Effects of Air Cargo Transport and Intermodal Transportation on Airport Efficiency

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Abstract. The study investigates the impact of air cargo logistics and multimodal transportation on airport operational efficiency. Six major domestic airports were selected based on domestic cargo throughput rankings and the degree of multimodal transportation. Data Envelopment Analysis (DEA) was utilized to assess the efficacy of the chosen airports. The research findings indicate that the quality of the logistics system surrounding the airport and the degree of multimodal transportation positively influence airport efficiency. Freight transportation has a positive impact on both the technical and scale efficiency of domestic airport operations. Airports with a greater share of freight volume tend to exhibit superior levels of overall technical efficiency, pure technical efficiency, and scale efficiency when contrasted with those characterized by lower proportions of freight volume. By evaluating the operation efficiency of airport cargo transportation modes and multimodal transportation through DEA, targeted guidance is provided for airports, along with corresponding improvement strategies. This study offers relative development recommendations for the overall advancement of airports, facilitating the joint development of the cargo transportation industry and the airport sector in China.

Keyword. Airport Efficiency; Air Cargo Transportation; Multimodal Transportation

1 Introduction

In recent years, the rapid progress in e-commerce, economic globalization, just-in-time production, logistics, and supply chain networks has created a substantial need for streamlined and proficient freight management. Individuals and businesses alike now heavily depend on freight systems for transporting goods.With the rapid development of high-speed rail domestically, high-speed rail and civil aviation transportation are not only in competitive relationships but can also achieve win-win cooperation. This involves exploring the network characteristics of airlines, as well as the complementary and intermodal services between airlines and high-speed rail.

The global economy is becoming increasingly interconnected, leading to tighter linkages among transportation, multimodal transport, and logistics systems. The aviation transport industry is making increasingly substantial contributions to the world economy[1]. The liberalization of the aviation transport market, coupled with the rise of the new economy, has spurred the growth of aviation. Originating in the 1980s in the United States and later in Europe, the liberalization drive fueled increased air traffic and the success of budget airlines. This trend is intricately

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linked with the emergence of the new economy, advancements in information and communication technologies, and globalization, all of which have bolstered the significance of aviation in facilitating the movement of both passengers and cargo.

Aviation transport serves as a vital means of generating revenue for stakeholders in airport interests, such as government agencies, private agents, airlines, and decision-makers. Therefore, airports are integral components of comprehensive transportation infrastructure, essential frameworks necessary to meet highly developed commercial positions, and to provide meaningful economic and social development for the region. By understanding the operational efficiency of airports, better promotion of rapid airport development can be achieved.

2 Utilization of Method Models and Evaluation Metrics

2.1DEA Methodology

In 1957, Arrell proposed a deterministic method for assessing the comparative efficiency of businesses by modeling the production frontier of an industry[1]. Subsequently, in 1978, Charnes et al. introduced Data Envelopment Analysis (DEA), a deterministic non-parametric technique designed to evaluate the relative performance of comparable units. DEA enables the estimation of both scale and technical efficiency, as well as the identification of scale returns characteristics. Enterprises operating within this production unit are considered technically inefficient. The inefficiency of decision units is quantified by their distance from the input-output point to the production frontier.DEA assesses the input scale and technical effectiveness of decision units, allowing for the comparison of the economic and social benefits generated after allocating resources such as capital and labor to similar enterprises. This method is instrumental in deriving technical and scale efficiencies and determining scale returns. By establishing a reference efficient frontier based on efficient production units and their linear combinations using mathematical programming methods, DEA provides a framework for performance evaluation.The DEA technique, as described by Coelli and Salazar, has found widespread application in empirical studies across various sectors including agriculture, banking, railways, financial institutions, schools, airlines, and airport departments. It offers flexibility through its input-oriented and output-oriented approaches. In the input-oriented model, the focus is on determining the minimum inputs necessary to achieve a given output level, while the output-oriented model aims to maximize output given a set level of inputs. Coelli and Perelman demonstrated that both orientations yield the same set of efficient entities, with negligible differences in efficiency scores. In their analysis of the domestic airport sector, they suggested that choosing an output-oriented specification over an input-oriented one could be justified due to increased competition among airports following liberalization.

2.2Construction of the DEA Model

Data Envelopment Analysis (DEA) is a methodological approach used to evaluate the efficiency of Decision Making Units (DMUs) based on multiple inputs and outputs. By employing mathematical programming models, DEA calculates the relative efficiency of each DMU within a set of n similar units, considering m input indicators and s output indicators[2].The traditional CCR method is utilized to calculate DEA efficiency. Input indicator data for DMUs can be represented by the matrix $X = X_{ij}$ (i=1,2,…,m; j=1,2,…,n), where X_{ij} denotes the ith input indicator of DMU_jSimilarly, matrix Y=y_{rj} (r=1,2,…,s; j=1,2,…,n) represents output indicator data.

$\theta_0 = \frac{\sum_{r=1}^{s}\mu_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$, θ_0 is referred to as the efficiency evaluation index ofDMU_0.The conventional CCR model calculates the following issues for each DMU_0 (1≤o≤n):

$$MAX\theta_0 = \frac{\sum_{r=1}^{s}\mu_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$

$$\text{s.t} \frac{\sum_{r=1}^{s}\mu_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad j = 1,2 \ldots\ldots n \quad r = 1,2 \ldots\ldots s \quad i = 1,2 \ldots\ldots m \tag{1}$$

Due to the nonlinearity of Model 1, it poses computational challenges. By employing a C^2 transformation, Model (1) is linearized into a linear programming model, as follows:

$$MAX\theta_0 = \sum_{r=1}^{s}\mu_r y_{r0}$$

$$\text{s.t} \sum_{r=1}^{s}\mu_r y_{r0} - \sum_{i=1}^{m} v_i\, x_{ij} \le 0;\ \sum_{i=1}^{m} v_i\, x_{i0} = 1 \quad \mu_r,\ v_i \ge 0$$

$$j = 1,2 \ldots\ldots n \quad r = 1,2 \ldots\ldots s \quad i = 1,2 \ldots\ldots m \tag{2}$$

In addition to assessing the efficiency of decision-making units[3], researchers often aim to understand the gaps between the utilization of indicators by decision-making units and the effectiveness of these units. Therefore, researchers have developed a complementary model to Model (2) called the envelopment DEA model to compute the input redundancy and output deficiency of DMUs. The model is as follows:

$$Min\theta_0$$

$$\text{s.t} \sum_{j=1}^{n}\lambda_j x_{ij} + s_i^- = \theta_0 x_{i0}.\ i = 1,2 \ldots\ldots m$$

$$\sum_{j=1}^{n}\lambda_j y_{rj} + s_r^+ = y_{r0} \quad r = 1,2 \ldots\ldots s$$

$$\lambda_j \ge 0.\ s_i^-, s_i^+ \ge 0\ \forall j, i, r \tag{3}$$

Here, s_i^- (i=1,2,...,m) and s_i^+ (r=1,2,...,s) respectively represent the input slack and output shortfall of DMU.

2.3 Selection of Evaluation Indicators

In the process of cargo transportation at airports, there are numerous factors that impact airport operational efficiency. These factors can be broadly categorized into four main groups: airport infrastructure, airport technology, airport human resources, and airport competitive factors. Airport infrastructure generally encompasses facilities such as the number and length of runways, the number of parking stands, cargo area size, and terminal area. Airport technology factors typically involve runway and taxiway design, cargo area functionality, and terminal layout. Airport human resources mainly include the quantity and overall quality of staff, as well as their annual income. Competitive factors within airports include competition from surrounding transportation infrastructure diverting cargo traffic and cooperation from other modes of transportation to jointly facilitate cargo transportation.

This study investigates the determinants of airport operational efficiency, taking into account the accessibility of airport data. It explores the interplay between airport operational efficiency and air transportation, along with multimodal transport within airports. Utilizing the DEA method, the selection of output and input variables is contingent upon data accessibility, factors impacting airport operational efficiency, and existing literature on airport efficiency. Notably, input indicators include the number of runways, cargo area size, and parking stand quantity, while output indicators comprise cargo and mail throughput volume, aircraft movements, and the growth rate of cargo and mail throughput volume compared to the preceding year[4].

3 Evaluation and analysis of airport operational efficiency in china

3.1 Sample evaluation

This paper examines the cargo throughput of airports and the relevant policies regarding multimodal transportation associated with these airports. Six domestic airports, including Guangzhou Baiyun International Airport, Shanghai Pudong International Airport, Shenzhen Bao'an International Airport, Zhengzhou Xinzheng International Airport, Chongqing Jiangbei International Airport, and Tianjin Binhai International Airport, have been chosen as evaluation samples.These six airports represent the strategic importance of freight transportation in China. The basic data for the six major airports in 2022 are selected as the foundation for evaluation. Table 1 and Table 2 present the basic data for these six airports. Table 3 conducts dimensionless processing on the basic data.

Table 1. Fundamental data

Airport	Runway Count	Seat/Count	Cargo Area (10,000 square meters)	Parking Stands	2022 Annual Cargo Throughput(t)	2022 Annual Aircraft Movements	2022 Year-on-Year Growth Rate of Cargo Throughput
Zhengzhou Xinzheng	2	23.79	158	2	624654.08	94427	-11.4%
Shanghai Pudong	4	40	340	4	3117215.59	204378	-21.7%
Guangzhou Baiyun	3	80	269	3	1884559	266627	-7.9%
Shenzhen Bao'an	2	171.2	199	2	1506955.03	235693	-3.9%
Chongqing Jiangbei	3	80	209	3	414775.41	188586	-13%
Tianjin Binhai	2	19	59	2	131516.91	60173	-32.5%

Data Source: Chinese Civil Aviation Statistical Bulletin

Table 2. Dimensionless data

Airport	Runway Count	Seat/Count	Cargo Area (10,000 square meters)	Parking Stands	2022 Annual Cargo Throughput(t)	2022 Annual Aircraft Movements	2022 Year-on-Year Growth Rate of Cargo Throughput
Zhengzhou Xinzheng	0.0000	0.0315	0.3523	0.1346	0.1511	0.4444	0.0000
Shanghai Pudong	2.0000	0.1380	1.0000	1.0000	0.9454	0.2407	2.0000

Guangzhou Baiyun	1.5000	0.4008	0.7473	0.4884	1.0000	1.0000	1.5000
Shenzhen Bao'an	0.0000	1.0000	0.4982	0.3626	0.8119	0.6204	0.0000
Chongqing Jiangbei	1.5000	579.5814	0.5338	0.0744	0.6547	0.9722	1.5000
Tianjin Binhai	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001	0.0001

3.2Static Evaluation Results and Analysis Based on the BCC Model

Using Data Envelopment Analysis (DEA) methodology, an assessment is conducted on overall technical, scale, and comprehensive efficiency. Based on collected input-output data from sampled airports, software is employed for computation. Table 3 presents the calculation results of the BCC model, encompassing technical efficiency, comprehensive efficiency, scale efficiency, and the effectiveness of DEA.

Table3. BCC Model Calculation Results: Validity Analysis

Airport	Technological Efficiency (TE)	Scale efficiency SE(k)	Overall Efficiency OE(θ)	Parking Stands	Looseness Variable S^-	slack variable S^+	Validity
Zhengzhou Xinzheng	1	1	1	0	0	1	DEA Strongly Efficient
Shanghai Pudong	1	1	1	0	0	1	DEA Strongly Efficient
Guangzhou Baiyun	1	1	1	0	0	1	DEA Strongly Efficient
Shenzhen Bao'an	1	1	1	0	0．004	1	DEA Weakly Efficient
Chongqing Jiangbei	1	1	1	0	0	1	DEA Strongly Efficient
Tianjin Binhai	0.994	0.976	0.879	0	0	0.994	DEA Inefficient

3.3 Efficiency Analysis

In DEA efficiency evaluation, technical efficiency reflects the efficiency brought by technical factors. A value of 1 indicates reasonable use of resources, whereas a value less than 1 suggests room for improvement in technical efficiency[5]. Scale efficiency reflects the efficiency brought by the scale of operations. A value of 1 indicates constant returns to scale (optimal state), a value less than 1 indicates increasing returns to scale (expanding the scale may increase efficiency), and a value greater than 1 indicates decreasing returns to scale (reducing the scale may increase efficiency)[6]. Comprehensive efficiency reflects the overall efficiency of decision-making units (DMUs), where the value equals the product of technical efficiency and scale efficiency and is thus less than or equal to 1. Slack variables, S^- representing 'how much input can be reduced to achieve target efficiency[7] and S^+ representing 'how much output can be increased to achieve target efficiency,' are indicative. Combining comprehensive efficiency indicators, S-, and S+, three metrics in total, the effectiveness of DEA can be determined. If comprehensive efficiency equals 1 and both S^- and S^+ are 0, it's labeled as 'DEA strong effective.' If comprehensive efficiency equals 1 but either S^- or S^+ is greater than 0, it's labeled as 'DEA weak effective. If comprehensive efficiency is less than 1, it's labeled as 'non-DEA effective.

The operational efficiency of airports hinges on both technical efficiency and scale efficiency. An airport's overall efficiency is deemed optimal only when both technical and scale efficiencies are maximized, resulting in a relative efficiency value of 1. As per Table 3, five airports—Shanghai Pudong, Guangzhou, Shenzhen, Chongqing, and Zhengzhou—demonstrate effective comprehensive efficiency. These airports exhibit judicious allocation of infrastructure resources, maximal utilization, and robust operational management. Conversely, Tianjin Airport's comprehensive efficiency shortfall underscores the imperative for enhancing scale efficiency in airport operations. Evaluation indicates that each airport's efficiency status varies based on the utilization level of tangible assets. For detailed airport analyses, employing the multi-objective DEA method empowers managers to discern trade-offs between outputs, facilitating the identification of alternative high-efficiency operational strategies and the formulation of targeted plans to attain desired output levels.

4 Conclusion

This research utilizes the Data Envelopment Analysis (DEA) technique to evaluate the operational efficiency of the six primary domestic cargo airports during the year 2022. It examines the extent to which the quality of multimodal transportation and the aviation transport system impact the technical and scale efficiencies of these airports[8]. The findings underscore the substantial influence of the national logistics system's quality on airport efficiency. Notably, intermodality significantly shapes airport efficiency, particularly evident in airports directly integrated with the high-speed rail network, which demonstrate superior technical and pure technical efficiencies. Additionally, the ease of goods or passenger boarding onto aircraft emerges as a pivotal factor in efficiency levels. Consequently, enhancing facilities, such as increasing the proportion of boarding gates equipped with jet bridges, to optimize airport-aircraft interfaces, leads to heightened efficiency levels.

The above research findings carry significant guidance. Achieving a highly efficient and integrated multimodal transport system necessitates seamless connectivity and effective integration across various transportation modes. High-speed rail lines operate independently of airports, and the robustness of the logistics network is contingent upon governmental services, investment, policies, and strategic planning. Pertinent authorities play pivotal roles in infrastructure development, fostering transportation regulatory frameworks, and devising and executing efficient customs procedures. Within the aviation transport sector, substantial investment in innovating the logistics transport process is recommended.

These findings also bear relevance for airport managers. The operational efficacy of airports hinges on adept management of passenger and cargo flows. The global supply chain demands cutting-edge logistics services, incorporating the utilization of new multimodal transport and information technology in material distribution and physical management[9]. Investments in logistics innovation should enhance security screenings, boarding procedures, personnel flows, and terminal operations. Additionally, the formulation and enhancement of hub management strategies necessitate support from logistics innovation.

Lastly, the study acknowledges its limitations and deficiencies. One prominent factor is the utilization of a limited dataset; hence, the validity of this study's results could be bolstered by a larger sample of airports. Furthermore, when assessing the impact of air cargo transport and multimodal transport on airport efficiency, incorporating more pertinent evaluation indicators of air cargo transport would facilitate a more thorough analysis of airport cargo operations efficiency.

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