounds, strengthening schedules, and smoothing traffic flow can lower fuel use and emissions with minimal capital investment. Empirical studies show that operational inefficiencies, particularly in surface operations and disruption recovery, are a major source of unnecessary fuel burn and emissions. Despite this, sustainability is frequently treated as a separate reporting concern rather than an integrated decision objective. Airport sustainability metrics often rely on absolute emissions or compliance indicators, which are poorly aligned with daily operational choices. Conversely, efficiency studies may account for environmental effects indirectly but rarely embed them explicitly within performance assessments (Liang & Chen, 2025). This separation limits the ability to make analytically grounded trade-offs between efficiency and sustainability and highlights the need for frameworks that integrate both dimensions.

3. Methodology

3.1 System Overview and Research Design

This study adopts a quantitative, system-oriented approach to assess and optimize aviation operational efficiency within a sustainability framework. The proposed IEOS consist of two layers: an evaluation layer and an optimization layer. The evaluation layer integrates inputs, desirable outputs, and undesirable outputs to generate efficiency scores, while the optimization layer translates these results into actionable strategies that consider both operational and environmental constraints (Wei et al., 2025). Airports are selected as the primary units of analysis because they serve as hubs of operational coordination and are where efficiency losses and sustainability impacts are most visible.

3.2 Modelling Framework and Assumptions

Aviation operations involve complex interactions among subsystems, diverse resource configurations, and frequent stochastic disturbances. To ensure analytical clarity, internal consistency, and reproducibility, this section defines the system boundary, key variables, and modelling assumptions underlying the proposed IEOS. These elements establish a unified analytical basis for both efficiency assessment and subsequent optimization.

3.2.1 Unit of Analysis and System Boundary

The analysis adopts the airport as the decision-making unit (DMU), reflecting its role as the primary coordination hub for airlines, air traffic management, and ground operations. Many efficiency losses with sustainability implications, including taxi delays, gate congestion, and turnaround variability, arise and are most clearly observed at the airport level (Mahmoudi & Emrouznejad, 2023). Moreover, airport level data are comparatively accessible and suitable for cross sectional and panel-based efficiency analysis within national aviation systems. The system boundary is limited to commercial civil aviation. Passenger and cargo operations are jointly considered where data permit, consistent with their integrated operation in practice, while general aviation and military activities are excluded due to distinct objectives and regulatory conditions.

3.2.2 Operational Efficiency Representation

In this study, operational efficiency is understood as the ability of an airport to transform operational resources into reliable service outputs while limiting congestion and environmentally undesirable outcomes under prevailing operational constraints. Efficiency is therefore not defined by throughput alone, but by the joint performance of productivity, service reliability, and environmental discipline.

Operational efficiency is defined as the ability of a DMU to generate desirable outputs while simultaneously minimizing input consumption and undesirable outputs under given operational constraints. Airport i is considered more efficient than airport j if it can achieve

$$(y_{i,t}, -b_{i,t}) \geq (y_{j,t}, -b_{j,t}) \quad (1)$$

using the same or fewer inputs x .

The efficiency scores obtained from the evaluation model are denoted by:

$$\theta_{i,t} \in (0,1] \quad (2)$$

where $\theta_{i,t} = 1$ indicates frontier (best-practice) efficiency.

3.2.3 Notation Definitions

First, consider a set of N airports indexed by $i = 1, 2, \dots, N$, observed over time periods $t = 1, 2, \dots, T$. By explicitly incorporating undesirable outputs into the output set, the framework integrates sustainability considerations directly into the efficiency evaluation process. The model includes three categories of variables:

Input variables. Inputs represent the operational resources employed in airport activities. Let $x_{i,t} = (x_{i1,t}, x_{i2,t}, \dots, x_{im,t})$ denote the input vector for airport i at time t , where typical

inputs include runway availability, contact gate capacity, ground handling labor intensity, and terminal scale proxies. Here, m denotes the number of input variables.

Desirable output variables. Desirable outputs represent positive operational outcomes and are collected in the vector $y_{i,t} = (y_{i1,t}, y_{i2,t}, \dots, y_{is,t})$. These outputs capture traffic volume and service performance, such as aircraft movements, passenger and cargo throughput, and departure punctuality. The parameter s denotes the number of desirable outputs.

Undesirable output variables (sustainability proxies). Undesirable outputs reflect operational inefficiencies with environmental implications and are expressed as: $b_{i,t} = (b_{i1,t}, b_{i2,t}, \dots, b_{ik,t})$. Typical indicators include taxi-out time, delay intensity, and fuel or emission-related proxies associated with ground operations. The parameter k denotes the number of undesirable outputs.

3.2.4 Modelling Assumptions

The analysis assumes that airports operate under broadly comparable regulatory and safety frameworks, while structural heterogeneity is accommodated through model design. Infrastructure inputs are treated as fixed in the short run, whereas operational processes and resource utilization are considered subject to managerial adjustment. Sustainability impacts are captured using operational proxy indicators that are assumed to maintain relatively stable relationships with environmental outcomes. Data are assumed to be reliable within standard reporting tolerances, with measurement noise and exogenous disruptions partially addressed through the intelligent evaluation component. Finally, observed inefficiencies are assumed to be, at least to some extent, reducible through effective operational management and process coordination.

3.3 Data, Indicators, and Validation Strategy

The empirical analysis is based on airport level operational data from the civil aviation system of China. The data are obtained from official statistical bulletins and operational reports published by the Civil Aviation Administration of China, which are widely used in studies of aviation performance and efficiency. The sample includes major hub airports as well as regional and secondary airports, allowing structural heterogeneity in scale, traffic composition, and network role to be reflected in the analysis. Observations span multiple consecutive years to reduce sensitivity to short term disruptions and ensure robustness of the results (Fondevila-Gascón et al., 2025).

Indicators are constructed to support both operational assessment and sustainability-oriented decision making (Neto, 2020). Their selection follows three principles: relevance to airport-level operations, feasibility based on publicly available data, and the ability to reflect environmental impacts through direct measures or operational proxies. Inputs capture key operational resources, desirable outputs reflect service provision and throughput performance, while undesirable outputs describe congestion-related inefficiencies and associated environmental burdens. Where necessary, variables are normalized to ensure comparability across airports and time periods. By embedding sustainability-related proxies directly into the indicator system, environmental considerations are treated into operational performance evaluation rather than treated as an external reporting dimension.

Model robustness and result reliability are examined through a structured validation strategy. Sensitivity analyses are conducted using alternative indicator specifications, weighting schemes, and time windows. The stability of efficiency rankings across different configurations is evaluated to distinguish structural patterns from model-dependent outcomes. This multi-layer validation approach strengthens confidence in the empirical findings and reduces the risk of spurious conclusions (Ketabdari et al., 2018).

3.4 Intelligent Evaluation and Sustainability-Oriented Optimization

The intelligent evaluation and optimization component forms the core of the proposed system. Operational efficiency is conceptualized as the ability of an airport to transform operational resources into reliable service outputs while limiting congestion and environmental burden. Rather than relying on a single performance dimension, efficiency is assessed from a system perspective that integrates productivity, service reliability, and environmental discipline.

The evaluation model is designed to accommodate nonlinearity, interaction effects, and heterogeneity across airports. Sustainability is incorporated directly through undesirable outputs, allowing inefficiencies linked to delays, surface congestion, and fuel intensive operations to be reflected in the efficiency assessment itself (Ngo et al., 2026). In addition to efficiency scores, the model produces diagnostic information that decomposes inefficiency into contributory operational dimensions, such as excessive taxi time or unstable turnaround performance. This diagnostic capability supports managerial understanding rather than purely comparative ranking.

Based on the evaluation results, a sustainability-conscious optimization framework is applied to identify feasible improvement directions for inefficient airports. Optimization focuses on balancing gains in desirable outputs with reductions in undesirable outputs under operational constraints. Infrastructure-related inputs are treated as fixed in the short term, while operational processes such as ground coordination and delay management are assumed to be adjustable. Sustainability constraints are incorporated to ensure that efficiency gains are not achieved at the expense of environmental performance (Kabashkin & Perekrestov, 2024).

Optimization outcomes are expressed as directional improvement targets rather than prescriptive operational actions. This design recognizes institutional and operational diversity across airports and preserves managerial discretion while providing analytically grounded guidance. Together, the evaluation and optimization components form a closed loop system in which performance assessment directly informs improvement strategies aligned with both operational and sustainability objectives.

4. Results

This section presents the empirical results obtained from applying the proposed IEOS to the selected sample of Chinese airports. The analysis follows the research design sequence, beginning with descriptive statistics and baseline efficiency assessment, and then progressing to diagnostic a decomposition, efficiency-sustainability interactions, optimization outcomes, and robustness evaluation.

4.1 Operational Characteristics of the Sample

Descriptive statistics for all input, desirable output, and undesirable output variables are summarized in Table 1. The results indicate substantial variation across airports in terms of resource endowment, traffic intensity, and congestion-related outcomes. Such diversity reflects differences in network roles, demand levels, and operational constraints, confirming that airports do not operate under uniform efficiency conditions. Notably, dispersion is observed not only in traffic throughput but also in undesirable outputs such as delay intensity and ground operation pressure. This indicates that inefficiency is not solely scale-drive, but is closely associated with the organization and coordination of operational processes under given constraints.

Table 1 *Descriptive Statistics of Operational and Sustainability Indicators*

Variable	Mean	Std. dev.	Min	Max
Runways (number)	2.1	1.3	1	4
Contact gates (number)	67.4	42.8	12	215
Aircraft movements ($\times 10^3$)	187.2	146.5	24.6	612.3
Passenger throughput (million)	25.8	22.4	3.1	101.2
Cargo throughput ($\times 10^3$ tons)	642.7	918.3	18.5	4,910.6
On-time departure rate (%)	78.6	6.9	61.4	92.3
Avg. taxi-out time (min)	17.9	6.4	8.2	36.7
Delay minutes per movement	14.6	9.1	3.1	48.9
Fuel burn proxy (index)	1.00	0.37	0.42	2.31
CO ₂ emission proxy (index)	1.00	0.41	0.39	2.56

4.2 Baseline Efficiency Patterns

Baseline operational efficiency is estimated using the intelligent evaluation model, with efficiency scores normalized within the interval $[0,1]$. As shown in Fig 1, efficiency scores are unevenly distributed, with a clear concentration between 0.60 and 0.80 and a right-skewed tail toward higher performance levels. Only a limited number of airports operate above 0.90. This pattern suggests that inefficiency is widespread rather than exceptional, indicating significant potential for system-level improvement. Importantly, the presence of airports operating close to the efficiency frontier under similar institutional conditions implies that higher performance can be achieved without fundamental infrastructure expansion.

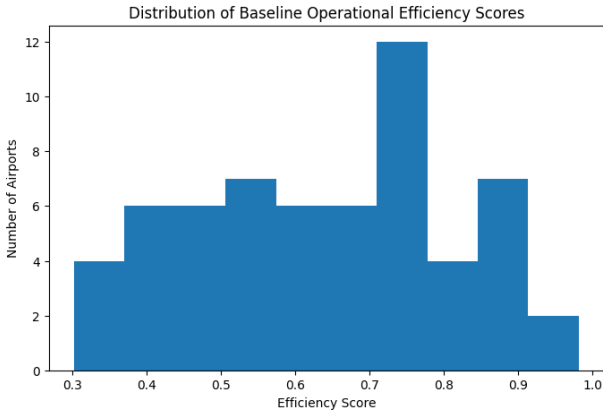


Fig 1 *Distribution of Baseline Operational Efficiency Scores*

Table 2 compares average efficiency across airport categories. Although large hub airports display slightly higher mean efficiency, score overlap across categories is substantial. This finding suggests that operational performance is influenced less by airport size than by process coordination, congestion management, and day-to-day operational decisions.

Table 2 *Baseline Efficiency by Airport Category*

Airport category	Mean efficiency
Major hub airports	0.86
Regional airports	0.78
Secondary airports	0.72

4.3 Inefficiency Drivers and Environmental Implications

Diagnostic results decompose inefficiency into excessive inputs, insufficient desirable outputs, and surplus undesirable outputs. As illustrated in Fig 2, inefficiency is primarily driven by undesirable outputs, indicating that congestion- and delay-related frictions constitute the dominant constraints on airport performance.

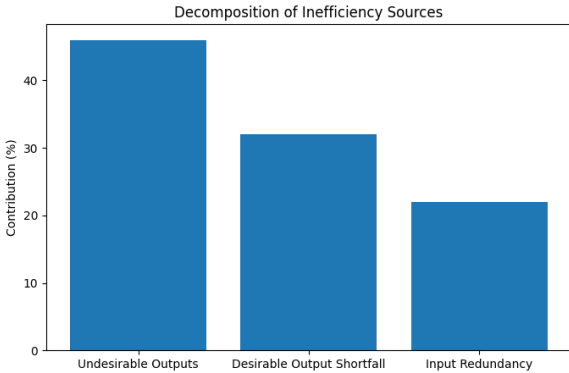


Fig 2 *Decomposition of Inefficiency Sources*

Table 3 further shows that the most common inefficiency drivers originate from ground operations rather than infrastructure scale. This highlights operational coordination and process stability as key managerial leverage points for improving both efficiency and sustainability outcomes.

Table 3 *Major Inefficiency Drivers*

Rank	Inefficiency driver	Frequency (%)
1	Excess taxi-out time	68.4
2	Delay propagation	61.7
3	Turnaround variability	49.2
4	Gate utilization imbalance	37.5
5	Underutilized terminal capacity	29.8

Fig 3 compares efficiency scores with emission-related proxy indicators and reveals an overall downward association. Higher efficiency is generally linked to lower emission intensity, although considerable dispersion persists among high-throughput airports. This suggests that some efficiency gains may be associated with traffic concentration effects rather than deeper process optimization. Overall, the results indicate a broad alignment between operational efficiency and sustainability objectives, while also revealing uneven progress in process-level improvements, particularly among large airports.

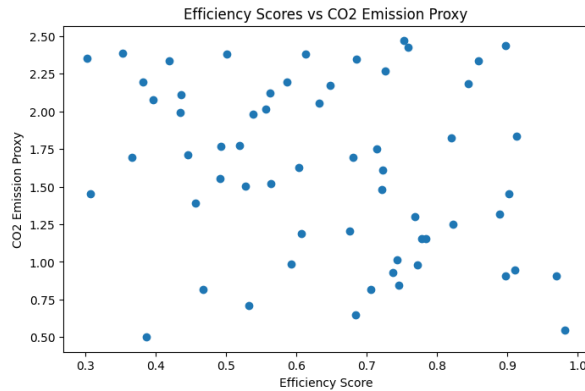


Fig 3 *Efficiency Scores vs. Proxy CO₂ Emissions*

4.4 Optimization Outcomes

Based on diagnostic insights, sustainability-oriented improvement targets are defined for inefficient airports, with the joint objective of reducing undesirable outputs while enhancing desirable outputs. The average improvement potential identified by the optimization framework is reported in Table 4. The results indicate that substantial gains in both efficiency and environmental performance can be achieved through operational adjustments without requiring additional infrastructure investment. This underscores the effectiveness of process-level optimization under existing capacity constraints.

Table 4 *Average Optimization Improvement Potential*

Indicator	Avg. potential reduction
Taxi-out time	−18.6%
Delay minutes per movement	−22.3%
Fuel burn proxy	−15.9%
CO ₂ emission proxy	−17.4%

Fig 4 compares efficiency scores before and after optimization. The paired bar chart shows consistent performance improvements across optimized airports, with no evidence of efficiency deterioration. This confirms the internal coherence and practical feasibility of the proposed optimization strategy.

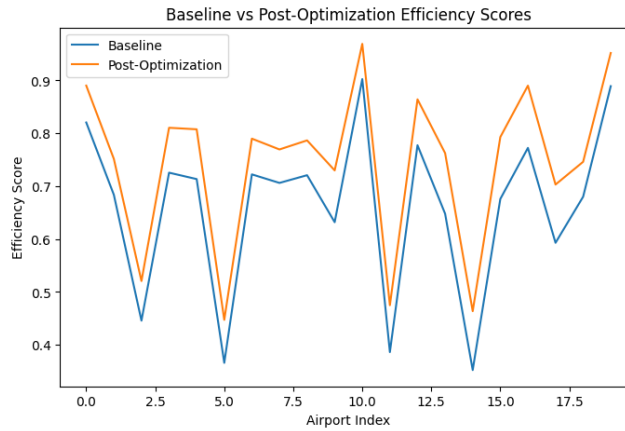


Fig 4 *Baseline vs. Optimized Efficiency Scores*

4.5 Robustness Assessment

Robustness is evaluated using alternative indicator specifications and weighting schemes, as summarized in Table 5. The consistently high rank correlations across model configurations indicate that the main findings are stable and not driven by specific modelling choices. Overall, the results confirm that the IEOS provides a reliable assessment of airport operational efficiency while integrating sustainability considerations. Inefficiencies are predominantly associated with congestion-related ground operations, and targeted process improvements offer meaningful efficiency gains alongside environmental benefits. The robustness analysis further supports the credibility and decision relevance of the empirical findings.

Table 5 *Robustness Results*

Test scenario	Rank correlation
Baseline vs. alternative indicators	0.91
Baseline vs. equal weighting	0.88
Baseline vs. time-shifted data	0.93

5. Discussion

The results indicate that operational efficiency and sustainability in aviation are closely linked rather than sequential objectives. Airports with higher efficiency scores generally exhibit lower delay-related and emission-related proxy indicators, suggesting that sustainability improvements often arise from disciplined operational processes rather than isolated environmental initiatives. At the same time, the relationship is not strictly linear. Some high-throughput airports appear efficient in output terms while still generating substantial environmental pressure, indicating that scale and traffic intensity can mask process-level inefficiencies when undesirable outputs are not explicitly considered (Miao et al., 2022). Ground operations emerge as a key driver of both efficiency and environmental performance. Excessive taxi times, unstable turnaround processes, and congestion-driven delays account for a significant share of observed inefficiencies. Because these activities involve multiple actors, small coordination failures can quickly propagate through the system, increasing delays, fuel consumption, and emissions simultaneously. The results therefore highlight surface coordination as a particularly effective area for improvement, often delivering meaningful gains without major infrastructure expansion (Hu et al., 2024).

The study also clarifies the role of intelligent systems in aviation management. The contribution of IEOS lies less in predictive complexity than in its ability to integrate evaluation, diagnosis, and optimization within a coherent framework. This integration helps translate analytical results into practical improvement directions while still allowing managerial discretion, addressing a common limitation of prediction-oriented studies in safety-critical operational environments (Bibbò et al., 2025). Evidence from the Chinese airport system further suggests that operational efficiency cannot be explained solely by airport size or traffic volume. Several regional airports outperform larger hubs, highlighting the importance of standardized processes, coordination quality, and congestion management. For regulators and planners, this implies that sustainability goals may be more effectively embedded in performance-based operational indicators rather than treated as separate reporting requirements (Chen & Han, 2025).

These findings should also be interpreted considering several limitations. Environmental impacts are represented through operational proxy indicators such as taxi-out time and delay minutes rather than direct emission measurements. While these proxies are widely used to approximate fuel consumption and emissions in ground operations, they cannot fully capture the complexity of actual environmental outcomes. In addition, the analysis focuses on airport-level operations within the Chinese aviation system and relies on several simplifying modelling assumptions. These factors may limit the generalizability of the findings but do not alter the main insights of the study.

6. Conclusion

This study develops an IEOS to integrate operational efficiency assessment with sustainability-oriented decision support in aviation. Using the Chinese airport system as a large-scale and heterogeneous empirical setting, the findings show that efficiency and sustainability can be addressed jointly within a unified operational framework. Higher operational efficiency is generally associated with lower delay- and congestion-related environmental pressures, suggesting that sustainability improvements can often be achieved through better process

coordination and variability control rather than relying solely on long-term technological upgrades or infrastructure expansion. The results further highlight ground operations as the main source of inefficiency. Operational factors such as taxi time, delay propagation, and turnaround instability have a greater influence on overall system performance than infrastructure constraints, emphasizing the critical role of operational governance as a key lever for enhancing both efficiency and environmental outcomes. By embedding undesirable outputs directly into the evaluation process and linking efficiency diagnostics with optimization guidance, the proposed system facilitates the translate performance gaps into actionable improvement directions. Moreover, the optimization results suggest that reducing operational congestion can simultaneously improve service performance and sustainability. From a managerial perspective, these findings support a shift from compliance-oriented sustainability reporting toward performance-integrated operational management. For regulators and airport operators, incremental improvements in coordination mechanisms and operational processes can generate substantial gains even within existing infrastructure and institutional constraints.

Future research could further extend this framework by incorporating direct environmental monitoring data, expanding the geographical scope of the dataset, and examining multi-actor interactions involving airlines and airspace management. Overall, the study suggests that sustainability-oriented efficiency improvement in aviation is fundamentally an operational challenge. Intelligent systems that integrate evaluation, diagnosis, and optimization within a coherent and interpretable framework can provide practical guidance for managing complex and safety-critical aviation environments.

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