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# Exploring the Effect of COVID-19 on Airline Environmental Efficiency Through an Interval Epsilon-based Measure Model

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# Exploring the effect of COVID-19 on airline environmental efficiency through an Interval Epsilon-Based Measure model

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**Abstract:** COVID-19 has dealt an unprecedented blow to the aviation industry since 2020. This paper applies the Interval Epsilon-Based Measure (IEBM) model to evaluate the optimal quarterly environmental efficiency of 14 global airlines of passenger and cargo subsystems during 2018-2020. Then, the Time Series Prediction method is applied to forecast the interval data of inputs and outputs from 2021 to 2022 and calculate the quarterly efficiency. Thus, the future development trends of airlines can be predicted. Furthermore, the results accord with reality can verify the credibility and accuracy of the model. Furthermore, the results show that: 1. COVID-19 has hit the passenger subsystem harder, while the freight subsystem has become more efficient; 2. The efficiency of the freight subsystem has inevitably declined in the post-epidemic era; 3. Therefore, the airlines will have a "√" shaped recovery curve in the next few years.

**Keywords:** airline environmental efficiency; parallel system; interval epsilon-based measure model; time series prediction

## 1. Introduction

From late 2019 to early 2020, the COVID-19 epidemic swept the world with sudden and unforeseen momentum. Many industries have suspended commercial transactions to prevent the virus from spreading widely. Aviation is one of the most affected industries. The border closures, flight cancellations, and aircraft grounding have led to a sharp drop in airline revenue and revenue passenger kilometers. According to the latest International Civil Aviation Organization (ICAO) report, the total number of passengers decreased by 2,699 million (-60%), and the entire passenger revenue lost $371 billion around the world in 2020 (ICAO, 2021). Singapore Airlines even reported a 99.4% drop in passenger traffic and a 50.7% drop in cargo traffic in the first quarter of 2020 (Singapore airlines report, 2021). Unlike the short V-shaped recovery curve during the SARS epidemic in 2003, the recovery curve of airlines in the post-COVID-19 era is more complex and changeable. In this context, it is of significant meaning to study the future development of global airlines.

Passenger transportation accounts for a large proportion of modern airline services, while the proportion of freight transportation is slowly increasing, enabling the global trade supply chain to function normally (Givoni and Chen, 2017). The COVID-19 has affected the two subsystems to varying degrees. The border blockade has restricted people's freedom of movement and made a disastrous impact on passenger transportation. At the same time, the freight system needs to undertake fast, accurate, and scalable transportation requirements. The quantity of cargo transportation in some airlines even increased in 2020. The airlines cannot ignore the importance of the freight system during the COVID-19 outbreak. What about the future trend of the two subsystems? This paper discusses the allocation of shared resources between the two parallel subsystems and their different influence on the overall efficiency of airlines.

On the discussion method of efficiency, Cui and Li (2018) used a neural network to predict the efficiency of 29 international airlines during 2021–2023. They then proposed a Network Epsilon-

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Based Measure with managerial disposability to discuss the differences. BP neural network has been widely used in airline input-output indices prediction because of its good performance in nonlinear function approximation. However, the traditional neural network has disadvantages such as slow convergence speed, sample dependence, and local extreme value, resulting in an unstable prediction process and poor accuracy. More importantly, the precise data predicted by the BP neural network may differ because many actual numbers are inaccurate, such as interval values, bounded values, and fuzzy values. Therefore, the time series prediction theory on interval data is adopted to obtain the inputs and outputs of 14 airlines in each quarter from 2021 to 2022. Referred to Cui and Li (2018), It can be known that the Epsilon-Based Measure (EBM) model proposed by Tone and Tsutsui (2010) can handle both radial and non-radial inputs and outputs and effectively improve the precision measurement of efficiency. This paper presents an interval EBM model to evaluate sample airlines' quarterly overall and subsystem efficiency with the predicted interval values. Furthermore, based on the characteristics of the inefficient subsystem, practical methods in combination with the assessment results are proposed.

Questions to be answered include 1. How to reasonably allocate the shared resources between passenger and freight subsystems? 2. How does time series theory reasonably predict the interval values of input and output indicators? 3. How to use the interval EBM model to evaluate the quarterly environmental efficiency from 2021 to 2022?

The rest of this article is organized as follows. Section 2 reviews the literature on airline efficiency prediction and evaluation and the latest articles on the impact of COVID-19 on airline efficiency. Section 3 introduces the time series theory principle and the construction of the interval EBM model. Section 4 outlines the empirical process: data collection, practical design, and experimental operation. The experimental results and analysis are presented in Section 5. The last section is the conclusion and future research directions.

## 2. Literature review

A variety of methods had been applied to research airline efficiency, such as the TOPSIS method (Barros and Wanke, 2015; Bae et al., 2021), factor analysis (Siregar and Norsworthy, 2001; Barbot et al., 2008; Pappachan, 2020); Stochastic Frontier Analysis (SFA) and Data Envelopment Analysis (DEA) method (Bhadra, 2009; Ouellette et al., 2010; Tavassoli, 2020). The SFA and DEA models have advantages in calculating a single efficiency index with multiple inputs and outputs, which can be identified as a benchmark for decision-making units (DMUs). Compared with SFA, DEA is a non-parametric method and has more obvious advantages. It has no specific provisions on the functional form and can get rid of the influence of subjective factors. Therefore, the DEA models have been widely applied in recent papers.

The existing DEA models can be divided into two types -- radial model and non-radial model. Scholars proposed the former earlier, such as Charnes-Cooper-Rhodes (CCR) and Banker-Charnes-Cooper (BCC) models (Hong and Zhang, 2010; Wang et al., 2011; Min and Joo, 2016; Adabavazeh and Nikbakht, 2020), and then combine the standard DEA model with other methods such as Malmquist productivity index and Fisher productivity index to calculate the efficiency of airlines in different nations and regions (Ray and Mukherjee, 1996; Greer, 2008; Merkert and Hensher, 2011; Wu and Liao, 2014; Pacagnella Junior et al., 2020). However, the nature of the radial model determines that it has many disadvantages. First, it assumes that inputs and outputs change in the same proportion while not precisely in practice. Secondly, the radial DEA model ignores the influence of non-radial slack on efficiency. That is when the efficiency of an airline is one. Still, the slack is not 0; it cannot be determined whether the airline is fully effective or weakly effective, resulting in biased estimation results.

The non-radial model appears in response to the time and conditions. In recent years, many non-radial models have been applied to airline efficiency evaluation, such as the Slacks-Based Measure (SBM) model (Tone,2001) and Range Adjusted Measure (RAM) model (Aida et al., 1998). Next came the expansion and deformation of the non-radial models. Cui et al. (2018) applied the Virtual Frontier SBM model to discuss the effect of carbon dioxide emissions on the efficiency of 22 airlines with strong and weak disposability. Heydari et al. (2020) proposed a fully-fuzzy network RAM model for evaluating 14 Iranian airlines and extended the network RAM model under the fully-fuzzy framework. Finally, Chen et al. (2021) introduced the two-stage adverse Network Slack-Based Measure (NSBM) method to explore the efficiency of the production stage and profit stage of 9 Chinese airlines. The results showed that airlines performed well in the economic benefit acquisition stage, and the low productivity conversion rate was the reason for the low overall efficiency.

However, the non-radial model is not perfect for any situation. When there is undesirable output in the model, the input and undesirable output are linked together, showing a radial relationship—while the input and the desired output tend towards separation, showing a non-radial relationship. The non-radial model cannot correctly deal with the two connections, resulting in the underrated efficiency. The Epsilon-Based Measure (EBM) model proposed by Tone and Tsutsui (2010) can overcome the above defects, introducing exponents ε to measure the diversity and interdependence between vectors. A small set of papers have applied the EBM model to evaluate the environmental efficiency of different industries. Tavana et al. (2013) proved the rationality of the Network EBM model by taking the semiconductor industry as an example and considering its internal networking activities. Xu and Cui (2017) applied the Network EBM model in combination with the network SBM model to evaluate the performance of 19 airlines and determined the influencing factors by regression analysis. Cui and Li (2018) proposed a NEBM model with managerial disposability to measure the influence of the CNG2020 strategy on multi-function airlines during the pilot phase (2021-2023). Wu et al. (2019) applied the EBM evaluation model on the productive efficiency of a large coal enterprise in China from 2015 to 2017 for the future of coal energy. Cui and Arjomandi (2021) modified the range-adjusted measure (RAM) model with an epsilon-based measure model and enriched the theoretical framework of airline performance appraisal. Wang et al. (2021) applied the Malmquist index and EBM model to 14 port companies in Vietnam to prove the validity and fairness of this hybrid model. By far, the EBM model has not been widely applied in the efficiency evaluation of the aviation industry. This paper used the EBM model combining the interval DEA model to study the efficiency of airlines.

The traditional DEA model assumes that input and output data are accurate, but it is not the case. DEA models need to deal with missing data, fuzzy data, bounded data or sequential preference data, and so on. Scholars have long studied how to evaluate the efficiency and put forward the Interval DEA Model (IDEA). Cooper et al. (1999) proposed an IDEA model with assurance region (AR). The boundaries were based on variables rather than data, which involved inaccurate data and the concept of cone-ratio envelopment. Lee et al. (2002) applied an additional DEA model to identify specific DMU inefficiencies in slack, peer groups and returns to scale. Wang et al. (2005) constructed a pair of new interval DEA models for measuring the lower bound and upper bound of the optimal relative efficiency of each DMU and introduced a minimax regret-based (MRA) approach to rank interval efficiency. Kuo (2011) proposed an effective method based on VIKOR, GRA, and interval-valued fuzzy sets to evaluate the service quality of cross-strait passenger airlines in China. Azizi and Wang (2013) proposed a pair of improved bounded DEA models to measure each country's performance in the 2004 Summer Olympic Games in Athens, overcoming the shortcomings of the traditional model that could not determine the interval efficiency. An et al. (2018) combined DEA and Analytic Hierarchy Process (AHP) to complete the ranking of decision-making units based on interval cross efficiency. Zhou et al. (2019) constructed a dynamic three-stage network DEA model considering decision-makers optimistic and pessimistic attitudes to evaluate the sustainable supply chain (SSC). Arana et al. (2020) developed a two-stage SBM model to assess the efficiency when the data were integer and interval values. Based on the BCC model and simple Russell model, Poordavoodi et al. (2020) combined the interval DEA model with interval entropy weight to evaluate the efficiency of Web services. Cheng et al. (2020) proposed a three-stage IDEA efficiency model to measure the efficiency of interval data and eliminate the influence of external environmental factors. Cui et al. (2020) applied the interval SBM model to measure the impact of Carbon Neutral Growth from the 2020 (CNG2020) strategy on the efficiency of 24 airlines during the period 2021-2022. Davoudabadi et al. (2021) combined DEA and fuzzy simulation of interval-valued intuitionistic fuzzy sets (IVIFSs) to evaluate the efficiency of renewable energy projects. The above traditional interval efficiency studies were primarily based on SBM and RAM models, and few studies applied EBM models. Therefore, this paper innovatively proposes the interval EBM (IEBM) model.

Before this, each airline was considered a whole with multiple inputs and outputs, and the "black box" had not yet been opened. Therefore, the experts began to propose a network DEA model to solve this problem. The network DEA model decomposes the decision-making unit into several subsystems and processes and judges their relationship through components and intermediates. Different subsystems may be in series, parallel, or a combination of both. This paper studies the parallel sectors of airlines—passenger and freight subsystems. Li and Cui (2018) calculated the efficiency of 29 airlines from 2008 to 2015 by using the three-stage network RAM model with shared inputs and obtained the optimal employee allocation ratios for pursuing the efficiency of airlines. The results showed that most airlines' maximum number of employees should be allocated to the sales phase. It is clear that there are shared inputs and outputs between different phases, but few papers discuss shared undesirable outputs. Following the research direction of the above paper, this paper applies the IEBM model to solve this problem with undesirable output—greenhouse gas emissions.

This paper focuses on the impact of COVID-19 whose outbreak has dealt a heavy blow to the aviation industry. In particular, passenger traffic around the world has collapsed, with a striking decline in the first half of 2020. A number of airlines have filed for bankruptcy. By 2021, things aren't much better. In addition to direct revenue decline, COVID-19 also affects airline operation mode, harmful gas emissions, input-output indicators. Therefore, a comprehensive study should be conducted on the changes in airline environmental performance in the context of COVID-19. Suau-Sanchez et al. (2020) found that the epidemic greatly reduced the industrial scale, with full-service airlines bearing the brunt. Ni Z Etic (2020) concluded that the epidemic had a significant impact on the revenues of the entire aviation industry, which was expected to recover next year. The main response measures implemented by the airlines in Budd (2020) were to change route operations, rationalize the fleet, reduce the number of employees and reconfigure capacity. Gzerny et al. (2021) also suggested increasing air cargo volume and giving play to the regulatory role of the government. However, not much has been written about the role of air cargo. The International Air Transport Association (IATA) report showed that the cargo revenue of the international airline industry increased by 15% in 2020 from 2019 due to the coronavirus disease. Many airlines convert passenger planes to cargo ones in order to meet the demand for cargo transportation. What is the recovery curve for passenger and freight subsystems in the post-epidemic era? Therefore, this paper re-screens the input-output indicators, reconstructs the evaluation system, and predicts the response of airlines to COVID-19 in the future.

In this paper, an interval EBM model with strong disposability is proposed to evaluate the efficiency of 14 large-scale airlines under the background of COVID-19 and then discuss the impact of COVID-19 on the overall efficiency and subsystem efficiency of airlines. Based on the quarterly data of 14 global airlines from 2018 to 2020, the grey theory is used to forecast the quarterly data during 2021—2022. Empirical results can provide decision-makers with concrete and practical measures.

## 3. Methodology

Airline environmental efficiency evaluation is one of the most potential applications with DEA models. The Epsilon-Based Measure (EBM) model has a more vital ability to discriminate the efficient DUMs. EBM model unifies radial and non-radial models in a composite framework by two parameters: a scalar and a vector. When solving these two values, the affinity index was introduced to replace the Pearson correlation coefficient. Slacks of the EBM model can provide information about inefficient DUMs so that decision-makers can remedy the case.

Suppose there are k decision-making units to be evaluated. Each DMU includes m inputs to produce n desirable outputs and l undesirable outputs. Traditional DEA models only focusing on the hot production index may be unreasonable. This paper treats the undesirable output with strong disposability since Cui et al. (2018) indicated that the strong disposability is more reasonable when dealing with the undesirable outputs than the weak disposability.

Then the input-oriented network EBM model is defined as follows:

$$\gamma^* = min \sum_{k=1}^{K} \left( \theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{x_{i0}^k} \right)$$

$$\begin{aligned} \text{s.t.} \quad & \theta_k X_{i0}^k = \lambda^k X^k + s^{k-}, \mathrm{i} = 1, \cdots, \mathrm{M} \\ & Y_{p0}^k \le \lambda^k Y^k, \mathrm{p} = 1, \cdots, \mathrm{N} \\ & \theta_k Z_{q0}^k = \lambda^k Z^k + s^{k-}, \mathrm{q} = 1, \cdots, \mathrm{L} \\ & \lambda^k \ge 0 \\ & s^{k-} \ge 0 \end{aligned} \tag{1}$$

In model (1), each of the DUMs can be subdivided into k subsystems. $x_i^k, y_p^k$ denote the ith input and the pth desirable output of $DMU_k$, $z_{qk}$ denotes the qth undesirable output of $DMU_k, k = 1,2,\cdots,K$. The undesirable output is treated as input in the same way as they are handled. $s_i^-$ stands for the slacks of the ith input. $\varepsilon_x^k$ is the core parameter combining radial $\theta_k$ and non-radial slacks. $w_i^{k-}$ is the relative importance of the input, which should be a unit-constant value in the input-oriented model (1).

In addition to input-oriented, there are also output-oriented and no-oriented network models:

$$\gamma^* = \min \frac{1}{\left(\sum_{k=1}^{K}\left(\theta_k + \varepsilon_y^k \sum_{p=1}^{n_k} \frac{w_i^{k+} s_i^{k+}}{y_{p0}^k}\right)\right)}$$

$$\begin{aligned}
\text{s.t.}\quad & \theta_k X_{i0}^k \geq \lambda^k X^k, \mathrm{i} = 1, \cdots, \mathrm{M} \\
& Y_{p0}^k = \lambda^k Y^k - s^{k+}, \mathrm{p} = 1, \cdots, \mathrm{N} \\
& \theta_k Z_{q0}^k \geq \lambda^k Z^k, \mathrm{q} = 1, \cdots, \mathrm{L} \\
& \lambda^k \geq 0 \\
& s^{k+} \geq 0
\end{aligned} \tag{2}$$

$$\gamma^* = min \sum_{k=1}^{K} \left( \frac{\theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{x_{i0}^k}}{\eta_k + \varepsilon_y^k \sum_{p=1}^{n_k} \frac{w_i^{k+} s_i^{k+}}{y_{p0}^k}} \right)$$

$$\begin{aligned}
\text{s.t.}\quad & \theta_k X_{i0}^k \geq \lambda^k X^k, \mathrm{i} = 1, \cdots, \mathrm{M} \\
& Y_{p0}^k \leq \lambda^k Y^k, \mathrm{p} = 1, \cdots, \mathrm{N} \\
& \theta_k Z_{q0}^k \geq \lambda^k Z^k, \mathrm{q} = 1, \cdots, \mathrm{L} \\
& \lambda^k \geq 0 \\
& s^{k-}, s^{k+} \geq 0
\end{aligned} \tag{3}$$

This paper applies the input-oriented model for research. The EBM model with the interval DEA are combined based on the assumption that the data of input and output indicators are inaccurate. For $DUM_0$, the most unfavorable situation is that the desirable outputs are the smallest while the inputs and undesirable outputs are the largest. The minimum efficiency can be gotten as this time. The situation of the maximum efficiency is the opposite. The minimum efficiency of $DUM_0$ is defined as follows:

$$min\ \underline{\gamma}^* = min \sum_{k=1}^{K} \left( \theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{\underline{x_{i0}^k}} \right)$$

$$\begin{aligned}
\text{s.t.}\quad & \theta_k \underline{X_{i0}^k} = \lambda^k \overline{X^k} + s^{k-}, \mathrm{i} = 1, \cdots, \mathrm{M} \\
& \overline{Y_{p0}^k} \leq \lambda^k \underline{Y^k}, \mathrm{p} = 1, \cdots, \mathrm{N} \\
& \theta_k \underline{Z_{q0}^k} = \lambda^k \overline{Z^k} + s^{k-}, \mathrm{q} = 1, \cdots, \mathrm{L} \\
& \lambda^k \geq 0 \\
& s^{k-} \geq 0
\end{aligned} \tag{4}$$

For $DUM_0$, the most favorable situation is that the desirable outputs are the largest while the inputs and undesirable outputs are the smallest. Similarly, the maximum efficiency is:

$$\max\ \bar{\gamma} *= min \sum_{k=1}^{K} \left( \theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{\overline{x_{i0}^k}} \right)$$

$$\begin{aligned}
\text{s.t.}\quad & \theta_k \overline{X_{i0}^k} = \lambda^k \underline{X^k} + s^{k-}, \mathrm{i} = 1, \cdots, \mathrm{M} \\
& \underline{Y_{p0}^k} \leq \lambda^k \overline{Y^k}, \mathrm{p} = 1, \cdots, \mathrm{N} \\
& \theta_k \overline{Z_{q0}^k} = \lambda^k \underline{Z^k} + s^{k-}, \mathrm{q} = 1, \cdots, \mathrm{L}
\end{aligned} \tag{5}$$

$$\lambda^k \geq 0$$
$$s^{k-} \geq 0$$

The interval efficiency of the subsystem k should be:

$$\left\{ \underline{\gamma}^* = \sum_{k=1}^{K}\left(\theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{\underline{x_{io}^k}}\right), \bar{\gamma} *= \sum_{k=1}^{K}\left(\theta_k - \varepsilon_x^k \sum_{i=1}^{m_k} \frac{w_i^{k-} s_i^{k-}}{\overline{x_{io}^k}}\right)\right\} \tag{6}$$

The key to applying interval EBM model is to determine the value of $\varepsilon_x$ and $w^-$. Referred to Tone and Tsutsui (2010), the two parameter values are calculated by following steps:

Step 1: Introduce the "diversity index".

In the model, $a \in R_+^n, b \in R_+^n$ are the specific observations for the inputs of k DMUs. The diversity index represents the degree of dispersion between vectors a, b and $\overline{c_j}$, and then can write it as:

$$c_j = \ln \frac{b_j}{a_j}$$

$$\overline{c_j} = \sum_{j=1}^{m} \frac{c_j}{n} \tag{7}$$

$$c_{min} = min(c_j)$$
$$c_{max} = max(c_j)$$

$$\mathrm{D}(a,b) = \frac{\sum_{j=1}^{m}|c_j - \bar{c}_j|}{n(c_{max} - c_{min})} \tag{8}$$

Step 2: Introduce the "affinity index".

Different from the Pearson correlation coefficient greatly affected by outliers, the affinity index $\mathrm{S}(a,b)$ is defined to perform correlation analysis of vectors a, b:

$$\mathrm{S}(a,b) = 1 - 2\mathrm{D}(a,b) \tag{9}$$

Because $0 \leq \mathrm{D}(a,b) \leq \frac{1}{2}$, then $0 \leq \mathrm{S}(a,b) \leq 1$.

Step 3: Calculate the values of parameter $\varepsilon_x$ and $w^-$:

$$\varepsilon_x = \frac{m - \rho_x}{m - 1} \quad (m > 1)$$

$$\varepsilon_x = 0 \qquad (m = 1) \tag{10}$$

$$w^- = \frac{w_x}{\sum_{i=1}^{m} w_{xi}} \tag{11}$$

In the above model, $\rho_x$ is the biggest eigenvalue of $\mathrm{S}(a,b)$, $w_{xi}$ is the corresponding vector of $\rho_x$.

# 4. Empirical study

The IEBM model introduced in Section 3 is applied to evaluate airlines' recovery and environmental efficiency in the post-epidemic period. Fourteen global airlines are set as the empirical research subjects after careful siftings. They are Aeroflot, Air China, All Nippon Airways, Cathay Pacific Airways, China Airlines, China Eastern Airlines, China Southern Airlines, Eva Air, Hainan Airlines, Juneyao Airlines, KLM Royal Dutch, Lufthansa Airlines, Singapore Airlines, and Spring Airlines. As a result, Lufthansa Airlines, China Eastern Airlines, China Southern Airlines, Air China, Singapore Airlines, and KLM Royal Dutch are among the top 20 airlines globally by passenger volume in 2020. In addition, sample airlines come from different countries and continents so that they can be certain representatives.

The selection of inputs and outputs makes a big difference. Based on the parallel structure of airlines, this paper needs to select the respective input and output indexes and shared indices of the passenger and freight systems. Referred to Wu (2015), Available Seat Kilometer (ASK) reflects the maximum passenger economic benefits airlines can obtain from operating routes and capacity resources. Therefore, it is a crucial business indicator to determine the airline passenger subsystem's performance. When the air transportation market is stagnant, changes in the ASK index are apparent. Revenue Passenger Kilometer (RPK) as a corresponding index reflects the number of passengers and profitability of air transportation. Likewise, Available Tonne Kilometer (ATK) and Revenue Tonne Kilometer (RTK) are selected as input and output unique to the freight system. There are shared resources between the passenger and freight systems in daily operations. Operating Costs (OC) and Operating Revenue (OR) are direct and common shared indicators. Carbon dioxide emissions ($co_2$) are selected as undesirable output, always dealt with by five disposability approaches in Cui (2020). This paper treats it with strong disposability. The parallel structure of the airline is shown in Figure 1.

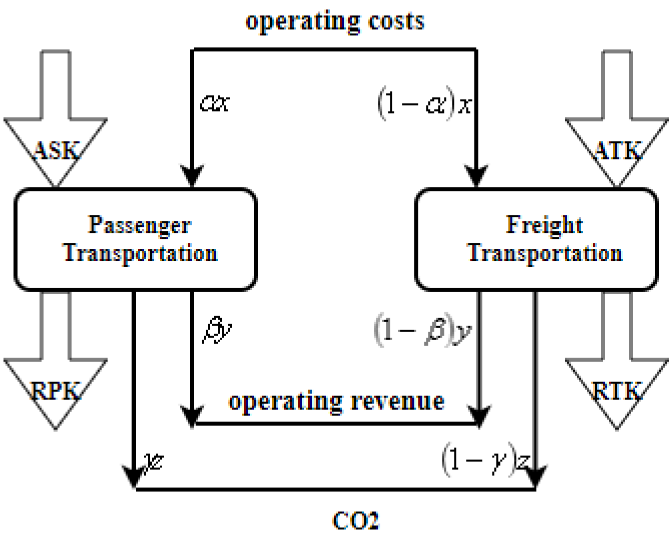


Figure 1. A parallel system comprised of two transportation subsystems.

Considering that the lack of monthly operational data leads to the inaccuracy of the forecast, the quarterly data from the first quarter of 2018 to the last quarter of 2020 are chosen for the measurement. The data of ASK, ATK, RPK, RTK, operating cost, and operating revenue are mainly from the airline's quarterly reports on its website. Some of the missing data come from monthly traffic data released by airlines. A few airlines published quarterly carbon dioxide emissions. Therefore, a rough calculation of $co_2$ emissions is done based on kerosene consumption for each quarter.

Descriptive statistics of quarterly input and output indicators are shown in Table 1. As shown Table 1, there is a significant gap between the indices of sample airlines, which indicates that each airline's operation mode and overall scale are different. The minimums typically appeared in the first and second quarters of 2020 when COVID-19 was very serious, almost one-hundredth of the maximum. Compared the standard deviations of passenger and freight transportation specific inputs and outputs, the former (26868.61, 22863.97) and the latter (2932.33, 2013.99), it can be found that the latter is much smaller. This suggests that freight transportation is less affected by COVID-19 than passenger subsystem. Airlines also differed in how quickly responding to the epidemic outbreak, so there are different levels of operational improvement.

The correlation coefficient and significance of quarterly input and output indicators are listed in Table 2. Most of the coefficients are positive and very high, also significant at the 1% level, which indicates that the selected inputs and outputs are closely related. For example, the correlation coefficient between operating cost and RTK is only 0.419, and the correlation coefficient between ATK and operating revenue is 0.494. However, the two groups are still significant at the level of 1%. The reason may be that the airlines' freight services in the proportion are minimal, and the order of magnitude of freight volume differs significantly with other indexes, resulting in a relatively small correlation with inputs.

Table 1 Descriptive statistics of the quarterly inputs and outputs during 2018-2021

| Variable | Mean | Std. dev | Min | Max |
|---|---|---|---|---|
| The inputs | | | | |
| Operating Costs (1,000,000 dollars) | 3,195.20 | 2,509.27 | 79.93 | 1,1934.74 |
| Available Seat Kilometers(million) | 36,506.96 | 26,868.61 | 496.00 | 99,503.00 |
| Available Tonne Kilometers(million) | 3,832.55 | 2,932.33 | 496.30 | 12,180.63 |
| The desirable outputs | | | | |
| Operating revenue (1,000,000 dollars) | 3,209.95 | 2,652.29 | 62.14 | 12,298.49 |
| Revenue Passenger Kilometers (million passenger-km) | 29,101.73 | 22,863.97 | 167.40 | 85,883.00 |
| Revenue Tonne Kilometers (million ton-km) | 2,589.42 | 2,013.99 | 281.90 | 8,631.73 |
| The undesirable output | | | | |
| $CO_2$ (1,000,000 tons) | 3.44 | 2.74 | 0.08 | 13.01 |

Table 2 Quarterly input-output correlations

| | Operating Revenue | RPK | RTK | $CO_2$ |
|---|---|---|---|---|
| Operating Costs | 0.960*** | 0.816*** | 0.419*** | 0.606*** |
| ASK | 0.884*** | 0.992*** | 0.759*** | 0.769*** |
| ATK | 0.494*** | 0.758*** | 0.989*** | 0.724*** |

Time series theory is applied to forecast the input and output indexes of the quarters in 2021 and 2022 to obtain each airline's recovery curve. According to the Economic Impact Analysis published by ICAO in April 2021, there are five shapes of economic recession and recovery:

V-shaped: the economy smoothly returned to normal after a sharp recession.

U-shaped: A long decline and weak economic recovery.

L-shaped: economic activity is falling rapidly into a straight line and will not return to its former state.

W-shaped: Repeated fluctuations occur before full recovery showing a downward upward pattern.

“Nike swoosh” shaped: the recovery speed is first fast and then slow.

The Time Series Prediction method has been most mature in time series prediction. Specific research can be seen in Li et al. (2018), Jia et al. (2020), and Ding et al. (2020). In Time Series Prediction, although the system's behavior is complex, the ordered data has the overall function.

Therefore, it can be applied to study incomplete and accurate calculation, modeling, prediction, and data processing system. Based on Time-Series Prediction and adjusting parameters, the quarterly forecast interval data can be obtained for the input-output indicators of 2021-2022. Descriptive statistics of them are listed in Table 3. The difference between the upper and lower input and output limits is relatively significant, but several minimum and maximum values items are the same. Therefore, the road to recovery of airlines is still unstable in the future. Table 4 shows the correlation coefficients and significance between inputs and outputs in 2021-2022. All coefficients are positive and significant at the 1% level, ensuring the tight relationship between inputs and outputs.

Table 3 Descriptive statistics of the quarterly inputs and outputs during 2021-2022

| Variable | Mean | | Std. dev | | Min | | Max | |
|---|---|---|---|---|---|---|---|---|
| *Inputs* | Low | Up | Low | Up | Low | Up | Low | Up |
| Operating Costs (1,000,000 dollars) | 1984.01 | 2019.83 | 1401.73 | 1495.73 | 79.32 | 79.32 | 5379.86 | 5969.24 |
| Available Seat Kilometers(million) | 18766.41 | 19427.58 | 14415.49 | 14426.04 | 839.73 | 1348.00 | 57232.80 | 57232.80 |
| Available Tonne Kilometers(million) | 2728.72 | 2747.54 | 2054.96 | 2079.73 | 949.30 | 1049.04 | 8924.17 | 8924.17 |
| *Desirable outputs* | | | | | | | | |
| Operating revenue (1,000,000 dollars) | 1495.96 | 1544.40 | 990.71 | 1047.25 | 61.66 | 61.66 | 3981.01 | 4636.64 |
| Revenue Passenger Kilometers (million passenger-km) | 12084.01 | 13384.51 | 9768.49 | 10246.13 | 224.00 | 224.00 | 42011.22 | 42011.22 |
| Revenue Tonne Kilometers (million ton-km) | 1759.40 | 1792.01 | 1137.62 | 1143.58 | 572.19 | 600.75 | 5491.91 | 5491.91 |
| *Undesirable outputs* | | | | | | | | |
| $CO_2$ (1,000,000 tons) | 1.68 | 1.77 | 1.43 | 1.49 | 0.02 | 0.08 | 4.99 | 4.99 |

Table 4 Input-output correlations during 2021-2022

| | Operating Revenue | | RPK | | PTK | | $CO_2$ | |
|---|---|---|---|---|---|---|---|---|
| | Low | Up | Low | Up | Low | Up | Low | Up |
| Operating Costs | 0.932*** | 0.971*** | 0.518*** | 0.641*** | 0.510*** | 0.534*** | 0.618*** | 0.615*** |
| ASK | 0.721*** | 0.796*** | 0.943*** | 0.984*** | 0.858*** | 0.846*** | 0.738*** | 0.771*** |
| ATK | 0.605*** | 0.650*** | 0.888*** | 0.872*** | 0.980*** | 0.984*** | 0.633*** | 0.662*** |

## 5. Results and discussion

The weight of a parallel system significantly impacts efficiency, so it needs to be set in advance. For example, referred to Li and Cui (2018), the passenger and freight subsystems have equal weights $\left[\frac{1}{2}, \frac{1}{2}\right]$.

The detailed Network EBM model is:

$$\gamma^* = min\left(\frac{1}{2}\times(\varphi_1+\varphi_2)-\frac{1}{2}\times\left(\varepsilon_{x1}\times\left(\frac{w^{\alpha OC}s_0^{\alpha OC}}{\alpha\mathrm{OC}}+\frac{w^{ATK}s_0^{ATK}}{\mathrm{ATK}}+\frac{w^{\gamma GHG}s_0^{\gamma GHG}}{\gamma GHG}\right)+\varepsilon_{x2}\times\left(\frac{w^{(1-\alpha)OC}s_0^{(1-\alpha)OC}}{(1-\alpha)\mathrm{OC}}+\frac{\mathrm{w}^{\mathrm{ASK}}\mathrm{s}_0^{\mathrm{ASK}}}{\mathrm{ASK}}+\frac{w^{(1-\gamma)GHG}s_0^{(1-\gamma)GHG}}{(1-\gamma)GHG}\right)\right)\right)$$

$$s.t.\quad \varphi_1 * ATK_0 = \sum_k^K \lambda_k * ATK_k + s_0^{ATK}$$

$$\varphi_1 * RTK_0 \le \sum_k^K \lambda_k * RTK_k$$

$$\varphi_1 * \alpha * OC_0 = \sum_k^K \lambda_k * \alpha * OC_k + s_0^{\alpha OC}$$

$$\varphi_1 * \beta * OR_0 \le \sum_k^K \lambda_k * \beta * OR_k$$

$$\varphi_1 * \gamma * GHG_0 = \sum_k^K \lambda_k * \gamma * GHG_k + s_0^{\gamma GHG}$$

$$\textstyle\sum_k^K \lambda_k = 1 \tag{12}$$

$$\varphi_2 * ASK_0 = \sum_k^K \mu_k * ASK_k + s_0^{ASK}$$

$$\varphi_2 * RPK_0 \le \sum_k^K \mu_k * RPK_k$$

$$\varphi_2 * (1-\alpha) * OC_0 = \sum_k^K \mu_k * (1-\alpha) * OC_k + s_0^{(1-\alpha)OC}$$

$$\varphi_2 * (1-\beta) * OR_0 \le \sum_k^K \mu_k * (1-\beta) * OR_k$$

$$\varphi_2 * (1-\gamma) * GHG_0 = \sum_k^K \mu_k * (1-\gamma) * GHG_k + s_0^{(1-\gamma)GHG}$$

$$\sum_k^K \mu^k = 1$$

In the model, all variables are non-negative.

The variables are:

$ATK_k$ Available Tonne Kilometers of airline $k$;

$RTK_k$ Revenue Tonne Kilometers of airline $k$;

$OC_k$ Operating costs of airline $k$;

$OR_k$ Operating Revenue of airline $k$;

$GHG_k$ $CO_2$ of airline $k$;

$ASK_k$ Available Seat Kilometers of airline $k$;

$RPK_k$ Revenue Passenger Kilometers of airline $k$;

The interval efficiency value is:

$$\left\{\begin{array}{l} \underline{\gamma}^* = \frac{1}{2}\times(\varphi_1+\varphi_2)-\frac{1}{2}\times\left(\varepsilon_{x1}\times\left(\frac{w^{\alpha OC}s_0^{\alpha OC}}{\underline{\alpha\mathrm{OC}}}+\frac{w^{ATK}s_0^{ATK}}{\underline{\mathrm{ATK}}}+\frac{w^{\gamma GHG}s_0^{\gamma GHG}}{\underline{\gamma GHG}}\right)+\varepsilon_{x2}\times\left(\frac{w^{(1-\alpha)OC}s_0^{(1-\alpha)OC}}{\underline{(1-\alpha)\mathrm{OC}}}+\frac{\mathrm{w}^{\mathrm{ASK}}\mathrm{s}_0^{\mathrm{ASK}}}{\underline{\mathrm{ASK}}}+\frac{w^{(1-\gamma)GHG}s_0^{(1-\gamma)GHG}}{\underline{(1-\gamma)GHG}}\right)\right), \\ \bar{\gamma} = \frac{1}{2}\times(\varphi_1+\varphi_2)-\frac{1}{2}\times\left(\varepsilon_{x1}\times\left(\frac{w^{\alpha OC}s_0^{\alpha OC}}{\overline{\alpha\mathrm{OC}}}+\frac{w^{ATK}s_0^{ATK}}{\overline{\mathrm{ATK}}}+\frac{w^{\gamma GHG}s_0^{\gamma GHG}}{\overline{\gamma GHG}}\right)+\varepsilon_{x2}\times\left(\frac{w^{(1-\alpha)OC}s_0^{(1-\alpha)OC}}{\overline{(1-\alpha)\mathrm{OC}}}+\frac{\mathrm{w}^{\mathrm{ASK}}\mathrm{s}_0^{\mathrm{ASK}}}{\overline{\mathrm{ASK}}}+\frac{w^{(1-\gamma)GHG}s_0^{(1-\gamma)GHG}}{\overline{(1-\gamma)GHG}}\right)\right) \end{array}\right\} \tag{13}$$

Meanwhile, the efficiency value of the freight subsystem and passenger subsystem is:

$$\varphi_1 = \varphi_1 - \varepsilon_{x1}\times\left(\frac{w^{\alpha OC}s_0^{\alpha OC}}{\alpha\mathrm{OC}}+\frac{w^{ATK}s_0^{ATK}}{\mathrm{ATK}}+\frac{w^{\gamma GHG}s_0^{\gamma GHG}}{\gamma GHG}\right) \tag{14}$$

$$\varphi_2 = \varphi_2 - \varepsilon_{x2} \times \left( \frac{w^{(1-\alpha)OC} s_0^{(1-\alpha)OC}}{(1-\alpha)\mathrm{OC}} + \frac{\mathrm{w}^{\mathrm{ASK}} \mathrm{s}_0^{\mathrm{ASK}}}{\mathrm{ASK}} + \frac{w^{(1-\gamma)GHG} s_0^{(1-\gamma)GHG}}{(1-\gamma)GHG} \right) \tag{15}$$

The 1stOpt software can help us get the optimal allocation ratio of 14 airlines and the optimal α, β, γ, as shown in Table 5.

Table 5 The optimal α, β, γ

| Airlines | α | β | γ |
|---|---|---|---|
| Aeroflot | 0.4373 | 0.5309 | 0.4479 |
| Air China | 0.4337 | 0.4728 | 0.6497 |
| All Nippon | 0.5301 | 0.5588 | 0.6423 |
| Cathay Pacific | 0.4604 | 0.5603 | 0.8118 |
| China Airlines | 0.4888 | 0.5494 | 0.7203 |
| China Eastern | 0.4938 | 0.4784 | 0.4264 |
| China Southern | 0.5024 | 0.4772 | 0.4068 |
| Eva Air | 0.4509 | 0.5204 | 0.5001 |
| Hainan | 0.5528 | 0.4701 | 0.6892 |
| Juneyao | 0.4909 | 0.4990 | 0.7465 |
| KLM Royal Dutch | 0.4282 | 0.5198 | 0.5053 |
| Lufthansa | 0.4857 | 0.4985 | 0.7468 |
| Singapore | 0.4874 | 0.6099 | 0.5823 |
| Spring | 0.5320 | 0.4677 | 0.5713 |

Then, the optimal solution of Model (12) is the overall quarterly efficiency of 14 airlines during 2018—2020, as shown in Table 6. The impact of COVID-19. Every quarter's number of efficient airlines is 6, 6, 10, 5, 5, 4, 9, 5, 3, 7, 8, 5. Starting from the fourth quarter of 2019, the quarterly efficiency of major airlines declined rapidly. The minimum values were all less than 0.900, and the maximum value was only 0.971, which is much lower than the efficiency of the previous two years. The standard deviation fluctuation ranges of efficiency values also changed from (0.009, 0.041) to (0.037,0.099). Because of the full outbreak of COVID-19 in the first quarter of 2020, the quarterly average efficiency value was only 0.894, which is the only one whose average was lower than 0.900. China Eastern Airlines is the least efficient (0.807). According to the published first-quarter report, the company completed a passenger turnover of 24,837.09 million passenger kilometers, 54.38% less than in 2019. It carried 13,702,800 passengers, which fell 57.06% from a year ago. The net profit loss was as high as ￥3.933 billion. Capacity cut, revenue decrease, and liquidity crisis are specific manifestations of the epidemic's impact on airlines, leading to decreased efficiency ultimately. The optimal overall performance of sample airlines is Cathay Pacific Airways, whose efficiency value has been 1.000 for four consecutive quarters. In 2020, Cathay Pacific Airways conducted several cost-cutting measures, such as delayed aircraft deliveries, a hiring moratorium, and two rounds of special leave for staff. The airline also received about HK $2.689 billion in government grants. The imbalance between available capacity and demand for medical supplies increased revenues. Cathay Pacific operated 5,648 full-cargo flights to boost power and refit four Boeing 777-300s to accommodate cargo in the cabin. Revenue from the freight subsystem in 2020 was HK $24.573 billion, up 16.2% from 2019, and significantly improved the overall environmental efficiency.

Table 6 Overall quarterly environmental efficiency of IEBM model during 2018-2020

| Airlines | 2018 | | | | 2019 | | | | 2020 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | One | Two | Three | Four | One | Two | Three | Four | One | Two | Three | Four |
| Aeroflot | 0.915 | 0.928 | 1.000 | 0.894 | 0.876 | 0.9145 | 1.000 | 0.91111 | 0.824 | 0.628 | 1.000 | 0.925 |
| Air China | 0.984 | 1.000 | 1.000 | 1.000 | 0.970 | 1.000 | 1.000 | 0.963 | 0.817 | 1.000 | 1.000 | 0.983 |
| All Nippon | 0.956 | 1.000 | 0.988 | 1.000 | 0.902 | 0.958 | 1.000 | 1.000 | 0.866 | 0.949 | 0.906 | 1.000 |
| Cathay Pacific | 0.997 | 1.000 | 1.000 | 0.998 | 1.000 | 1.000 | 0.989 | 1.000 | 1.000 | 1.000 | 1.000 | 0.956 |
| China Airlines | 1.000 | 0.963 | 0.991 | 0.963 | 1.000 | 0.985 | 1.000 | 0.985 | 1.000 | 1.000 | 1.000 | 0.940 |
| China Eastern | 0.999 | 1.000 | 1.000 | 0.962 | 0.998 | 0.981 | 1.000 | 0.986 | 0.807 | 0.838 | 0.886 | 0.891 |
| China Southern | 0.982 | 0.964 | 1.000 | 0.937 | 0.988 | 0.951 | 1.000 | 1.000 | 0.986 | 0.964 | 1.000 | 0.896 |
| Eva Air | 1.000 | 0.943 | 0.977 | 0.941 | 1.000 | 1.000 | 0.930 | 0.873 | 1.000 | 1.000 | 0.989 | 1.000 |
| Hainan | 1.000 | 1.000 | 1.000 | 0.977 | 1.000 | 1.000 | 1.000 | 0.949 | 0.925 | 0.898 | 0.964 | 1.000 |
| Juneyao | 1.000 | 1.000 | 1.000 | 0.976 | 0.983 | 0.991 | 0.983 | 0.989 | 0.846 | 0.925 | 1.000 | 1.000 |
| KLM Royal Dutch | 1.000 | 0.988 | 1.000 | 1.000 | 1.000 | 0.953 | 0.992 | 1.000 | 0.893 | 1.000 | 0.811 | 0.948 |
| Lufthansa | 0.980 | 0.953 | 1.000 | 1.000 | 0.906 | 0.955 | 0.946 | 0.996 | 0.872 | 1.000 | 0.884 | 0.946 |
| Singapore | 1.000 | 0.995 | 1.000 | 1.000 | 0.975 | 0.965 | 1.000 | 1.000 | 0.859 | 1.000 | 1.000 | 1.000 |
| Spring | 0.964 | 0.973 | 0.972 | 0.930 | 0.995 | 0.989 | 1.000 | 0.947 | 0.824 | 0.907 | 1.000 | 0.977 |
| *Min* | *0.956* | *0.943* | *0.972* | *0.930* | *0.902* | *0.951* | *0.930* | *0.873* | *0.807* | *0.838* | *0.811* | *0.891* |
| *Mean* | *0.984* | *0.979* | *0.995* | *0.970* | *0.971* | *0.974* | *0.989* | *0.971* | *0.894* | *0.936* | *0.960* | *0.962* |
| *Std* | *0.024* | *0.024* | *0.009* | *0.033* | *0.041* | *0.025* | *0.021* | *0.038* | *0.071* | *0.099* | *0.060* | *0.037* |

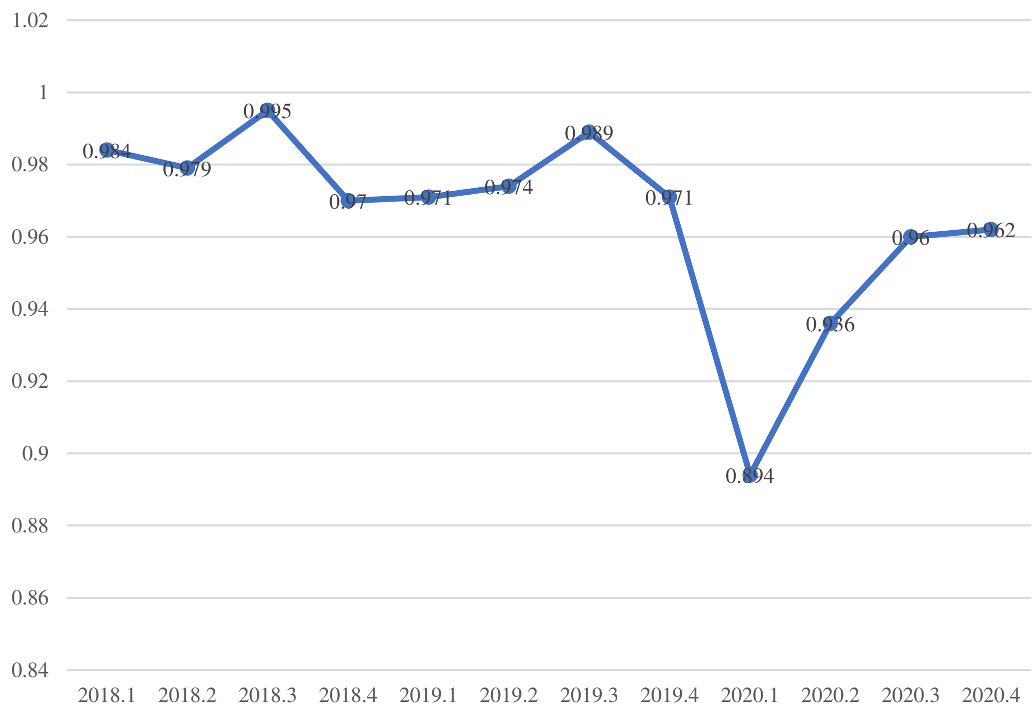


Figure 2 The average quarterly environmental efficiency of 14 airlines during 2018-2020

The quarterly efficiency is calculated to further research the efficiency of the passenger and freight subsystems. There are shared resources between passenger transport and freight transport systems. Among the input-output indicators selected in this paper, operating cost, operating revenue, and carbon dioxide emissions are all shared indicators. The 1st Opt software is run to carry out the general global optimization algorithm to get the optimal allocation ratio of these three indices. This algorithm does not need to provide an initial value. Then the EBM model is rerun to get the results listed in Table 7 and Table 8. Combined with the overall efficiency in Table 6 and the average efficiency in Figure 2, the quarterly average efficiency values show a "Nike swoosh"(√) type, namely the efficiencies after the first drop slowly rising, especially in the third and fourth quarters of 2020. The overall average efficiencies were 0.971, 0.894, 0.936, 0.960 and 0.962, meanwhile the passenger subsystem (0.942, 0.861, 0.889, 0.894, 0.870) and the freight subsystem (0.949, 0.873, 0.858, 0.926, 0.942). This gives us the inspiration for predicting the data during 2021-2022.

Table 7 Quarterly environmental efficiency of passenger subsystem with IEBM model during 2018-2020

| Airlines | 2018 | | | | 2019 | | | | 2020 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Aeroflot | 0.820 | 0.859 | 0.939 | 0.757 | 0.812 | 0.885 | 0.982 | 0.816 | 0.758 | 0.538 | 0.828 | 0.615 |
| Air China | 0.955 | 0.968 | 1.000 | 0.975 | 0.964 | 1.000 | 1.000 | 0.954 | 0.798 | 1.000 | 1.000 | 0.972 |
| All Nippon | 0.882 | 0.959 | 0.943 | 0.952 | 0.878 | 0.932 | 1.000 | 0.978 | 0.777 | 0.879 | 0.781 | 0.909 |
| Cathay Pacific | 0.995 | 0.995 | 1.000 | 0.997 | 1.000 | 1.000 | 0.989 | 0.989 | 1.000 | 0.887 | 1.000 | 0.969 |
| China Airlines | 1.000 | 0.854 | 0.850 | 0.839 | 0.901 | 0.904 | 0.921 | 0.914 | 1.000 | 1.000 | 0.898 | 0.871 |
| China Eastern | 1.000 | 1.000 | 1.000 | 0.945 | 0.993 | 0.975 | 1.000 | 0.952 | 0.777 | 0.720 | 0.866 | 0.824 |
| China Southern | 0.981 | 0.914 | 1.000 | 0.880 | 0.987 | 0.915 | 1.000 | 1.000 | 0.956 | 0.829 | 1.000 | 0.832 |
| Eva Air | 0.965 | 0.881 | 0.916 | 0.878 | 1.000 | 1.000 | 0.898 | 0.811 | 0.982 | 0.997 | 0.952 | 0.805 |
| Hainan | 1.000 | 0.986 | 1.000 | 0.933 | 1.000 | 1.000 | 1.000 | 0.913 | 0.879 | 0.809 | 0.945 | 1.000 |
| Juneyao | 0.993 | 0.982 | 1.000 | 0.941 | 0.983 | 0.972 | 0.967 | 0.962 | 0.820 | 0.925 | 1.000 | 0.973 |
| KLM Royal Dutch | 1.000 | 0.991 | 1.000 | 1.000 | 1.000 | 0.958 | 0.991 | 1.000 | 0.888 | 1.000 | 0.497 | 0.687 |
| Lufthansa | 0.898 | 0.905 | 1.000 | 1.000 | 0.878 | 0.950 | 0.913 | 0.993 | 0.813 | 1.000 | 0.754 | 0.772 |
| Singapore | 1.000 | 0.963 | 0.981 | 1.000 | 0.977 | 0.964 | 1.000 | 1.000 | 0.806 | 1.000 | 1.000 | 1.000 |
| Spring | 0.952 | 0.950 | 0.966 | 0.891 | 0.986 | 0.966 | 1.000 | 0.911 | 0.804 | 0.868 | 1.000 | 0.948 |
| *Min* | *0.882* | *0.854* | *0.850* | *0.839* | *0.878* | *0.904* | *0.898* | *0.811* | *0.777* | *0.720* | *0.497* | *0.687* |
| *Mean* | *0.960* | *0.943* | *0.971* | *0.928* | *0.954* | *0.959* | *0.976* | *0.942* | *0.861* | *0.889* | *0.894* | *0.870* |
| *Std* | *0.054* | *0.049* | *0.043* | *0.069* | *0.059* | *0.036* | *0.035* | *0.061* | *0.085* | *0.130* | *0.138* | *0.116* |

Table 8 Quarterly environmental efficiency of freight subsystem with IEBM model during 2018-2020

| Airlines | 2018 | | | | 2019 | | | | 2020 | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Aeroflot | 0.917 | 0.927 | 1.000 | 0.886 | 0.875 | 0.914 | 1.000 | 0.908 | 0.763 | 0.618 | 1.000 | 0.882 |
| Air China | 0.945 | 1.000 | 0.975 | 1.000 | 0.901 | 1.000 | 1.000 | 0.939 | 0.804 | 1.000 | 1.000 | 0.987 |
| All Nippon | 0.946 | 1.000 | 0.973 | 0.988 | 0.865 | 0.955 | 1.000 | 0.991 | 0.866 | 0.852 | 0.896 | 1.000 |
| Cathay Pacific | 0.996 | 1.000 | 1.000 | 0.999 | 1.000 | 0.998 | 0.988 | 1.000 | 1.000 | 1.000 | 1.000 | 0.998 |
| China Airlines | 0.769 | 0.879 | 0.916 | 0.883 | 0.953 | 0.917 | 0.932 | 0.881 | 1.000 | 0.917 | 0.901 | 0.910 |
| China Eastern | 0.992 | 1.000 | 1.000 | 0.883 | 0.974 | 0.978 | 1.000 | 0.983 | 0.780 | 0.702 | 0.881 | 0.849 |
| China Southern | 0.970 | 0.927 | 1.000 | 0.892 | 0.969 | 0.922 | 1.000 | 1.000 | 0.971 | 0.770 | 1.000 | 0.820 |

| | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Eva Air | 0.987 | 0.922 | 0.955 | 0.922 | 1.000 | 1.000 | 0.908 | 0.842 | 0.942 | 0.905 | 0.885 | 1.000 |
| Hainan | 0.996 | 1.000 | 1.000 | 0.968 | 1.000 | 1.000 | 0.990 | 0.887 | 0.912 | 0.857 | 0.930 | 1.000 |
| Juneyao | 0.994 | 0.993 | 1.000 | 0.947 | 0.973 | 0.962 | 0.957 | 0.957 | 0.851 | 0.877 | 1.000 | 1.000 |
| KLM Royal Dutch | 1.000 | 0.929 | 0.972 | 1.000 | 0.976 | 0.821 | 0.930 | 1.000 | 0.848 | 1.000 | 0.813 | 0.942 |
| Lufthansa | 0.959 | 0.929 | 1.000 | 1.000 | 0.883 | 0.916 | 0.898 | 0.983 | 0.842 | 0.791 | 0.814 | 0.847 |
| Singapore | 0.995 | 0.968 | 0.974 | 1.000 | 0.972 | 0.949 | 0.959 | 1.000 | 0.821 | 0.826 | 0.840 | 0.977 |
| Spring | 0.947 | 0.951 | 0.965 | 0.896 | 0.980 | 0.971 | 1.000 | 0.918 | 0.822 | 0.902 | 1.000 | 0.970 |
| *Min* | *0.769* | *0.879* | *0.916* | *0.883* | *0.865* | *0.821* | *0.898* | *0.842* | *0.763* | *0.618* | *0.813* | *0.820* |
| *Mean* | *0.958* | *0.959* | *0.981* | *0.947* | *0.952* | *0.950* | *0.969* | *0.949* | *0.873* | *0.858* | *0.926* | *0.942* |
| *Std* | *0.058* | *0.039* | *0.024* | *0.049* | *0.047* | *0.048* | *0.036* | *0.052* | *0.076* | *0.108* | *0.071* | *0.064* |

In the five quarters after the outbreak of COVID-19, the average efficiency of the freight subsystem (0.949, 0.873, 0.858, 0.926, 0.942) mainly was higher than that of the passenger subsystem (0.942, 0.861, 0.889, 0.894, 0.870). During the seven quarters of 2018-2019, the average efficiency values of the passenger and freight subsystems were 0.956 and 0.959, respectively, and then changed to 0.891 and 0.910 during the COVID-19 outbreak. This shows that COVID-19 has more influence on the passenger subsystem, and the efficiency gap between passenger and freight has become significant. Efficiency average minimums (0.698, 0.771) and standard deviations (0.106, 0.074) of them can also confirm this finding.

As the benchmark airline, Cathay Pacific Airways performed well in both passenger and cargo subsystems. The efficiency values of the five quarters were (0.989, 1.000, 0.887, 1.000, 0.969) and (0.989, 1.000, 0.887, 1.000, 0.969) respectively. This proves that only when all subsystems are effective can the whole be effective in the DEA model. Singapore Airlines' efficiency values were also outstanding, which were (1.000, 0.806, 1.000, 1.000, 1.000) and (1.000, 0.821, 0.826, 0.840, 0.977). The contribution of the passenger system in Singapore Airlines is more prominent. This shows that the capacity of most airlines' cargo systems increased during COVID-19, but not exclusively.

Airlines can find room for improvement based on efficiency values and learn from benchmark airlines so that they can recover quickly in the post-pandemic period. In particular, some subsystem efficiency of airlines is extreme, such as Aeroflot passenger efficiency (0.538) and freight efficiency (0.618) in Q2 2020, KLM Royal Dutch passenger efficiency (0.497) in Q3 2020. An almost complete suspension of flights in April and May 2020 and the expenses on keeping the grounded fleet airworthy are the reason for Aeroflot. On the other hand, the leading cause of KLM Royal Dutch is the reduction in load factors for long-distance operations. Therefore, the slack value in the model is more specific and targeted, directly from the input and output indices.

Table 9 The predicted and actual values of environmental efficiency in the first quarter of 2021

| Airlines | Predicted | Actual |
|---|---|---|
| Aeroflot | [1.000, 1.000] | 0.990 |
| Air China | [0.878, 0.880] | 0.878 |
| All Nippon | [1.000, 1.000] | 0.803 |
| Cathay Pacific | [1.000, 1.000] | 1.000 |
| China Airlines | [0.851, 0.856] | 1.000 |

| | | |
|---|---|---|
| China Eastern | [0.882, 0.884] | 0.827 |
| China Southern | [1.000, 1.000] | 0.877 |
| Eva Air | [1.000, 1.000] | 1.000 |
| Hainan | [0.962, 0.966] | 1.000 |
| Juneyao | [0.912, 0.912] | 0.963 |
| KLM Royal Dutch | [1.000, 1.000] | 0.896 |
| Lufthansa | [0.999, 1.000] | 1.000 |
| Singapore | [1.000, 1.000] | 0.896 |
| Spring | [0.896, 0.899] | 1.000 |
| *Mean* | [0.956, 0.957] | 0.938 |

Table 10 Overall quarterly environmental efficiency of IEBM model during 2021-2022

| Airlines | 2021 | | | 2022 | | | |
|---|---|---|---|---|---|---|---|
| | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Aeroflot | [0.797, 0.900] | [0.790, 0.902] | [0.896, 0.944] | [0.934, 1.000] | [0.998, 1.000] | [0.990, 1.000] | [1.000, 1.000] |
| Air China | [0.932, 0.962] | [0.932, 0.976] | [0.946, 1.000] | [0.938, 1.000] | [0.926, 0.999] | [0.959, 0.998] | [0.955, 0.996] |
| All Nippon | [0.912, 0.922] | [0.911, 0.979] | [0.909, 1.000] | [0.909, 0.916] | [0.917, 1.000] | [0.921, 0.991] | [0.924, 0.983] |
| Cathay Pacific | [0.993, 1.000] | [0.990, 0.994] | [0.992, 1.000] | [0.906, 1.000] | [0.907, 1.000] | [0.914, 0.996] | [0.911, 0.995] |
| China Airlines | [1.000, 1.000] | [0.934, 0.976] | [0.989, 1.000] | [1.000, 1.000] | [0.972, 1.000] | [0.943, 1.000] | [0.917, 1.000] |
| China Eastern | [0.855, 0.877] | [0.839, 0.868] | [0.822, 0.861] | [0.854, 0.859] | [0.866, 0.870] | [0.874, 0.874] | [0.881, 0.882] |
| China Southern | [0.929, 0.938] | [0.930, 0.941] | [0.931, 0.946] | [0.913, 0.932] | [0.916, 0.943] | [0.919, 0.920] | [0.923, 0.923] |
| Eva Air | [0.938, 1.000] | [0.951, 0.952] | [0.971, 1.000] | [1.000, 1.000] | [0.999, 1.000] | [0.999, 1.000] | [1.000, 1.000] |
| Hainan | [0.908, 0.915] | [0.900, 0.950] | [0.893, 1.000] | [0.887, 0.906] | [0.909, 0.983] | [0.915, 0.963] | [0.922, 0.965] |
| Juneyao | [0.925, 0.940] | [0.924, 0.949] | [0.922, 1.000] | [0.927, 0.939] | [0.944, 0.947] | [0.935, 0.943] | [0.940, 0.948] |
| KLM Royal Dutch | [0.948, 0.960] | [0.971, 0.972] | [0.984, 1.000] | [0.954, 1.000] | [0.938, 0.996] | [0.923, 0.984] | [0.908, 0.974] |
| Lufthansa | [0.924, 0.937] | [0.915, 0.942] | [0.948, 1.000] | [0.957, 0.982] | [0.970, 0.987] | [0.951, 1.000] | [0.938, 0.965] |
| Singapore | [0.985, 1.000] | [0.990, 1.000] | [0.994, 1.000] | [0.816, 1.000] | [0.830, 0.970] | [0.848, 0.966] | [0.865, 0.961] |
| Spring | [0.922, 0.933] | [0.923, 0.970] | [0.946, 1.000] | [0.901, 0.974] | [0.904, 0.942] | [0.941, 1.000] | [0.943, 1.000] |
| *Mean* | [0.926, 0.949] | [0.921, 0.955] | [0.939, 0.982] | [0.921, 0.965] | [0.928, 0.974] | [0.931, 0.974] | [0.931, 0.971] |

Table 11 Quarterly environmental efficiency of passenger subsystem with IEBM model during 2021-2022

| Airlines | 2021 | | | 2022 | | | |
|---|---|---|---|---|---|---|---|
| | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Aeroflot | [0.658, 0.906] | [0.655, 0.908] | [0.714, 0.920] | [0.931, 1.000] | [1.000, 1.000] | [0.999, 1.000] | [1.000, 1.000] |
| Air China | [0.958, 0.983] | [0.978, 0.988] | [0.994, 1.000] | [1.000, 1.000] | [0.986, 1.000] | [0.987, 0.998] | [0.982, 0.996] |
| All Nippon | [0.797, 0.840] | [0.782, 0.832] | [0.825, 0.843] | [0.817, 0.825] | [0.811, 0.833] | [0.819, 0.841] | [0.826, 0.849] |
| Cathay Pacific | [0.992, 1.000] | [0.958, 0.994] | [0.978, 0.997] | [0.919, 1.000] | [0.928, 1.000] | [0.923, 0.997] | [0.931, 0.995] |
| China Airlines | [0.897, 1.000] | [0.913, 0.926] | [0.907, 1.000] | [0.830, 0.910] | [0.796, 0.998] | [0.766, 1.000] | [0.740, 1.000] |
| China Eastern | [0.746, 0.997] | [0.710, 0.992] | [0.670, 0.997] | [0.664, 1.000] | [0.683, 0.978] | [0.702, 0.946] | [0.721, 0.955] |
| China Southern | [0.825, 0.956] | [0.806, 0.965] | [0.785, 0.977] | [0.879, 0.988] | [0.881, 1.000] | [0.882, 0.966] | [0.884, 0.967] |
| Eva Air | [0.953, 1.000] | [0.763, 0.954] | [0.736, 0.979] | [0.930, 0.985] | [0.916, 0.919] | [0.903, 0.912] | [0.904, 0.909] |
| Hainan | [0.911, 0.929] | [0.936, 0.948] | [0.954, 1.000] | [0.898, 0.996] | [0.898, 1.000] | [0.904, 0.944] | [0.910, 0.945] |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Juneyao | [0.906, 0.980] | [0.919, 0.983] | [0.937, 0.991] | [0.933, 1.000] | [0.928, 1.000] | [0.923, 0.993] | [0.920, 0.987] |
| KLM Royal Dutch | [0.537, 0.939] | [0.434, 0.940] | [0.834, 0.937] | [0.691, 0.938] | [0.708, 0.907] | [0.728, 0.910] | [0.744, 0.912] |
| Lufthansa | [0.787, 0.949] | [0.888, 0.954] | [0.960, 1.000] | [0.968, 0.969] | [0.968, 0.972] | [0.961, 0.988] | [0.938, 0.953] |
| Singapore | [0.963, 1.000] | [0.968, 1.000] | [0.974, 1.000] | [0.784, 0.981] | [0.806, 0.982] | [0.827, 0.974] | [0.847, 0.967] |
| Spring | [0.909, 0.988] | [0.952, 0.998] | [0.979, 0.998] | [0.878, 1.000] | [0.885, 0.991] | [0.989, 1.000] | [0.989, 1.000] |
| *Mean* | [0.860, 0.948] | [0.837, 0.952] | [0.891, 0.958] | [0.871, 0.965] | [0.874, 0.967] | [0.885, 0.956] | [0.885, 0.956] |

Table 12 Quarterly environmental efficiency of freight subsystem with IEBM model during 2021-2022

| Airlines | 2021 | | | 2022 | | | |
|---|---|---|---|---|---|---|---|
| | Q2 | Q3 | Q4 | Q1 | Q2 | Q3 | Q4 |
| Aeroflot | [0.802, 0.921] | [0.795, 0.926] | [0.898, 1.000] | [0.882, 1.000] | [0.959, 1.000] | [0.944, 0.983] | [0.945, 1.000] |
| Air China | [0.937, 0.960] | [0.955, 0.966] | [1.000, 1.000] | [0.922, 1.000] | [0.924, 0.935] | [0.926, 0.947] | [0.951, 0.929] |
| All Nippon | [0.906, 0.915] | [0.918, 0.929] | [0.922, 0.955] | [0.909, 0.928] | [0.910, 1.000] | [0.913, 0.987] | [0.914, 0.977] |
| Cathay Pacific | [0.659, 0.894] | [0.903, 0.959] | [0.914, 0.969] | [0.916, 0.929] | [0.906, 0.970] | [0.913, 0.940] | [0.918, 0.928] |
| China Airlines | [0.883, 0.897] | [0.908, 0.943] | [0.936, 1.000] | [0.956, 1.000] | [0.922, 1.000] | [0.891, 0.991] | [0.878, 0.986] |
| China Eastern | [0.772, 0.987] | [0.746, 0.979] | [0.718, 0.984] | [0.799, 0.991] | [0.810, 1.000] | [0.820, 0.964] | [0.831, 0.964] |
| China Southern | [0.836, 0.971] | [0.827, 0.973] | [0.836, 0.984] | [0.844, 1.000] | [0.853, 1.000] | [0.861, 0.972] | [0.869, 0.973] |
| Eva Air | [0.884, 0.967] | [0.925, 0.972] | [0.989, 1.000] | [1.000, 1.000] | [0.999, 1.000] | [0.993, 0.999] | [1.000, 1.000] |
| Hainan | [0.887, 0.934] | [0.932, 0.932] | [0.956, 1.000] | [0.855, 0.982] | [0.859, 0.980] | [0.867, 0.958] | [0.874, 0.942] |
| Juneyao | [0.932, 0.975] | [0.920, 0.989] | [0.970, 0.985] | [0.914, 1.000] | [0.943, 0.992] | [0.924, 0.968] | [0.917, 0.955] |
| KLM Royal Dutch | [0.895, 0.936] | [0.927, 0.963] | [0.964, 1.000] | [0.937, 1.000] | [0.885, 0.922] | [0.857, 0.907] | [0.832, 0.894] |
| Lufthansa | [0.745, 0.802] | [0.764, 0.868] | [0.784, 1.000] | [0.794, 1.000] | [0.804, 0.818] | [0.770, 0.815] | [0.753, 0.825] |
| Singapore | [0.809, 0.814] | [0.830, 0.969] | [0.854, 1.000] | [0.730, 0.875] | [0.744, 0.807] | [0.760, 0.786] | [0.767, 0.775] |
| Spring | [0.929, 0.995] | [0.989, 0.962] | [0.994, 1.000] | [0.894, 1.000] | [0.905, 0.986] | [0.981, 1.000] | [0.988, 1.000] |
| *Mean* | [0.856, 0.918] | [0.907, 0.927] | [0.909, 0.991] | [0.883, 0.964] | [0.893, 0.952] | [0.898, 0.933] | [0.902, 0.926] |

Table 13 The quarterly average environmental efficiency and subsystem efficiency of airlines during 2021-2022

| Airlines | passenger | freight | overall |
|---|---|---|---|
| Aeroflot | [0.838, 0.958] | [0.920, 0.962] | [0.926, 0.968] |
| Air China | [0.965, 0.990] | [0.932, 0.970] | [0.933, 0.976] |
| All Nippon | [0.817, 0.832] | [0.921, 0.960] | [0.925, 0.974] |
| Cathay Pacific | [0.988, 0.990] | [0.900, 0.940] | [0.952, 0.998] |
| China Airlines | [0.951, 0.926] | [0.906, 0.954] | [0.951, 0.979] |
| China Eastern | [0.843, 0.981] | [0.784, 0.982] | [0.859, 0.872] |
| China Southern | [0.889, 0.977] | [0.851, 0.984] | [0.933, 0.943] |
| Eva Air | [0.901, 0.948] | [0.968, 0.984] | [0.982, 0.994] |
| Hainan | [0.957, 0.959] | [0.899, 0.966] | [0.912, 0.956] |
| Juneyao | [0.955, 0.992] | [0.929, 0.983] | [0.929, 0.947] |
| KLM Royal Dutch | [0.773, 0.909] | [0.940, 0.925] | [0.953, 0.986] |
| Lufthansa | [0.923, 0.943] | [0.820, 0.821] | [0.950, 0.977] |
| Singapore | [0.965, 0.926] | [0.831, 0.859] | [0.916, 0.987] |
| Spring | [0.961, 0.994] | [0.946, 0.992] | [0.922, 0.965] |

| | | | |
|---|---|---|---|
| average | [0.909, 0.952] | [0.896, 0.949] | [0.932, 0.966] |

Models (12) - (14) are applied to calculate the overall environmental efficiency value and subsystem environmental efficiency value of 14 airlines with the forecast interval data from 2021 to 2022. Since 14 airlines successively released reports for the first quarter of 2021 during the empirical process, the operational data is collected to calculate the actual efficiency and compared it with the predicted value. As shown in Table 9, the expected efficiency value is not much different from the real value, which illustrates the feasibility of the prediction method in this paper.

The results are shown in Tables 10, 11, and 12. The two-year average total and subsystem efficiencies of the 14 airlines are shown in Table 13. Except for China Eastern Airlines, the average efficiency values of other airlines are all higher than 0.900, which indicates that the operating conditions of airlines will slowly improve in the future. Combined with the average quarterly efficiencies in Table 7, the efficiency values gradually increase, from [0.956, 0.957] in Q1 2021 to [0.931, 0.971] in Q4 2022. Among them, the change of passenger traffic is from [0.840, 0.913] to [0.885, 0.956], and the change of freight traffic is from [0.922, 0.978] to [0.902, 0.926]. The efficiency of the freight subsystem decreases, which is inevitable during the recovery phase after the surge in 2020.

Only each subsystem is efficient; the overall efficiency can be efficient. However, the chance of that happening is meager. None of the airlines in Table 13 is completely efficient; the upper and lower efficiency are both 1. From the point of a lower bound, airlines with high efficiency are Eva Air, Cathay Pacific, China Airlines, KLM Royal Dutch, and Lufthansa. Then from the upper bound, Air China, Cathay Pacific, China Airlines, Eva Air, KLM Royal Dutch, Singapore, and Lufthansa are relatively efficient. The predicted upper-efficiency value Cathay Pacific is the largest (0.998), but its lower value (0.952) is less than Eva Air (0.982). After analyzing the importance of the subsystem, it can be found that the low efficiency of freight (0.900) leads to inefficiency in the end. This shows that when Cathay Pacific Airways recovers in the future, the cargo system will have more oversized slacks and a broader space for revenue generation. Unlike Cathay Pacific, Eva Air's high efficiency is mainly due to the cargo subsystem [0.968, 0.984]. China Eastern Airlines has the lowest efficiency value [0.859, 0.872], which needs to take positive measures when facing a complex and severe external situation.

European airlines' recovery situation is better in regional terms, such as Aeroflot, KLM Royal Dutch, and Lufthansa. The average efficiency value on the low bound of the three airlines is 0.943, 0.011 higher than the overall average value. And the upper average efficiency is 0.977, also higher than the overall average of 0.011. The good development trend of Aeroflot Airlines lies in the formulation of targeted strategic decisions. The Aeroflot develops short-term plans (including the 2021 budget) and approves medium-term network and fleet plans. The airline received 4 B737 aircraft from Rossiya Airline in 2020 and 10 SSJ-100 aircraft for fleet renewal. Meanwhile, it develops intergroup cooperation and prepares the code-share agreements. In addition to their own efforts, KLM Royal Dutch and Lufthansa also support the European Union.

Chinese airlines (Air China, China Airlines, China Eastern, China Southern, Hainan, Juneyao, and Spring) do not perform well. Their average overall efficiency on the low bound is 0.920, and the upper value is 0.948, both lower than the overall average efficiency (0.932, 0.966). However, observing the interval efficiency value of their subsystems, it can be found that the efficiency score of freight transportation is relatively low, indicating that Chinese airlines still have a lot of room for progress in freight service.

## 6. Conclusions

In the short and medium-term, the COVID-19 outbreak will lead to a significant decline in passenger and cargo volume and economic benefits of airlines. In the medium and long term, it will profoundly impact the operation strategy, passenger and cargo source structure, and market competition mode. This paper proposes a novel interval EBM model to study the impact of COVID-19 on airline environmental efficiency and the future recovery trend of airlines. First, the airline operation is divided into two parallel subsystems -- passenger and cargo, and select inputs and outputs: Operating Costs, Available Seat Kilometers, Available Tonne Kilometers, Operating Revenue, Revenue Passenger Kilometers, Revenue Tonne Kilometers, and Carbon dioxide emission. Then 1st Opt software is used to determine the optimal allocation ratio of shared resources and apply grey prediction theory to predict the input-output interval data of 14 airlines. Finally, the overall and subsystem efficiencies are obtained by the IEBM model.

The main contributions of this paper are as follows. First, this is the first paper to discuss the impact of the COVID-19 on global airlines from the perspective of quarterly efficiency and interval data. This greatly improves the accuracy of the evaluation. Second, the proposed Interval EBM model overcomes the shortcomings of the traditional DEA models and combines the radial and non-radial models to evaluate the internal structure of the decision-making units. Third, use strong disposability to deal with the undesirable output; the result is more reasonable.

This paper draws some interesting conclusions. First, the impact of the COVID-19 on airline passenger transportation is more significant than that on freight transportation. In the post-epidemic era, the efficiency of the freight subsystem will decline. Second, Cathay Pacific and EVA Air performed well and became the benchmark airlines, while China Eastern Airlines has the lowest efficiency value among the 14 airlines. Third, the airline's recovery curve is in a "√" shape, and operating conditions will gradually improve during 2021-2022. Fourth, European airlines are more efficient, and Chinese airlines still need to pay more attention to the cargo subsystem.

The types of airlines (full-service carrier or low-cost carrier) should be considered in future research. Because different types of airlines have different operation strategies, and this is worthy of in-depth study. Combined with the Malmquist production index, the efficiency differences between different regions can be explored. In addition to the leading passenger and freight subsystems, other departments can finally serve as the third possibility. Finally, our model does not consider intermediate output, which is also a point that can be discussed later.

## Conflict of interest

The authors have no conflict of interest.

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## Author contributions

Ye Li and Qiang Cui designed the study. Qiang Cui. and Xingchun Huang performed the analysis and prepared the manuscript. Xingchun Huang complied the original data. All authors participated in the writing of the manuscript.

## Data availability

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

## Ethics approval

The authors whose names are listed immediately below certify that they have no affiliations with or involvement in any organization or entity with any financial interest or nonfinancial interest in the subject matter or materials discussed in this manuscript.

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## Consent to participate

We voluntarily agree to participate in this research study.

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## Competing interests

The authors declare that they have no competing interests.

## Consent to Publish

Not applicable.

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