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Research on the Efficiency of Major Airports in China's Six Major Airport Cluster: Based on Common Frontier Super-Efficiency DEA and Malmquist Method

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ABSTRACT

Airport clusters are of great significance to the sustainable development of the civil aviation transportation industry. The study utilises common frontier and super-efficiency DEA methods to assess the efficiency of China's six major airport groups. It then employs the Malmquist index method to analyse changes in airport productivity. The results highlight regional disparities in airport efficiency. The East China Airport Group and the Southwest Airport Group consistently demonstrate excellent efficiency values, while the North China Airport Group and the Northeast Airport Group have significant room for improvement. Most airports within the groups operate at low and ineffective levels, with efficiency initially increasing and then decreasing. Moreover, the technology gap ratio (TGR) for each airport group somewhat shows a downward trend. The Malmquist index indicates that the overall factor productivity of each airport has generally remained stable, with efficiency growth primarily dependent on scale efficiency. On average, technical efficiency has increased by 1.5%. However, in terms of technological changes, most airports have experienced technological regression, indicating insufficient focus on technological improvement. Therefore, it is crucial to prioritise technological innovation and enhance management efficiency to achieve efficiency improvements in airport clusters. It is necessary to formulate strategies accurately based on the specific conditions of different regions, promote coordinated development, foster regional exchanges and cooperation, address regional disparities, ensure sustainable development of China's airport clusters, and establish a world-class airport cluster.

KEYWORDS

airport cluster; meta-frontier; super efficiency DEA; technology gap ratio; Malmquist total factor productivity.

1. INTRODUCTION

The air transportation industry in China has experienced remarkable growth in tandem with the rapid development of the nation's economy and the evolution of its social environment. Over the decade spanning from 2012 to 2021, there has been a notable surge in investment within the industry. Specifically, investment in civil aviation infrastructure and technological advancements has escalated from 71.22 billion yuan to 122,247 billion yuan, marking an impressive increase of 71.65%. Examining the expansion of scheduled flight routes during this period reveals a substantial rise from 2,457 to 4,864, nearly doubling the growth. Notably, the number of cities in mainland China with regular flights has risen from 178 to 244. The count of transport airlines has concurrently increased, with 65 such airlines recorded in 2021, reflecting a net growth of 19 compared to the figures from 2012. Furthermore, the number of listed airlines has expanded from 5 in 2012 to 8 in 2021, indicating an accelerated capitalisation process within the industry.

Civil transportation airports, serving as crucial national public transportation infrastructure, constitute the cornerstone for the advancement of the civil aviation industry and hold a pivotal position within the broader transportation system. Since the approval of the National Civil Airport Layout Plan (excluding general aviation airports) by the State Council of China in 2008, there has been a substantial increase in the number of transportation airports. Consequently, the nationwide density of airports has progressively risen. Notably, the international hub status of airports in Beijing, Shanghai and Guangzhou has experienced significant enhancement. Simultaneously, the regional hub functions of airports in Chengdu, Shenzhen, Kunming, Xi'an, Chongqing, Hangzhou, Xiamen, Changsha, Wuhan and Urumqi, among others, have undergone notable augmentation. Several major airports, including Shanghai Hongqiao, Xi'an, Zhengzhou and Wuhan, have evolved into vital comprehensive transportation hubs, assuming an increasingly prominent role in the comprehensive transportation system.

According to the “National Civil Transport Airport Layout Plan”, China’s airports are divided into six major airport groups: North China, Northeast China, East China, Central South China, Southwest China and Northwest China. By 2025, on the basis of existing (including under construction) airports, the national civil transport airports, about 320 airports, are planned to be built. However, the substantial surge in investment within the airport industry has led to a degree of oversupply in certain airport facilities. While some airports demonstrate robust operational performance, others exhibit deficiencies in service quality and facility functionality. Consequently, amidst the challenging backdrop of pressure on the civil aviation industry and a decline in business volume, it holds significant practical importance to systematically analyse the efficiency variations among airports across different regions. This analysis, based on airport positioning and development stages, will facilitate the precise understanding of the developmental strategies necessary for distinct airports, thereby contributing to the sustainable evolution of the airport industry.

Within the realm of civil aviation in China, airports registering an annual passenger throughput below 2 million passengers are classified as regional airports. Accordingly, our study focuses on airports exceeding an annual passenger throughput of 2 million passengers, which serve as the primary airports within China’s six major airport groups. The operational quality of these airports holds paramount significance for the sustainable progression of China’s air transportation industry.

This article aims to address several key inquiries. What is the current development status of China’s airport clusters? To what extent does a technological gap exist between various airport groups? How has operating efficiency evolved during the study period? To unravel these questions, our study targets the operational efficiency of 45 airports situated in these six airport clusters. We propose employing a research methodology grounded in common frontier super-efficiency data envelopment analysis and utilising the Malmquist index to examine shifts in the efficiency of each airport cluster in China.

Our research contributions can be encapsulated as follows. Methodologically, we employ the meta-frontier super-efficiency data envelopment analysis (DEA) model. This model is instrumental in evaluating traditional DEA for decision-making units, especially in instances where multiple decision-making units exhibit effectiveness in DEA. We compare and rank decision-making units to facilitate a more precise evaluation of airport performance. Additionally, the meta-frontier method involves organising decision-making units into a group frontier, comprehensively addressing regional differences, and then studying the difference between the region and the whole. Finally, the Malmquist index is employed to analyse changes in total factor productivity and efficiency decomposition within each airport group in China. In terms of research data, we used data from 2013 – 2022 to draw useful insights into the rapidly developing air transport industry, and to provide some suggestions for the sustainable development of China’s airport clusters.

The remainder of this article is organised as follows. Section 2 summarises the literature review on airport efficiency research. The third part introduces the theoretical methodology, and the fourth part introduces the situation and empirical results and discussions of 45 airports in China’s six major airport groups. Finally, the fifth section gives the main conclusions and several suggestions.

2. LITERATURE REVIEW

Airports constitute a crucial element of civil aviation transportation, and their operational efficiency significantly influences the overall service level of air transportation. Research on airport operational efficiency has garnered considerable attention from scholars globally. Currently, many scholars employ data envelopment analysis (DEA) to investigate airport efficiency, examining national, regional or airport-specific indicators. The research on airport efficiency has progressed significantly, with varied focuses and directions.

Scholars analyse operational efficiency by considering variable selection for input and output variables, performance measurement methods, data time span and differences among airports in various regions.

Efficiency evaluation methods generally fall into two categories: parametric and non-parametric methods. Mainstream methods include stochastic frontier analysis (SFA), data envelopment analysis (DEA), Malmquist index, among others. In cases with multiple inputs and outputs, DEA is commonly used by researchers. The non-parametric data envelopment method is a commonly used method to measure the relative effectiveness of efficiency. This method does not require parameter estimation of the production function. It is widely used in efficiency evaluation and has a very important impact on efficiency evaluation.

When the conventional DEA model assesses decision-making units, it faces limitations in distinguishing situations where multiple units demonstrate effectiveness in DEA. To tackle this issue, researchers have refined the CCR model to enable the evaluation of effective decision-making units. This enhanced model is referred to as the super-efficiency DEA model. Consequently, our approach will be grounded in the super-efficiency DEA model, aiming to precisely measure the efficiency of major airports within China's airport clusters.

Gillen et al. [1] pioneered the application of the DEA (data envelopment analysis) model to assess the efficiency of 21 airports in the United States, marking the inception of various improved derivative models in subsequent research. Lam et al. [2] evaluated the efficiency of 11 major airports in the Asia-Pacific region, and Lozano [3] et al. explored the efficiency of 39 airports in Spain using the SBM-DEA model (data envelopment analysis based on slack variables). Rapee et al. [4] combined DEA and AHP (analytical hierarchy process) to assess the efficiency of major airports in Thailand. Örkcü et al. [5] used the Malmquist productivity index to evaluate the performance of 21 airports in Turkey, and Storto [6] employed the NSBM-DEA method (data envelopment analysis based on network slack variables) to study the efficiency of Italian airports. Huynh et al. [7] adopted a two-stage method to examine the efficiency of Southeast Asian airports.

While most of previous studies focus on analysing and evaluating airport performance at the national and regional levels, with limited attention to airport clusters, Chae and Kim [8] delved into the impact of hub airport cluster development policies on airport efficiency. Wang et al. [9] employed the system dynamics method to establish an airport cluster efficiency evaluation model, investigating the efficiency performance of each airport in the Beijing-Tianjin-Hebei airport cluster. Zhang et al. [10] measured the static collaboration degree and dynamic collaborative development degree of the Chengdu-Chongqing airport cluster from a group collaborative development perspective.

Despite these related studies on airport clusters, few have specifically focused on efficiency, with existing research primarily concentrating on collaboration and efficiency evaluation within specific airport clusters. Consequently, there is a notable absence of comprehensive analyses of China's airport clusters. This article seeks to address this gap by conducting a thorough analysis and comparison of China's six major airport clusters, aiming to provide insightful suggestions for their development.

3. METHODOLOGY AND VARIABLES

Our goal is to assess airport efficiency, and this chapter provides a brief overview of the models and methods to be used.

3.1 Methodology

Meta-frontier super-efficiency DEA model

When utilising the conventional DEA model to evaluate decision-making units (DMUs), numerous situations arise where the evaluation results yield equivalent DEA values of 1, making it impossible to further assess and compare effective decision-making units. To address this limitation, Andersen and Petersen [13] introduced the super-efficiency DEA model, which aligns with the traditional model's variable definitions. The primary distinction lies in the efficiency analysis process, where the production frontier undergoes alterations. Specifically, the i-th DMU is excluded, and a new production frontier is established through a linear combination of the input and output from the remaining DMUs. Subsequently, the efficiency of each DMU is compared in a sequential manner. This modification overcomes the challenges encountered by the traditional DEA model in evaluating differences among effective units.

The super-efficiency DEA model can be used to evaluate the performance of an enterprise or organisation. It can measure the efficiency level of an enterprise or organisation in utilising resources and identify potential room for improvement in resource utilisation. The super-efficiency DEA model is developed from the traditional DEA model and is an advanced form of traditional DEA. Its advantage is that it can eliminate the impact of some external factors on performance and provide a more accurate efficiency assessment. Super-efficiency DEA models can be divided into CCR models with CRS and BCC models with VRS. In this study, both the CRS and super-efficiency DEA models were employed to gauge the efficiency of each airport unit.

DEA is only applicable to the relative efficiency assessment of multiple DMUs. Moreover, due to the large differences in geographical location, supporting facilities, economic development level and other factors of airports in different regions, there are differences in the production technology frontier of airports in various regions. In order to distinguish the regional production efficiency among various airports in China due to the differences, the common frontier method was introduced in the study.

The principle of the common frontier is to group all DMUs based on the heterogeneity of production technologies of different decision-making units. Each group forms its own production frontier, and all groups jointly form a production frontier, that is, a common frontier. The common frontier model can measure the efficiency under different frontiers and is more comprehensively comparable.

An inherent advantage of this model lies in its ability to calculate comparable technical efficiency for entities operating under diverse technologies. Given the substantial disparities in geographical location, supporting policies and economic development levels among airports in different regions, their production technology frontiers vary significantly. Therefore, this article employs the common frontier method to assess the efficiency of decision-making units in distinct environments. The common frontier model is integrated with the super-efficiency DEA model to collectively study the efficiency of each airport, providing a robust and comprehensive analysis.

Suppose there is an airport $DMU_j(j=1,2,\dots,n)$， each DMU_j have m item input amount $(i=1,2,\dots,m)$ and s item output $(r=1,2,\dots,m)$. The corresponding vectors can be expressed as: $X_j=(x_{1j},x_{2j},\dots,x_{mj})^T>0$， $X_j=(x_{1j},x_{2j},\dots,x_{mj})^T>0$， $Y_j=(y_{1j},y_{2j},\dots,y_{sj})^T>0$， $j=1,2,\dots,n$， S^-enter the slack variable; S^+ is the output slack variable. All decision-making units ($DMUS$) are divided into k ($K>1$) groups, then there are;

the common technology set of the kth group of DMUs is:

$$T^k=\{(x,y):x\geq 0,y\geq 0,x\rightarrow y\}\ k=1,2,\cdots,k \tag{1}$$

the input-output relationship of the kth group is:

$$P^k(x)=\{y:(x,y)\in T^k\} \tag{2}$$

the common technology set of all units is:

$$T=\{(x,y):x\geq 0,y\geq 0,x\rightarrow y\} \tag{3}$$

the corresponding production possibility set is:

$$P(x)=\{y:(x,y)\in T\} \tag{4}$$

then there are:

$$T=\{T^1 \cup T^2 \cup \cdots T^k\} \tag{5}$$

$P^k(x)$ determine the frontier surface to be the group frontier, all $P^k(x)$ the frontier formed together is called the common frontier $P(x)$.

Therefore, the directional distance function of the decision-making unit DMU0 from the common frontier is:

$$\begin{aligned} &min[\theta-\varepsilon(\hat{e}^{\mathrm{T}}S^-+e^{\mathrm{T}}S^+)] \\ &\text{s.t.}\sum_{j=1}^{n}x_j\lambda_j+S^-=\theta x_0 \\ &\sum_{j=1}^{n}y_j\lambda_j-S^+=y_0 \\ &\lambda_j\geq 0 \\ &S^-\geq 0,S^+\geq 0 \\ &j=1,2,\cdots,n \end{aligned} \tag{6}$$

In the formula, λ is the weight vector; θ is the efficiency value, ε is a non-Archimedean infinitesimal quantity.

When the decision-making unit *DMU0* belongs to the *k*-th group, the directional distance function between *DMU0* and the group frontier of the k group is:

$$\begin{aligned} & min[\varphi - \varepsilon(\hat{e}^{\mathrm{T}} S^- + e^{\mathrm{T}} S^+)] \\ & \text{s.t.} \sum_{j=1}^{n} x^k{}_j \lambda_j + S^- = \varphi x_0 \\ & \sum_{j=1}^{n} y^k{}_j \lambda_j - S^+ = y_0 \\ & \lambda_j \geq 0 \\ & S^- \geq 0, S^+ \geq 0 \\ & j = 1,2,\cdots,n^k \end{aligned} \tag{7}$$

In the formula, x^k_j, y^k_j are the input and output variables of region j in the *k*-th group respectively; φ is the efficiency value.

When θ =1or φ =1, it shows that the decision-making unit is located on the frontier, and there is a $\theta \leq \varphi$ relationship between the common frontier and the group frontier.

The technology gap ratio (TGR) is defined as the ratio between the common frontier value (i.e. the efficiency value derived from the common frontier) and the group frontier value (i.e. the efficiency value derived from the group frontier). Mathematically, this ratio can be expressed as:

$$\mathrm{TGR} = \frac{\theta}{\varphi} \quad \mathrm{TGR} \in (0,1) \tag{8}$$

The closer the TGR is to 1, the smaller the technical efficiency gap between the common frontier and the group frontier.

Malmquist productivity index

While the DEA model is effective for analysing the relative efficiency of decision-making units (*DMUs*), the Malmquist productivity index offers an insightful measurement of efficiency changes between periods t and t+1. The Malmquist productivity index is divided into two key components: technical efficiency change (MEFFCH) and technological progress (MTECH). The Malmquist productivity index from period t to t+1 can be expressed as:

$$\begin{aligned} & M_t^{t+1} = \left[\frac{D_{\mathrm{o}}^t(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\mathrm{o}}^t(x^t, y^t, b^t)} \frac{D_{\mathrm{o}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\mathrm{o}}^{t+1}(x^t, y^t, b^t)}\right]^{1/2} \\ & \mathrm{MEFFCH}_t^{t+1} = \frac{D_{\mathrm{o}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\mathrm{o}}^t(x^t, y^t, b^t)} \\ & \mathrm{MTECH}_t^{t+1} = \left[\frac{D_{\mathrm{o}}^t(x^{t+1}, y^{t+1}, b^{t+1})}{D_{\mathrm{o}}^{t+1}(x^{t+1}, y^{t+1}, b^{t+1})} \frac{D_{\mathrm{o}}^t(x^t, y^t, b^t)}{D_{\mathrm{o}}^{t+1}(x^t, y^t, b^t)}\right]^{1/2} \end{aligned} \tag{9}$$

If M > 1, it signifies an augmentation in *DMU* productivity from period t to period t+1; conversely, a value less than 1 denotes a decrement in productivity. Similarly, MEFFCH > 1 denotes an escalation in technical efficiency, while a value below 1 indicates a decline in technical efficiency. Moreover, MTECH > 1 signifies technological progress, whereas a value less than 1 implies technological decline. To undertake a thorough efficiency analysis, this study investigates the dynamic shifts in airport efficiency through the application of the Malmquist productivity index.

3.2 Variables

This section will introduce the efficiency evaluation index system, which includes both input and output variables and interprets and analyses the variables.

Input variables

In this paper, the terminal area, the number of aircraft slots and the runway length are selected as input indicators to reflect the resource conditions of airport infrastructure. The area of the terminal building includes the area of the domestic terminal building and the international terminal building. The terminal building is a place for passengers to go through check-in, security check, boarding and other formalities, and to provide waiting, rest, catering and other services, and also provides diversified service facilities such as VIP lounges, children's recreation areas, barrier-free facilities and other facilities, which need to meet the personalised needs of different types of passengers and the area, facilities and functions of the terminal building directly determine the number of passengers and handling passenger flow that the airport can accommodate, and are a key indicator of airport landside capacity. Its area, facilities and functions directly determine the number of passengers that the airport can accommodate and the passenger flow it can handle, which is a key indicator of the airport's landside capacity. Runway length is the length aircraft need to taxi on the runway during take-off and landing in order to obtain sufficient lift or deceleration. For larger aircraft, due to their weight, inertia, engine thrust, airport elevation and wind speed, a longer runway length is required to meet the take-off and landing requirements. If the runway length is insufficient, the aircraft cannot take off or land safely, and the aircraft requires more power for take-off and landing, resulting in increased fuel consumption and decreased economy, it also restricts the use of airports and affects the navigational capacity of airports. For example, according to the ICAO classification by aircraft geometry, the A380 belongs to Class E aircraft, i.e. heavy aircraft, which requires a taxiing distance of about 3,000 m to take off at maximum load capacity; therefore, a sufficiently long runway length can help to support the take-off and landing of larger aircraft, which affects the operational capacity and flexibility of airports. In addition, the more runways there are, the more aircraft land and take-off there are per unit of time at airports. Therefore, runway length is an indicator of the airside capacity of an airport; and the number of slots consists of near-side slots and far-side slots. Near-side slots are usually close to the terminal building, while far-side slots are located in the fringe area of the airport, and more slots mean that more planes can be parked, thus accommodating more flights. This is especially important for busy airports, as it can effectively alleviate airport saturation and delays. Sufficient slots can enable aircraft to find a parking position faster upon arrival, reducing taxiing time and improving the overall operational efficiency of the airport; and sufficient slots can shorten the downtime of the aircraft, allowing the aircraft to be ready for the next round of flights more quickly and improving flight turnover rates. Therefore, the number of slots is a key factor in the airside capacity of an airport, and an increase in the number of slots can increase the handling capacity of an airport (airport handling capacity = number of slots x average daily take-offs and landings per slot, where average daily take-offs and landings refers to the average number of take-offs and landings per day per slot). These indicators take into account the airport's landside and airside capacity and are an important basis for assessing the overall size and operational capacity of the airport.

Output variables

The study selected passenger throughput, cargo and mail throughput, and number of take-offs and landings as output indicators, which comprehensively reflect the operating status of the airport. Passenger throughput means measuring the number of passengers handled by the airport and is a key indicator to evaluate the airport's passenger flow and service efficiency. It reflects the airport's ability to handle passengers within a certain period of time and is crucial to understanding the airport's operational scale and passenger service levels. Cargo mail throughput measures the handling volume of cargo and mail at the airport. It is an indicator to evaluate the busyness of the airport's cargo business. It can reflect the activity of the airport in freight and logistics and is important for understanding the comprehensive operating capabilities of the airport. The number of take-offs and landings refers to the sum of the number of take-offs and landings of aircraft and is an important indicator for evaluating airport flow and traffic busyness. The number of take-offs and landings is directly related to the flight activities at the airport, which is crucial for understanding the busyness of the airport and air traffic conditions. The above output indicators can more comprehensively evaluate the airport's performance in passenger services, cargo and air traffic, and provide an important reference for airport management and planning.

3.3 Data sources

In our study, a sample comprising 45 Chinese airport companies was utilised. The data for this analysis were sourced from the "National Airport Production Statistical Bulletin" by the Civil Aviation Administration of China, as well as official website data from various airports, among other reliable sources. *Table 1* presents the descriptive statistics for each indicator within the sample.

Table 1 – Descriptive statistics of input-output indicators of China's airport sample (N=45) from 2013 to 2022

Variable	Sample size	Min.	Max.	Mean	Std. dev.
terminal area	450	2.5	145.6	28.01	31.33
number of airport stands	450	18	340	82.86	73.78
runway length	450	2400	15000	4869.44	2595.56
passenger volume	450	917325	100983290	18197697.27	17020024.70
cargo volume	450	4856.26	3982616.4	325063	619407.33
aircraft movement	450	20296	614022	146397.48	115601.52

4. RESULT

This chapter applies the model and indicator system established in the previous article to measure the efficiency of China's airport cluster and analyse its efficiency performance.

Meta-frontier airport efficiency analysis

This paper employs the global reference super-efficiency DEA model to evaluate decision-making units across distinct periods under the global optimal production frontier. This methodology effectively mitigates issues associated with infeasible solutions and inter-temporal incomparability in efficiency measurement. Additionally, the meta-frontier method is applied to categorise China's major airports into six groups: North China Airport Group, Northeast Airport Group, East China Airport Group, Central and South Airport Group, Southwest Airport Group and Northwest Airport Group. Over the period from 2013 to 2022, the study computes efficiency scores for 45 airport units under both the group frontier and common frontier. The determination of annual super-efficiency values is carried out, followed by an annual static efficiency analysis. The detailed outcomes of this analysis are presented in *Table 2*.

Table 2 – Main airports of each airport group

Area	Airport	IATA Code	Area	Airport	IATA code
North China Airport Group	Beijing/Capital	PEK	Northwest Airport Group	Xi'an/Xianyang	XIY
	Tianjin/Binhai	TSN		Urumqi/Diwopu	URC
	Taiyuan/Wusu	TYN		Lanzhou/Zhongchuan	LHW
	Hohhot/Baita	HET		Yinchuan/Hedong	INC
	Shijiazhuang/Zhengding	SJW		Xining/Caojiabao	XNN
Northeast Airport Group	Harbin/Taiping	HRB	Southwest Airport Group	Chengdu/Shuangliu	CTU
				Kunming/Changshui	KMG
	Shenyang/Taoxian	SHE		Chongqing/Jiangbei	CKG
				Guiyang/Longdongbao	KWE
	Dalian/Zhoushuizi	DLC		Lijiang/Sanyi	LJG
				Xishuangbanna/Gasa	JHG
	Changchun/Longjia	CGQ		Lhasa/Gonggar	LXA
				Mianyang/Southern Suburbs	MIG
East China Airport Group	Pudong, Shanghai	PVG	Central and South Airport Group	Guangzhou/Baiyun	CAN
	Shanghai Hongqiao	SHA		Shenzhen/Baoan	SZX
	Hangzhou/Xiaoshan	HGH		Zhengzhou/Xinzheng	CGO
	Nanjing/Lukou	NKG		Wuhan/Tianhe	WUH
	Xiamen/Gaoqi	XMN		Changsha/Huanghua	CSX
	Jinan/Yaoqiang	TNA		Haikou/Meilan	HAK
	Fuzhou/Changle	FOC		Sanya/Phoenix	SYX
	Ningbo/Lishe	NGB		Nanning/Wuxu	NNG
	Wenzhou/Longwan	WNZ		Nanchang/Changbei	KHN
	Quanzhou/Jinjiang	JJN		Zhuhai/Jinwan	ZUH
	Wuxi/Shuofang	WUX		Guilin/Liangjiang	KWL
				Jieyang/Chaoshan	SWA

According to the results in *Table 3*, it can be seen from the time series analysis that the efficiency values of China's airport clusters generally showed an upward trend from 2013 to 2019, which shows that the aviation industry at all airports in China is constantly progressing and developing, while the efficiency value shows a downward trend from 2019 to 2022; in 2019, the efficiency values of each airport group reached the highest, with efficiency values exceeding 0.6. Judging from the efficiency performance of each airport group over the years, the East China Airport Group and the Southwest Airport Group have excellent efficiency values all year round and make full use of existing infrastructure. The Central South Airport Group and the Northwest Airport Group are second, and the efficiency of the Central South Airport Group is gradually slowing down; there is still a lot of room for improvement in the efficiency performance of the North China Airport Group and the Northeast Airport Group. Especially in the North China Airport Group, homogeneous competition is serious, and there is a lack of coordination in airport planning, construction, etc., which in turn affects airport efficiency. Analysing in terms of mean value, it can be seen that the efficiency value of the 6 major airport clusters in the past 10 years presents as Southwest (0.645) > East China (0.641) > Central and South China (0.593) > Northwest (0.561) > Northeast (0.520) > North China (0.470).

Combined with the global reference common frontier super-efficiency DEA model, *Table 4* lists the common frontier airport efficiency from 2013 to 2022, and *Table 5* lists the group frontier airport efficiency from 2013 to 2022.

In terms of common frontiers, it can be seen from *Table 4* that the efficiency of each airport performs poorly, with a large gap. From the perspective of common frontiers, SZX and PVG are leading the way, and other airports with relatively high efficiency include MIG. In addition, the INC efficiency value is 0.328 and the SWA efficiency value is 0.263, the worst performance, reflecting that the low efficiency of the airport is not consistent with the regional development of the airport. Even some airports in economically developed coastal areas perform poorly. PVG and SHA are both Shanghai airports, and there is a clear gap in the average efficiency of the two (PVG: 0.968; SHA0.684). Pudong Airport is Shanghai's main airport, while Hongqiao Airport plays a supporting role, and there are differences in management and operations. The efficiency values of the sample airports from 2013 to 2019 showed an overall upward trend (0.570→0.763), while the efficiency values from 2019 to 2022 showed a fluctuating downward trend (0.763→0.390). This decline in efficiency values during the latter period is attributed to the impact of the pandemic on residents' travel, subsequently reducing airport efficiency.

From the perspective of the group frontier, as shown in *Table 5*, there are differences in the efficiency of different airports, and there is a certain degree of improvement compared to the common frontier efficiency value. In the group, SZX and PVG still performed best, with average efficiencies of 1.055 and 0.971, respectively, while SWA still had the lowest average efficiency, only 0.314. The main reasons for the outstanding performance of SZX and PVG airports are advanced hardware facilities, scientific operation management, excellent human resources and strong policy support. While SWA airport was established late, the route network is imperfect, and the management level needs to be improved. In addition, the mean efficiency of PVG (0.968→0.971) remains unchanged, while the mean efficiency of SHA (0.684→0.719) has improved to a certain extent, indicating that Hongqiao Airport's efficiency performance is relatively high in the East China airport cluster.

Table 3 – Average airport efficiency of the six major airport groups from 2013 to 2022

	North China Airport Group	**Northeast Airport Group**	**East China Airport Group**	**Central and South Airport Group**	**Southwest Airport Group**	**Northwest Airport Group**
2013	0.455	0.450	0.561	0.577	0.569	0.565
2014	0.460	0.474	0.614	0.595	0.599	0.553
2015	0.464	0.510	0.619	0.603	0.633	0.492
2016	0.484	0.571	0.660	0.608	0.687	0.567
2017	0.559	0.669	0.731	0.666	0.696	0.641
2018	0.613	0.683	0.763	0.682	0.737	0.689
2019	0.617	0.662	0.797	0.707	0.793	0.744
2020	0.390	0.417	0.617	0.529	0.638	0.503
2021	0.410	0.449	0.619	0.570	0.650	0.559
2022	0.247	0.313	0.433	0.391	0.445	0.296
Mean	0.470	0.520	0.641	0.593	0.645	0.561

Table 4 – Common frontier efficiency values of each airport from 2013 to 2022

Airport	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Ave
PEK	0.912	0.927	0.943	0.969	0.975	1.036	0.990	0.522	0.568	0.352	0.819
PVG	0.921	1.054	1.012	0.923	1.015	1.019	0.993	0.964	0.997	0.780	0.968
CAN	0.952	1.068	0.821	0.881	0.961	0.851	0.874	0.705	0.752	0.637	0.850
CTU	0.684	0.746	0.800	0.873	0.924	0.966	1.055	0.846	0.812	0.502	0.821
SZX	1.675	0.748	0.798	0.853	0.902	0.951	1.051	0.917	0.969	0.837	0.970
KMG	0.520	0.556	0.630	0.693	0.742	0.772	0.777	0.566	0.567	0.392	0.622
XIY	0.592	0.656	0.728	0.807	0.901	0.950	1.005	0.695	0.687	0.323	0.734
SHA	0.679	0.722	0.743	0.769	0.773	0.805	0.843	0.583	0.618	0.302	0.684
CKG	0.496	0.559	0.607	0.663	0.537	0.509	0.544	0.448	0.460	0.306	0.513
HGH	0.628	0.708	0.774	0.843	0.920	0.973	1.060	0.940	1.125	0.908	0.888
NKG	0.731	0.490	0.413	0.471	0.534	0.575	0.613	0.443	0.385	0.319	0.498
CGO	0.731	0.882	0.947	0.429	0.479	0.516	0.538	0.486	0.480	0.353	0.584
XMN	0.956	1.035	0.880	0.905	0.941	0.992	1.032	0.687	0.635	0.487	0.855
WUH	0.344	0.371	0.395	0.426	0.458	0.475	0.620	0.322	0.497	0.324	0.423
CSX	0.704	0.784	0.798	0.887	0.593	0.589	0.624	0.469	0.490	0.324	0.626
HAK	0.533	0.610	0.708	0.810	0.941	0.998	1.005	0.720	0.768	0.528	0.762
URC	0.656	0.692	0.765	0.824	0.866	0.920	0.946	0.479	0.696	0.430	0.727
TSN	0.479	0.541	0.498	0.436	0.522	0.558	0.534	0.347	0.381	0.186	0.448
KWE	0.451	0.543	0.567	0.636	0.751	0.819	0.880	0.684	0.693	0.414	0.644
HRB	0.586	0.688	0.777	0.885	1.078	0.969	0.937	0.638	0.611	0.445	0.762
SHE	0.564	0.542	0.548	0.639	0.721	0.784	0.836	0.581	0.613	0.436	0.626
SYX	0.707	0.810	0.872	0.924	1.077	1.031	1.001	0.793	0.855	0.518	0.859
DLC	0.692	0.695	0.720	0.778	0.879	0.928	0.959	0.457	0.530	0.360	0.700
TNA	0.452	0.478	0.509	0.607	0.720	0.818	0.859	0.646	0.712	0.469	0.627
NNG	0.369	0.420	0.458	0.501	0.588	0.626	0.673	0.478	0.496	0.356	0.496
LHW	0.790	0.899	0.410	0.554	0.644	0.692	0.759	0.571	0.622	0.323	0.626
FOC	0.432	0.452	0.514	0.536	0.563	0.640	0.566	0.375	0.383	0.258	0.472
TYN	0.466	0.462	0.510	0.554	0.690	0.749	0.765	0.516	0.574	0.333	0.562
CGQ	0.406	0.443	0.504	0.554	0.669	0.734	0.580	0.410	0.491	0.326	0.512
KHN	0.362	0.379	0.391	0.400	0.549	0.673	0.676	0.522	0.539	0.264	0.476
HET	0.470	0.493	0.564	0.620	0.763	0.869	0.934	0.608	0.664	0.357	0.634
NGB	0.492	0.576	0.604	0.705	0.824	0.943	1.072	0.818	0.504	0.346	0.688
WNZ	0.710	0.731	0.776	0.855	0.943	0.628	0.605	0.452	0.483	0.305	0.649
ZUH	0.244	0.289	0.302	0.376	0.497	0.585	0.624	0.425	0.450	0.250	0.404
SJW	0.401	0.334	0.268	0.324	0.403	0.464	0.481	0.349	0.270	0.251	0.355
INC	0.221	0.243	0.274	0.319	0.398	0.434	0.502	0.343	0.352	0.197	0.328
KWL	0.505	0.598	0.544	0.571	0.661	0.535	0.410	0.220	0.231	0.099	0.437
JJN	0.221	0.236	0.297	0.309	0.421	0.574	0.644	0.457	0.481	0.310	0.395
WUX	0.244	0.276	0.287	0.336	0.392	0.425	0.477	0.422	0.481	0.275	0.361
SWA	0.172	0.185	0.206	0.236	0.286	0.356	0.384	0.288	0.318	0.201	0.263
XNN	0.378	0.274	0.283	0.332	0.397	0.449	0.507	0.428	0.438	0.207	0.369
LJG	0.430	0.511	0.575	0.682	0.708	0.747	0.712	0.523	0.454	0.308	0.565
JHG	0.370	0.401	0.475	0.491	0.450	0.497	0.617	0.474	0.495	0.281	0.455
LXA	0.363	0.408	0.467	0.527	0.572	0.651	0.694	0.651	0.763	0.449	0.554
MIG	0.937	1.069	0.947	0.929	0.885	0.934	1.063	0.910	0.953	0.905	0.953
Ave	0.570	0.591	0.598	0.637	0.700	0.734	0.763	0.560	0.585	0.390	

Table 5 – Frontier efficiency values of each airport group from 2013 to 2022

Airport	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	Ave
PEK	0.925	0.948	0.961	0.987	0.979	1.037	0.990	0.584	0.676	0.477	0.856
PVG	0.922	1.054	1.018	0.935	1.015	1.028	1.002	0.964	0.997	0.780	0.971
CAN	0.957	1.077	0.832	0.897	0.975	0.964	0.993	0.784	0.908	0.836	0.922
CTU	0.746	0.811	0.828	0.910	0.957	0.990	1.055	0.921	0.937	0.789	0.894
SZX	2.127	0.773	0.824	0.867	0.919	0.961	1.070	0.953	1.097	0.961	1.055
KMG	0.528	0.564	0.638	0.701	0.751	0.780	0.784	0.574	0.576	0.426	0.632
XIY	0.654	0.711	0.773	0.842	0.923	0.956	1.148	0.956	1.036	0.521	0.852
SHA	0.707	0.751	0.773	0.800	0.819	0.853	0.893	0.610	0.650	0.339	0.719
CKG	0.557	0.628	0.682	0.746	0.577	0.534	0.570	0.471	0.503	0.419	0.569
HGH	0.655	0.733	0.798	0.863	0.932	0.979	1.060	0.940	1.125	0.908	0.899
NKG	0.774	0.559	0.485	0.540	0.601	0.627	0.664	0.536	0.468	0.386	0.564
CGO	0.828	0.956	1.051	0.519	0.570	0.613	0.636	0.544	0.534	0.459	0.671
XMN	0.964	1.056	0.931	0.949	0.967	1.009	1.032	0.737	0.697	0.558	0.890
WUH	0.464	0.492	0.515	0.551	0.582	0.597	0.656	0.360	0.545	0.359	0.512
CSX	0.822	0.908	0.914	1.025	0.634	0.640	0.673	0.531	0.554	0.388	0.709
HAK	0.578	0.651	0.751	0.840	0.952	1.002	1.005	0.777	0.832	0.629	0.802
URC	0.757	0.803	0.837	0.888	0.918	0.965	0.975	0.597	0.759	0.490	0.799
TSN	0.738	0.840	0.854	0.849	0.983	1.063	1.009	0.674	0.721	0.407	0.814
KWE	0.463	0.558	0.582	0.652	0.772	0.851	0.922	0.706	0.719	0.425	0.665
HRB	0.740	0.854	0.930	1.030	1.156	1.015	1.016	0.722	0.724	0.552	0.874
SHE	0.800	0.719	0.738	0.809	0.876	0.947	1.135	0.894	0.903	0.689	0.851
SYX	0.747	0.840	0.897	0.944	1.099	1.038	1.001	0.834	0.895	0.590	0.888
DLC	0.803	0.812	0.832	0.904	1.018	1.072	1.072	0.709	0.793	0.729	0.874
TNA	0.621	0.643	0.663	0.770	0.889	0.976	1.073	0.856	0.954	0.701	0.815
NNG	0.466	0.525	0.568	0.617	0.714	0.753	0.765	0.577	0.605	0.436	0.603
LHW	0.901	1.166	0.609	0.784	0.870	0.922	1.111	0.851	0.910	0.576	0.870
FOC	0.490	0.511	0.565	0.574	0.587	0.676	0.614	0.450	0.452	0.317	0.524
TYN	0.682	0.652	0.707	0.736	0.908	0.983	1.031	0.707	0.793	0.500	0.770
CGQ	0.627	0.678	0.717	0.798	0.827	0.847	0.687	0.506	0.598	0.415	0.670
KHN	0.425	0.434	0.447	0.442	0.602	0.731	0.729	0.579	0.604	0.327	0.532
HET	0.635	0.693	0.724	0.772	0.864	0.939	1.108	0.823	0.869	0.550	0.798
NGB	0.558	0.662	0.671	0.845	0.960	0.963	1.072	0.968	0.542	0.392	0.763
WNZ	0.790	0.794	0.829	0.912	1.000	0.699	0.648	0.505	0.552	0.363	0.709
ZUH	0.339	0.386	0.383	0.466	0.566	0.648	0.675	0.504	0.524	0.299	0.479
SJW	0.702	0.528	0.402	0.487	0.571	0.637	0.645	0.501	0.380	0.378	0.523
INC	0.299	0.328	0.359	0.411	0.511	0.565	0.633	0.460	0.480	0.279	0.432
KWL	0.575	0.690	0.613	0.651	0.729	0.600	0.475	0.270	0.285	0.139	0.503
JJN	0.303	0.326	0.385	0.404	0.519	0.679	0.734	0.582	0.597	0.412	0.494
WUX	0.395	0.439	0.432	0.493	0.564	0.617	0.701	0.675	0.758	0.444	0.552
SWA	0.232	0.250	0.279	0.305	0.351	0.398	0.408	0.319	0.360	0.236	0.314
XNN	0.503	0.432	0.443	0.523	0.621	0.704	0.789	0.718	0.729	0.366	0.583
LJG	0.561	0.671	0.762	0.909	0.946	1.050	0.962	0.704	0.624	0.426	0.762
JHG	0.514	0.556	0.674	0.712	0.671	0.737	0.887	0.671	0.727	0.421	0.657
LXA	0.480	0.538	0.613	0.699	0.775	0.907	0.953	0.929	1.128	0.642	0.766
MIG	0.937	1.071	0.947	0.930	0.885	0.938	1.076	0.914	0.953	0.905	0.956
Ave	0.673	0.690	0.694	0.740	0.798	0.833	0.870	0.677	0.713	0.503	

On an overall scale, the efficiency of most airport groups in China remains comparatively inefficient, displaying a trend of initial improvement followed by subsequent decline. Looking ahead, air passenger throughput and cargo and mail throughput for each airport group is expected to experience continued rapid growth. The development of the six major airport groups is anticipated to offer robust support for the advancement of China's civil aviation industry, thereby playing a crucial role in ensuring the country's economic and social development.

Technology gap in airport efficiency

Technological disparities exist among various regions, and the common frontier model serves as a valuable tool for assessing these differences. This model facilitates the analysis of technological gaps by measuring the distance of each group from the common frontier, expressed as the technology gap ratio (TGR). The TGR reflects the extent of deviation from optimal production technology and is employed to gauge the frontier production technology across diverse groups. A higher TGR value, nearing 1, signifies an elevated technical proficiency of the decision-making unit, while a lower value indicates the opposite. *Table 6* presents the TGR results for each airport group.

Table 6 – TGR of each airport group from 2013 to 2022

	North China Airport Group	Northeast Airport Group	East China Airport Group	Central and South Airport Group	Southwest Airport Group	Northwest Airport Group
2013	0.726	0.752	0.872	0.843	0.876	0.828
2014	0.735	0.768	0.869	0.869	0.876	0.786
2015	0.746	0.786	0.879	0.876	0.879	0.786
2016	0.743	0.801	0.881	0.879	0.876	0.801
2017	0.775	0.857	0.897	0.903	0.877	0.816
2018	0.788	0.879	0.911	0.905	0.873	0.821
2019	0.772	0.849	0.916	0.926	0.881	0.793
2020	0.715	0.748	0.859	0.892	0.871	0.708
2021	0.713	0.753	0.866	0.879	0.852	0.719
2022	0.635	0.680	0.834	0.823	0.794	0.666
Ave	0.735	0.787	0.878	0.880	0.865	0.772

Table 6 reveals discernible variations in technological disparities between cutting-edge production technology and the potential optimal production technology within each group. The Central South Airport Group exhibits the highest average technology gap ratio (TGR) among the six major airport groups, standing at 0.880. This signifies a relatively advanced production technology, with the airport production technology level trailing by 12% from the potential optimal technology. Following suit, the East China and Southwest Airport Groups demonstrate commendable technological strength, while the Northeast and Northwest airport clusters exhibit moderate levels. Conversely, the North China airport cluster reports an average TGR of 0.735, indicating that the production technology level in this region lags by 26.5% from the optimal technology.

To comprehend the dynamic changes in technology gap ratios (TGR), *Figure 1* provides a comparative analysis of TGR trends among the six major airport groups spanning the years 2013 to 2022.

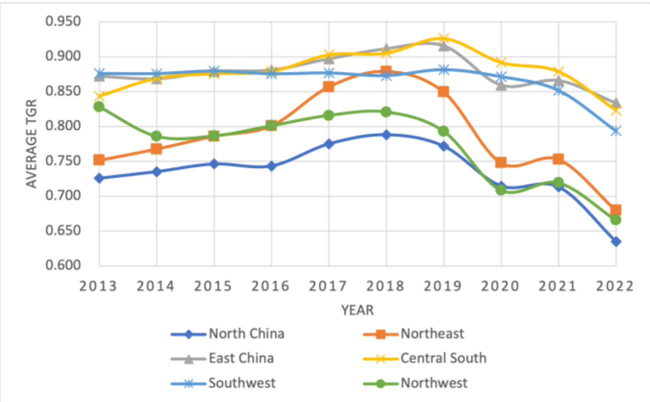

Figure 1 – Average TGR of the six major airport groups analysed by the common frontier

As depicted in *Figure 1*, the technology gap ratios (TGR) for Southwest, East China and Central South China consistently exhibit higher values, followed by the TGR of Northeast, Northwest and North China. Notably, the North China Airport Group records the lowest TGR, indicative of a substantial gap between the two frontiers. This discrepancy highlights non-uniform development among airports in the region. Specifically, passenger throughput is concentrated at PEK, with other regional airports experiencing comparatively lower throughput. Consequently, certain airport resources remain underutilised, constraining collaborative development and contributing to an overall lower technical level within the airport group.

The Southwest region maintains a relatively stable TGR, hovering around 0.87 for the majority of the study period, with a slight decrease observed towards the study's conclusion. Conversely, East China and Central South China initially show an upward trajectory, followed by a decline post-2019. Meanwhile, Northeast, Northwest and North China exhibit discernible upward trends, followed by a subsequent decline, with the Northeast Airport Group experiencing the most pronounced fluctuations. Generally, TGR across all airport groups displays a decreasing trend over time. To address operational inefficiencies, airports in various regions must strive to align with benchmark airports within their group and industry standards. Airports with low operating efficiency in various regions must not only strive to align with benchmark airports within the group but also align with industry benchmark airports, and focus on comparative analysis of efficiency improvement practices among airports in the same region.

Decomposition analysis of airport efficiency changes

To investigate the dynamics of airport efficiency changes, the Malmquist method was employed to gauge alterations in the Malmquist productivity index for the six major airport groups. *Table 7* presents the Malmquist index along with its decomposition for 45 airports across multiple years. The table illustrates variations in airport efficiency concerning different inputs and outputs during each period. An index value exceeding 1 signifies an augmentation in total factor productivity, a value below 1 indicates a decline in total factor productivity, and an index value equal to 1 denotes no change in total factor productivity.

Table 7 – Malmquist index and its decomposition of 45 airports in China over the years

	effch	techch	pech	sech	tfpch
2013-2014	1.099	0.959	0.992	1.108	1.055
2014-2015	1.029	1.006	0.998	1.031	1.036
2015-2016	1.033	1.046	0.996	1.037	1.081
2016-2017	1.034	1.072	1.002	1.032	1.108
2017-2018	1.020	1.033	1.000	1.021	1.054
2018-2019	1.014	1.011	1.012	1.002	1.025
2019-2020	0.916	0.786	0.968	0.946	0.720
2020-2021	1.039	0.993	1.019	1.020	1.032
2021-2022	0.962	0.641	0.979	0.983	0.617
Ave	1.015	0.939	0.996	1.019	0.953

Table 7 and *Figure 2* reveal that over the period from 2013 to 2022, the total factor productivity of each airport generally remained stable. However, notable declines were observed in 2019 – 2020 and 2021 – 2022, with indices of 0.72 and 0.617, respectively. These decreases suggest a reduction in the total factor productivity of decision-making units, indicating a decline in operational efficiency for China's airports. This decline is attributed to a reduction in technological change (techch), as total factor productivity is closely linked to technological advancements.

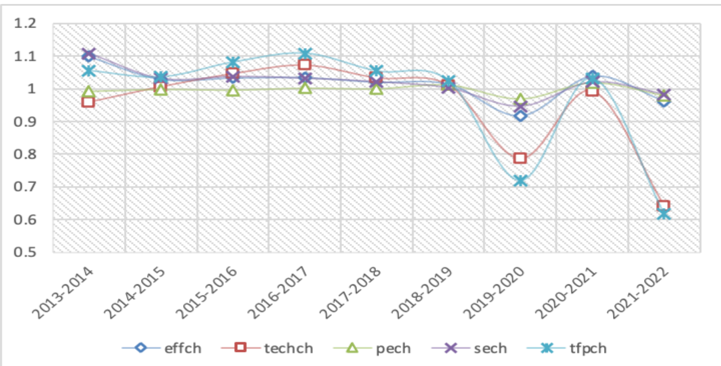

Figure 2 – Malmquist index and its decomposition of the airport over the years

The average Malmquist index for airports over the study period is 0.953, reflecting an overall drop of 4.7% in airport total factor productivity. A plausible explanation for this trend is the travel restrictions imposed during the epidemic in the aforementioned years, leading to decreased passenger and cargo throughput and consequently impacting the average efficiency of airport units over time.

Over the past decade, the average values for technical efficiency, pure technical efficiency and scale efficiency were 1.015, 0.996 and 1.019, respectively. This suggests that the growth in airport efficiency primarily hinges on scale efficiency.

Table 8 – Malmquist index and its decomposition of China's six major airport clusters

	effch	**techch**	**pech**	**sech**	**tfpch**
North China Airport Group	0.994	0.935	0.976	1.017	0.928
Airport Group East China	1.028	0.929	1.004	1.024	0.954
Northeast Airport Group	1.022	0.940	0.996	1.026	0.960
Central and South Airport Group	1.008	0.942	0.997	1.011	0.950
Southwest Airport Group	1.036	0.941	1.011	1.025	0.974
Northwest Airport Group	1.007	0.936	0.989	1.019	0.943
Ave	1.016	0.937	0.996	1.020	0.952

Examining the pure technical efficiency of the airport groups as presented in *Table 8,* it is noteworthy that the pure technical efficiency values for Northeast and Southwest exceed 1, whereas those for North China, East China, Central South and Northwest China are all below 1. This indicates that, over the past decade, there has been no substantial improvement in the pure technical efficiency of the airport groups as a whole.

Considering scale efficiency, all regions demonstrate values surpassing 1, with an average of 1.020 over the past 10 years. Technical efficiency experienced a 1.6% increase, reaching 1.016, signalling a modest growth in the output accomplished per unit input. This suggests that the expansion of business volume for each airport primarily relies on scale efficiency, while the average technical change remains relatively stable at 0.937.

Taking a regional perspective, both the pure technical efficiency and scale efficiency of the Northeast and Southwest airport clusters exhibit an upward trend, showcasing excellent technical efficiency performance in these regions.

Table 9 provides a comprehensive overview of the Malmquist index and its decomposition for 45 airports in China spanning the period from 2013 to 2022. A technical efficiency value greater than 1 signifies an improvement in operational efficiency, achieved by catching up with efficient decision-making units (DMUs). Conversely, a value less than 1 indicates a decline in efficiency. The technical change reflects the extent to which an airport enhances, reduces or maintains its efficiency through technological progress.

Over the past decade, the average technical efficiency for all airports is 1.015, indicating a 1.5% increase in average technical efficiency. Notably, over 60% of airports demonstrate technical efficiency values exceeding 1. Concerning technical changes, except for the HGH airport (1.035), all other airports register values below 1. This implies that the majority of airports have experienced technological regression, with the average technical change decreasing by 6.1% from 2013 to 2022, settling at 0.939.

The results indicate that over the past 10 years, airports have exerted efforts to enhance technical efficiency, yet insufficient attention has been directed towards technological improvements. Noteworthy exceptions include six airports – HGH, TNA, JJN, WUX, SWA and LXA – that have demonstrated an upward trend in total factor productivity, while the remaining airports have exhibited a downward trajectory during the same period.

Table 9 – Malmquist index and its decomposition of 45 airports in China

Airport	effch	techch	pech	sech	tfpch
PEK	0.913	0.950	0.928	0.983	0.868
PVG	1.000	0.954	1.000	1.000	0.954
CAN	0.983	0.958	1.000	0.983	0.941
CTU	0.991	0.962	1.007	0.985	0.954
SZX	1.000	0.928	1.000	1.000	0.928
KMG	1.022	0.944	1.039	0.984	0.965
XIY	0.992	0.939	0.995	0.997	0.931
SHA	0.980	0.925	0.981	0.998	0.906
CKG	1.021	0.925	1.025	0.996	0.944
HGH	1.000	1.035	1.000	1.000	1.035
NKG	0.968	0.932	0.952	1.017	0.902
CGO	0.942	0.947	0.949	0.993	0.892
XMN	0.997	0.926	1.000	0.997	0.922
WUH	1.036	0.958	1.026	1.010	0.993
CSX	0.972	0.940	0.968	1.004	0.914
HAK	1.060	0.942	1.023	1.036	0.999
URC	1.023	0.932	1.007	1.016	0.953
TSN	0.951	0.957	0.932	1.020	0.910
KWE	1.057	0.935	1.016	1.040	0.988
HRB	1.042	0.925	1.012	1.030	0.964
SHE	1.039	0.937	1.004	1.034	0.973
SYX	1.000	0.949	1.000	1.000	0.949
DLC	0.975	0.948	0.988	0.988	0.924
TNA	1.069	0.954	1.022	1.046	1.020
NNG	1.048	0.938	1.010	1.038	0.984
LHW	0.967	0.939	0.971	0.997	0.908
FOC	1.012	0.925	1.002	1.010	0.936
TYN	1.040	0.925	1.004	1.036	0.962
CGQ	1.056	0.906	1.013	1.042	0.956
KHN	1.019	0.951	1.002	1.017	0.969
HET	1.050	0.921	1.014	1.035	0.967
NGB	1.016	0.930	0.997	1.019	0.945
WNZ	0.957	0.938	0.984	0.973	0.898
ZUH	1.067	0.931	1.008	1.058	0.993
SJW	1.015	0.921	1.004	1.011	0.934
INC	1.045	0.944	1.004	1.041	0.987
KWL	0.891	0.924	0.972	0.917	0.823
JJN	1.136	0.910	1.005	1.131	1.034
WUX	1.103	0.915	1.009	1.093	1.010
SWA	1.076	0.943	1.004	1.071	1.014
XNN	1.010	0.927	0.969	1.042	0.937
LJG	1.047	0.919	1.000	1.047	0.962
JHG	1.056	0.918	1.000	1.056	0.969
LXA	1.095	0.933	1.000	1.095	1.023
MIG	1.000	0.989	1.000	1.000	0.989
Ave	1.015	0.939	0.996	1.019	0.953

5. CONCLUSIONS

This article assesses the efficiency and productivity changes among major airports in China's six primary airport clusters over the period from 2013 to 2022. The research primarily centres on static and dynamic efficiency evaluations, employing the meta-DEA method, super-efficiency DEA, and Malmquist index method to scrutinise regional disparities in airport efficiency and productivity. Initially, the article delves into the current status of China's airport efficiency development, with a specific focus on airport clusters. Subsequently, the analysis incorporates the common frontier method, considering regional efficiency differences and investigating the operational efficiency and disparities among airports in China based on both the common frontier and group frontier. The article explores strategies aimed at enhancing the efficiency of each airport, emphasising the imperative for all airports to catch up with benchmark counterparts. It advocates for proactive measures, including the assimilation of advanced technology and management practices from industry benchmark airports, to elevate airport management standards and operational efficiency, ultimately fostering high-quality airport development.

Enhancing efficiency holds paramount significance for energy conservation, emission reduction, cost-effectiveness, efficiency optimisation and sustainable development. Research findings indicate that the operational efficiency of China's airport clusters currently falls short. Substantial differences in technology gap ratios among airports in various regions highlight ample room for improvement. Notably, the average efficiency of airports within the common frontier is lower than that under the group frontier, showcasing regional disparities.

Specifically, the Southwest, East and Central-South airport clusters exhibit relatively high-efficiency performance, while the Northeast, Northwest and North China airport clusters follow suit. The Malmquist index reveals a slight decline in airport productivity in recent years, with distinct regional characteristics. Productivity improvement primarily stems from advancements in scale efficiency, indicating a prevalent focus on expanding infrastructure. Meanwhile, the enhancement of service quality results from scientific management and technological progress. As such, each airport must diligently strive to elevate its technical proficiency to contribute to overall efficiency improvement.

Based on the above research results, we put forward some important implications and suggestions. First of all, to achieve sustainable development of airports, when formulating development strategies for each airport cluster, the Chinese government should accurately formulate strategies suitable for different airport clusters based on the actual conditions of different regions, to achieve one policy for each region and achieve balanced development in different regions, especially for airports in the Midwest that have benefited relatively little in the past few years.

Secondly, considering the relatively favourable efficiency levels of airports in the Eastern, Central and Southern regions, there exists an opportunity for further enhancement through increased focus on technological progress and investments in technological development. For airports in the Northern and Western regions, which exhibit slightly lower efficiency, targeted improvements in technological progress and technical efficiency are recommended. These improvements could be achieved by optimising operating processes, facilitating regional exchanges and cooperation, and enhancing management capabilities to prevent unnecessary waste of resource investments. These strategic measures aim to reduce regional differences and foster a more balanced and efficient airport landscape across the country.

The study underscores the need for a strategic focus on efficiency improvement in the Western and Northern regions while advocating for the steady enhancement of production efficiency in airports situated in the Eastern and Central-Southern coastal regions. Looking ahead, the anticipated growth in throughput for the six major airport clusters calls for concerted efforts from each airport within these clusters to reinforce coordinated development. This entails building on complementary strengths, actively pursuing international aviation business, and striving to establish internationally competitive aviation enterprises and airports.

The overarching goal is to construct a modern integrated transportation system for China, featuring a world-class airport cluster management system. This comprehensive approach is envisioned to provide robust support for advancing high-quality economic and social development, thereby contributing significantly to the construction of a robust civil aviation country and fostering economic and social progress. The collective efforts of the airport clusters are poised to make substantial contributions to the overarching objectives of achieving a powerful civil aviation sector and promoting comprehensive economic and social development.

The shortcoming of this study is that the selection of airport efficiency evaluation indicators needs to be further improved, to more comprehensively reflect the operational level of all aspects of the airport group. In addition, this article selects 45 airports within China's six major airport groups for case study. However, Qingdao Liuting International Airport (TAO) and Beijing Nanyuan Airport (NAY) have suspended flights, so the study was not conducted. Beijing Daxing International Airport (PKX), Chengdu Tianfu International Airport (TFU) and Qingdao Jiaodong International Airport (TAO) did not participate in the efficiency measurement study due to their late opening time and insufficient data required for the study. The above-listed airports will affect the development of the airport group to some extent. Future studies will include the above-listed airports.

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REFERENCES

[1] Gillen D, Lall A. Developing measures of airport productivity and performance: An application of data envelopment analysis. *Transportation Research Part E: Logistics and Transportation Review*. 1997;33(4):261–273. DOI: 10.1016/S1366-5545(97)00028-8.

[2] Lam SW, Low JMW, Tang LC. Operational efficiencies across Asia Pacific airports. *Transportation Research Part E: Logistics and Transportation Review*. 2009;45(4):654–665. DOI: 10.1016/j.tre.2008.11.003.

[3] Lozano S, Gutiérrez E. Slacks-based measure of efficiency of airports with airplanes delays as undesirable outputs. *Computers & Operations Research*. 2011;38(1):131–139. DOI: 10.1016/j.cor.2010.04.007.

[4] Rapee P, Peng KC. Measuring Efficiency of Main Airports in Thailand by an Integrated DEA-AHP Method. *Advanced Materials Research*. 2014;1030–1032:2203–2206. DOI: 10.4028/www.scientific.net/AMR.1030-1032.2203.

[5] Örkcü HH, et al. An evaluation of the operational efficiency of turkish airports using data envelopment analysis and the Malmquist productivity index: 2009–2014 case. *Transport Policy*. 2016;48:92–104. DOI: 10.1016/j.tranpol.2016.02.008.

[6] Lo Storto C. The analysis of the cost-revenue production cycle efficiency of the Italian airports: A NSBM DEA approach. *Journal of Air Transport Management*. 2018;72:77–85. DOI: 10.1016/j.jairtraman.2018.05.010.

[7] Huynh TM, Kim G, Ha HK. Comparative analysis of efficiency for major Southeast Asia airports: A two-stage approach. *Journal of Air Transport Management*. 2020;89:101898. DOI: 10.1016/j.jairtraman.2020.101898.

[8] Chae M, Kim TS. Factors affecting the development of hub airport clusters: Focusing on the roles of low-cost carriers in the Asia-Pacific region. *International Journal of Urban Sciences*. 2015;19(3):305–319. DOI: 10.1080/12265934.2015.1100091.

[9] Wang CY, Wu WW, Zhang J. Research on the efficiency of Beijing-Tianjin-Hebei airport group based on system dynamics. *Journal of Physics: Conference Series*. 2019;1187(4):042069. DOI: 10.1088/1742-6596/1187/4/042069.

[10] Zhang P, et al. Synergetic development measure of airport groups composite system and its influencing factors analysis: Some evidence from China. *Journal of Advanced Transportation*. 2023;2023:1–12. DOI: 10.1155/2023/5676795.

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中国六大机场群主要机场效率研究：基于共同前沿超效率 DEA 与 Malmquist 方法

摘要

机场群对于民航运输业的可持续发展具有重要意义。采用共同前沿与超效率 DEA 方法测算中国六大机场群的效率，然后利用 Malmquist 指数方法探讨机场生产率的变化情况。结果表明，机场效率具有区域差异的特点，华东机场群与西南机场群常年处于效率值优异，华北机场群与东北机场群效率表现仍有较大的进步空间；大多数机

场群内机场效率仍然处于偏低、无效状态，效率呈现先上升后下降的趋势；各机场群的 TGR 均呈现一定程度的下降趋势。Malmquist 指数显示，各机场全要素生产率基本保持稳定，而机场的效率增长主要依靠规模效率，平均技术效率增长了 1.5%，而技术变化方面，绝大多数机场技术出现退步现象，对于技术的提升关注不足。因此，注重技术创新和提高管理效率，实现机场群效率进步，根据不同地区的实际情况精准制定策略，加强协同发展，开展区域交流与合作，平衡区域差异，实现中国机场群的可持续发展，打造世界级机场群。

关键词
机场群；共同前沿；超效率 DEA；技术差距率；Malmquist 全要素生产率