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Performance Evaluation of Major Asian Airline Companies Using DEA Window Model and Grey Theory

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Abstract: Being an essential part of the global transport system, airline transportation is capable of delivering fast service for passengers and commodities. In the past decade, the Asia aviation industry has experienced a high growth rate of transport due to higher economic development in this area, and this trend is expected to continue in the next two decades. However, competition in the Asia aviation industry will increase dramatically. To survive in the Asia aviation industry, the Asia airline companies should understand their current and future performance. A methodology for this purpose is required. This paper proposes a hybrid approach, combining Grey model GM(1,1) and Data Envelopment Analysis (DEA) Window model, to satisfy this need. The hybrid approach proposed in this research has been used to evaluate the current and future performance of 16 major Asia airline companies. The DEA Window analysis showed that airline companies Emirates, Cebu Pacific, and Sri Lankan were leading companies in the time period of 2012 to 2016, while Singapore Airlines, Japan Airlines, and All Nippon Airways followed behind. We found that Chinese airline corporations are rising in the Asia aviation industry. All 16 Asia airline companies studied in the research were found to improve their productivity in the time period of 2017 to 2021 as their Malmquist productivity indexes (MPIs) are greater than 1.

Keywords: data envelopment analysis; DEA Window model; GM(1,1); Malmquist; aviation

1. Introduction

The aviation business has a prosperous future due to increasing transports of travelers and commodities. The aviation industry has generated numerous jobs and contributed substantial economic growth for many countries. Pointed out by the CEO of IATA (the International Air Transport Association), 58 million jobs and 2400 billion US dollars of revenue have been generated for the aviation industry [1].

In addition, air transport also helps cross-country exchanges, including cultural exchanges. Combinations with other transport means, such as water and land, can lead to greater benefit and convenience for customers. The development of airline transport is unstoppable.

The Asia airline industry has experienced incredible growth in the last decade. In 2015, the Asian airline industry had achieved a positive cash flow since 2010, and there are 230 Asian airline companies that together own 27% of all planes worldwide [2]. In 2016, Asian aviation generated a $7.3 billion net profit and demand growth was expected to be 9.2%, a figure much higher than supply growth of 8.1%. In 2016, the load factor hit a record high, standing at 80%, while the operational expenses were

reduced due to lower fuel price and increased productivity. Asia was expected to have the highest traveling traffic, with an annual growth rate of ~5.7%. In 2036, passenger traffic was expected to be 40% of global passenger traffic [3].

Figure 1 shows the potential average growth rate for the Asia aviation industry from 2016 to 2020. Rapid population growth, high economic development, and low-cost travel are considered to be the three factors driving the growth for the Asia aviation industry. Compared with other continents, Asia is expected to have a higher population growth rate and 65% of its population is 2035 will be middle class [4]. In the next two decades, the expected average annual GDP growth rate in Asia is ~3.9%, which contributes ~33–40% to the world GDP until 2036 [3]. Low-priced tourism is another factor driving the growth of Asia airline aviation, which can become a long-term development focus for the Asia aviation industry [5].
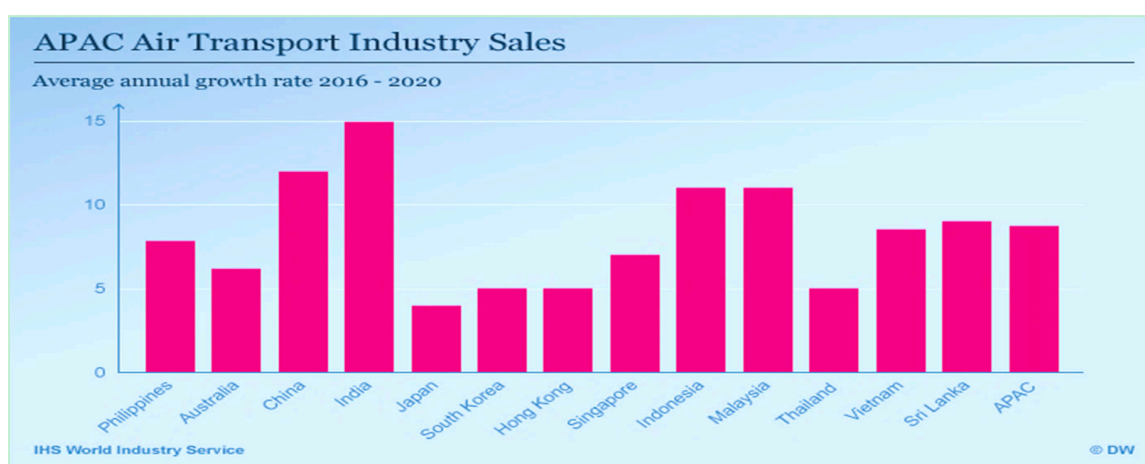

Figure 1. Average annual growth rate of Asia aviation industry for the time period of 2016 to 2020. **Sources:** http://www.dw.com.

With a prosperous future, competition between airline companies in Asia is expected to increase. To better survive in the Asia airline industry, airline companies have to understand their past, current, and future performance compared with other competitors. For this purpose, a methodology for assessing their performance is required. In this research, a hybrid approach, combining the GM(1,1) model with the Data Envelop Analysis (DEA) Window model, is thus proposed for assessing the performance of Asia airline companies that are termed as decision making units (DMUs) in the DEA approach. From our literature review we found that there are more than 1000 DEA studies in the database of Web of Sciences. However, few of them have focused on the aviation industry and none of them have combined forecasting models to predict future performance for Asia airline companies. This lack has attracted our attention. The proposed approach has also been successfully applied to assess the current as well as future performance of 16 selected Asia airline companies. The main results have been summarized in the conclusion section.

The rest part of this article is organized as follows. Section 2 has a literature review. Section 3 addresses the methodology. Section 4 details the empirical study. Section 5 makes a conclusion and suggests future research direction.

2. Literature Review

2.1. Data Envelopment Analysis

Data envelopment analysis (DEA) is a linear programming (LP)-based technique that can be applied for measuring the relative performance of DMUs. This technique has been used in many areas, such as banking, insurance, education, and medical. Relevant studies applying DEA in the aviation industry are reviewed in this research. Distexhe and Perelman [6] used the DEA model and Malmquist

productivity index to estimate the technological efficiency and productivity growth for 34 aviation companies for the time period of 1977 to 1988. Barbot et al. [7] used DEA and total factor productivity to examine the efficiency of US airline firms and the factors affecting efficiency change. Having determined the input and output variables, Barros and Peypoch [8] proposed an inventive two-stage DEA model for the assessment of operational efficiency of the European Airlines for the time period of 2000 to 2005. The Merkert and Hensher [9] used a two-stage DEA methodology to evaluate the efficiency of 58 passenger airlines companies. Partially bootstrapped random effects Tobit regression was employed in the second stage to evaluate key determinants affecting the airlines performance. Assaf and Josiassen [10] proposed a DEA bootstrap technique to evaluate the efficiency of UK airlines. Arjomandi and Seufert [11] also employed the bootstrapped DEA models, with variable returns to scale, to evaluate environmental and technical efficiencies of largest airlines in the world. Lee and Worthington [12] employed a two-stage DEA approach to evaluate the operational efficiency between private-owned airlines and traditional airlines in Europe. Lozano and Gutierrez (2014) [13] used a slacks-based network DEA to evaluate the efficiency of European airlines. Mallikarjun [14] applied the unoriented DEA network methodology to measure US airlines' performance relative to that of peer airlines, in addition to identifying the sources of inefficiency. Tavassoli et al. [15] proposed a novel slacks-based measure network DEA (SBM-NDEA) to analyze both technical efficiency and service effectiveness of Iranian airlines in 2010. However, there is still a lack of evaluation on Asia airline companies. In addition, the combination of forecasting models to predicate their further performance is also not available.

2.2. Grey Forecasting

Proposed by Deng [16], Grey system theory is able to handle systems with ambiguity [17]. One branch of Grey system theory is Grey forecasting, which uses Grey models for prediction. Various Grey forecasting models have been proposed for different applications. These studies are introduced as follows. Hsu [18] used an innovative Grey model algorithm ITGM(1,1) to evaluate the performance for the time period of 1990 to 2008 for Taiwan optic-electronics industry. Compared with other forecasting models, including GM(1,1), rolling GM(1,1), and transformed GM(1,1), the ITGM(1,1) had better performance. In that study, mean absolute percentage error (MAPE) and root mean square percentage error (RMSPE) were used to evaluate the performance of these different approaches. Chen and Wang [19] proposed a new version, upgraded GM(1,1), to predict the global future need on energy and assess the energy engineering management. Hamzacebi and Es [20] proposed anther version, optimized Grey GM(1,1), to forecast the future need on electric energy for Turkey in the time period 2013–2025. In another study, Shaikh et al. [21] employed two optimized nonlinear grey models, the Grey Verhulst Model and the Nonlinear Grey Bernoulli Model, to predicate the future need on natural gas for China. As the grey model GM(1,1) is simple, efficient, and only dependent on few data [22], this kind of forecasting model is used in this research.

3. Methodology

This research includes two kinds of methodologies: GM(1,1) and DEA Window models. In addition, measurements, such as the Malmquist Productivity Index (MPI), Efficiency Change Index, and Technological Change Index, were used as evaluation measurements. In the GM(1,1) model, it needs to select DMUs, input, and output variables, which are detailed in this section.

3.1. The Selection of DMUs

Selecting DMUs is the first step when using DEA approach. However, when doing this there were some difficulties: One is that few airline companies have released their annual financial reports on their websites regularly. Another is that some firms are subsidiaries of a controlling company so that their financial reports are consolidated with the controlling company. For example, Scoot and Tiger Airways are subsidiaries of Budget Aviation Holdings established by Singapore Airlines. In addition,

Singapore Airlines holds Sri Lankan Airlines. As a result, the business results of these companies were consolidated together.

After careful consideration, 16 airline companies (DMUs) listed in the website of Skytrax in 2017 were selected as DMUs in this research. The reason of selecting these airline companies is due to their importance in the Asia aviation industry and the availability of their financial data. The 16 airline companies are listed in Table 1 and each company is assigned with a DMU code.

Table 1. List of 16 airline companies (DMUs).

No	Airline Company	Country	DMU Code
1	Emirates	United Arab Emirates	DMU
2	Thai Airways	Thailand	DMU2
3	Cathay Pacific Group	Hong Kong	DMU3
4	Jet Airways	India	DMU4
5	Air China	China	DMU5
6	China Southern Airlines	China	DMU6
7	China Eastern Airlines	China	DMU7
8	All Nippon Airways	Japan	DMU8
9	Cebu Pacific	Philippines	DMU9
10	Japan Airlines	Japan	DMU10
11	Eva Air	Taiwan	DMU11
12	China Airlines	Taiwan	DMU12
13	Oman Air	Oman	DMU13
14	Sri Lankan Airlines	Sri Lankan	DMU14
15	Garuda Indonesia Airways	Indonesia	DMU15
16	Singapore Airlines	Singapore	DMU16

3.2. The Selection of Inputs and Outputs Variables

Selecting the input and output variables is the second step for DEA approach. This step is important as the selected variables can affect the evaluation results. To determine these variables, some relevant studies with DEA approaches for the aviation industry have been referred. The input and output variables used in these researches are listed in Table 2.

Table 2. Input and output variables used in previous researches.

Previous Researches	Input Variable	Output Variable
Fethi et al. [23]	ATK (available tone kilometer), operating cost Nonflight assets	RPK (revenue passenger kilometer), Non passenger revenue
Rashmi, M. [24]	Operating cost as percentage of revenue Fixed assets turnover ratio	Passenger Load Factor
Gramani, M.C. [25]	Aircraft Fuel, Wages Salaries Benefits Cost per available seatmate	Flight Revenue Flight Income
Barbot et al. [7]	Labor (number of core business workers) Fleet (number of operating aircraft) Fuel (in gallons consumed)	ASK (available seat kilometer) RPK (revenue passenger kilometer) RTK (revenue ton kilometers)
Żółtaszek & Pisarek [26]	Fleet Number of employee Number of destinations	Total revenue Number of passenger Load factor
Lee & Worthington [27]	ATK Operating cost Nonflight assets	RPK Non passenger revenue

Table 2. *Cont.*

Previous Researches	Input Variable	Output Variable
Jain & Natarajan (2015) [28]	Total Available ton kilometer (ATKM) Operating cost	RPK Non Passenger revenue
Assaf & Josiassen [10]	Staff number Total Assets Fuel Operating expenses	RPK Incidental revenues
Merkert and Williams [29]	ASK FTE	RPK Realized Departures

Referring to Table 2, the "Fleet", "Total Assets", and "Operating Expenses" are selected as input variables and the "Revenue Passenger Kilometers (RPKs)" and "Available Set Kilometers (ASKs)" are selected as output variables as they have been widely used in past studies. These input and output variables are defined as follows:

- Total Assets: This input variable refers to the sum of all cash, investments, furniture, fixtures, equipment, receivables, intangibles, and any other items of value owned by a person or a business entity.
- Operating expenses: This input variable refers to expenses required to carry out an organization's day-to-day activities. Relevant items include payroll, sales commissions, employee benefits and pension contributions, transportation and travel, amortization and depreciation, rent, repairs, and taxes. These items are not directly associated with production.
- Fleet: Refers to the number of operating airplanes of an airline company.
- Available seat kilometers (ASKs): This output variable refers to the number of seats available for sale multiplied by the kilometers flown.
- Revenue passenger kilometers (RPKs): This output variable is calculated by multiplying the number of revenue-paying passengers aboard the planes by the distance traveled.

Whether these selected variables are suitable for evaluating the selected DMUs is a question that can be answered by using Equation (1), which is used to calculate Pearson correlation coefficient.

$$r = \frac{\sum XY - \frac{(\sum X)(\sum Y)}{n}}{\sqrt{\left(\sum X^2 - \frac{(\sum X)^2}{n}\right)\left(\sum Y^2 - \frac{(\sum Y)^2}{n}\right)}} \tag{1}$$

The Pearson correlation coefficient is one of the best statistical tests for measuring the correlation between two variables. Information about the magnitude of correlation as well as the direction of the relationship can be generated. The degrees of correlation are specified as follows; if the Pearson correlation coefficient is >0.8 then the degree of correlation is considered extremely high; if the Pearson correlation coefficient is between 0.6 and 0.8 then the degree of correlation is considered high; if the Pearson correlation coefficient is between 0.4 and 0.6 then the degree of correlation is considered medium; if the Pearson correlation coefficient is between 0.2 and 0.4 then the degree of correlation is considered low; and if the Pearson correlation coefficient is <0.2 then the degree of correlation is considered extremely low.

3.3. Malmquist Productivity Index

The Malmquist productivity index (MPI), which is the product of catch-up and frontier-shift, is defined as follows. It uses distance functions to measure productivity change.

$$MPI = (\text{Catch} - \text{up effect}) \times (\text{Frontier} - \text{shift effect}) = C \times F \tag{2}$$

where the catch-up effect is defined in Equation (3)

$$C = \frac{\delta^2\big((x_0, y_0)^2\big)}{\delta^1\big((x_0, y_0)^1\big)} \tag{3}$$

The frontier-shift effect is defined in Equation (4)

$$F = \left[\frac{\delta^1\big((x_0, y_0)^1\big)}{\delta^1\big((x_0, y_0)^1\big)} \times \frac{\delta^2\big((x_0, y_0)^2\big)}{\delta^2\big((x_0, y_0)^2\big)}\right]^{1/2} \tag{4}$$

The MPI is useful for determining the overall productivity change of a DMU. If *MPI* > 1, it indicates the improvement of productivity of a DMU; otherwise, there is no change or even regression. The "catch-up effect" (*C*), also known as the efficiency change index, can indicate the degree of efficiency change of a DMU. If *C* > 1, it indicates an improvement of a DMU; otherwise, no change or even regression. The "frontier-shift effect" (*F*) is known as the technological change index, and can indicate the degree of technological change. If *F* > 1, it indicates an improvement of a DMU; otherwise, no improvement or even regression.

3.4. DEA Window Model

The DEA Window model is a nonparametric approach. If DMU_n ($n = 1, 2, 3, \ldots, N$; where N is the total number of DMUs) denotes the nth DMU that uses m inputs to produce s outputs. Let DMU_n^t denote the nth DMU in the time period t ($t = 1, 2, 3, \ldots, T$), then the input and output vectors of the DMU_n^t are denoted as X_n^t and Y_n^t and are represented as Equations (5) and (6), respectively:

$$X_n^t = \begin{bmatrix} x_n^{1t} \\ \vdots \\ x_n^{mt} \end{bmatrix} \tag{5}$$

and

$$Y_n^t = \begin{bmatrix} y_n^{1t} \\ \vdots \\ y_n^{st} \end{bmatrix} \tag{6}$$

Consider that the window starts at the time point k ($1 \leq k \leq T$) and the window width is w ($1 \leq w \leq T - k$), then the input (X_{kw}) and output (Y_{kw}) matrix of each window (kw) are presented by Equations (7) and (8), respectively:

$$X_{kw} = \begin{bmatrix} x_1^k & x_2^k & \cdots & x_N^k \\ x_1^{k+1} & x_2^{k+1} & \cdots & x_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ x_1^{k+w} & x_2^{k+w} & \cdots & x_N^{k+w} \end{bmatrix} \tag{7}$$

and

$$Y_{kw} = \begin{bmatrix} y_1^k & y_2^k & \cdots & y_N^k \\ y_1^{k+1} & y_2^{k+1} & \cdots & y_N^{k+1} \\ \vdots & \vdots & \ddots & \vdots \\ y_1^{k+w} & y_2^{k+w} & \cdots & y_N^{k+w} \end{bmatrix} \tag{8}$$

Substituting inputs and outputs of DMU_n^t into Equations (7) and (8) can result in DEA Window analysis.

3.5. GM (1,1)

The GM(1,1) model is the most commonly-used Grey forecasting model. It is a kind of time series prediction model that depends on the first-order differential equation. It has been proven to be effective and reliable. Thus, GM(1,1) is used in this research. In GM(1,1), the raw data sequence is presented as Equation (9), where n indicates the total number of raw data.

$$X^{(0)} = \left((X^0(1),\ X^0(2), \ldots,\ X^0(n)) \right) \tag{9}$$

Then, the accumulated series $X^{(1)}$ of $X^{(0)}$ is defined as Equation (10).

$$X^{(1)} = \left(X^{(1)}(1),\ X^{(1)}(2), \ldots,\ X^{(1)}(n) \right) \tag{10}$$

where $X^{(1)}(1) = X^{(0)}(1)$, $X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i)$, $k = 1, 2, \ldots, n$.

The generated mean sequence $Z^{(1)}$ of $X^{(1)}$ is calculated by Equation (11).

$$Z^{(1)} = \left(Z^{(1)}(1), Z^{(1)}(2), \ldots, Z^{(1)}(n) \right) \tag{11}$$

where $Z^{(1)}(k) = \frac{1}{2} \times \left(X^{(1)}(k) + X^{(1)}(k-1) \right)$, $k = 2, 3, \ldots, n$.

GM(1,1) is defined by a first-order differential equation, such as Equation (12).

$$\frac{dX^{(1)}(k)}{dk} + aX^1(k) = b \tag{12}$$

The coefficients a and b can be obtained by Equation (13).

$$\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^T B \right)^{-1} B^T\ Y \tag{13}$$

where Y and B can be derived by Equation (14).

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots \\ \cdots \\ x^{(0)}(n) \end{bmatrix} \quad \text{and} \quad B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots & \vdots \\ \cdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{14}$$

Discrete solution of the differential equation can be derived by Equation (15).

$$\ddot{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a} \tag{15}$$

Finally, the predicted values can be found by Equation (16).

$$\ddot{X}^{(0)}(k) = \begin{cases} X^0(1), & if\ k = 0 \\ \ddot{X}^{(1)}(k+1) - \ddot{X}^{(1)}(k), & if\ k = 1, \ldots, n \end{cases} \tag{16}$$

3.6. Measurement of Forecasting Accuracy

The mean absolute percentage error (MAPE), defined in Equation (17), is used for measuring forecasting accuracy. Due to the scale independency and interpretability, the MAPE has been widely used (Kim & Kim, 2016). The forecast error is presented as a percentage.

$$MAPE = \frac{1}{n} \sum \left(\frac{|Actual - Forecast|}{Actual} \right) \times 100 \qquad (17)$$

In terms of MAPE, the forecasting accuracy can be judged by the following criteria; if the MAPE <10%, then the accuracy level is considered as excellent; if the MAPE is between 10 and 20%, then the forecasting accuracy is considered as good; if the MAPE is between 20 and 50%, then the forecasting accuracy is considered as reasonable; and if the MAPE is >50%, then the forecasting accuracy is considered as poor.

4. Empirical Study Results

4.1. Data Collection

The input and output data for the time period of 2012 to 2016 for the 16 DMUs were collected. In the next section, the Person correlation test will be conducted to evaluate suitability of these variables. If highly correlated, these variables will be applied to evaluate the 16 DMUs for the time period of 2012 to 2016, and then to predicate the performance of these DMUs for the time period of 2017 to 2021. Then, the efficiency of these DMUs will be evaluated.

4.2. Pearson Correlation Test

Based on Equation (1), Tables 3–7 show the Person correlation coefficients of the input and output variables for DMU in the years of 2012, 2013, 2014, 2015, and 2016, respectively.

Table 3. Pearson correlation coefficients of input and output variables in 2012.

	Fleet	Total Asset	Operating Expenses	RPK	ASK
Fleet	1	0.766713	0.727115	0.724468	0.729144
Total Asset	0.766713	1	0.967721	0.883336	0.902239
Operating expenses	0.727115	0.967721	1	0.896062	0.920124
RPK	0.724468	0.883336	0.896062	1	0.997899
ASK	0.729144	0.902239	0.920124	0.997899	1

Table 4. Pearson correlation coefficients of input and output variables in 2013.

	Fleet	Total Asset	Operating Expenses	RPK	ASK
Fleet	1	0.795090	0.712596	0.704832	0.707295
Total Asset	0.795090	1	0.952161	0.900676	0.909052
Operating expenses	0.712596	0.952161	1	0.916749	0.935786
RPK	0.704832	0.900676	0.916749	1	0.997813
ASK	0.707295	0.909052	0.935786	0.997813	1

Table 5. Pearson correlation coefficients of input and output variables in 2014.

	Fleet	Total Asset	Operating Expenses	RPK	ASK
Fleet	1	0.819426	0.705601	0.705590	0.719359
Total Asset	0.819426	1	0.958505	0.922943	0.924216
Operating expenses	0.705601	0.958505	1	0.937495	0.945536
RPK	0.705590	0.922943	0.937495	1	0.995516
ASK	0.719359	0.924216	0.945536	0.995516	1

Table 6. Pearson correlation coefficients of input and output variables in 2015.

	Fleet	Total Asset	Operating Expenses	RPK	ASK
Fleet	1	0.808687	0.697654	0.729319	0.714401
Total Asset	0.808687	1	0.958421	0.942910	0.936114
Operating expenses	0.697654	0.958421	1	0.940155	0.945504
RPK	0.729319	0.942910	0.940155	1	0.99780
ASK	0.714401	0.936114	0.945504	0.99780	1

Table 7. Pearson correlation coefficients of input and output variables in 2016.

	Fleet	Total Asset	Operating Expenses	RPK	ASK
Fleet	1	0.790132	0.654574	0.739650	0.713132
Total Asset	0.790132	1	0.951402	0.936297	0.926245
Operating expenses	0.654574	0.951402	1	0.928332	0.935735
RPK	0.739650	0.936297	0.928332	1	0.997681
ASK	0.713132	0.926245	0.935735	0.997681	1

The above tables show that the correlation coefficients are all positive values ranging from 0.7 to 1. It is therefore concluded that these input and output variables are highly correlated, indicating that they are suitable variables.

4.3. Grey Forecasting

The Grey model GM(1,1) was used to forecast future values of DMUs for the time period of 2017 to 2021. The forecasting procedure is illustrated by taking the DMU-Emirates as an example. Table 8 shows the raw input and output data of the DMU-Emirates for the time period of 2012 to 2016. The bolded values in the "Fleet" column were used to illustrate the forecasting procedure of using the GM(1,1). The data in other columns can be calculated in a same procedure.

Table 8. Input and output data of DMU-Emirates for the time period of 2012 to 2016.

DMU	Input Variables			Output Variables	
	Fleet (N)	Total Asset (M)	Operating Expenses (M)	RPK (M)	ASK (M)
2012	**197**	25,810	19,132	188,618	236,645
2013	**205**	27,663	21,339	215,353	271,133
2014	**217**	30,319	22,577	235,498	295,740
2015	**236**	32,446	20,885	255,176	333,726
2016	**244**	33,095	22,496	276,608	368,102

N: number of planes; M: Millions of dollars.

Stage 1: The original series $X^{(0)}$ of the "Fleet" column is derived by Equation (9) as follows.

$$X^{(0)} = (197, 205, 217, 236, 244)$$

Stage 2: The accumulated series $X^{(1)}$ is derived by Equation (10) as follows.

$$X^{(1)} = (197, 402, 619, 855, 1099)$$

in which

$$X^{(1)}(1) = X^{(0)}(1) = 197$$
$$X^{(1)}(2) = X^{(0)}(1) + X^{(0)}(2) = 402$$
$$X^{(1)}(3) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3) = 619$$
$$X^{(1)}(4) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3) + X^{(0)}(4) = 855$$
$$X^{(1)}(5) = X^{(0)}(1) + X^{(0)}(2) + X^{(0)}(3) + X^{(0)}(4) + X^{(0)}(5) = 1099$$

Stage 3: The mean sequence $Z^{(1)}$ of $X^{(1)}$ is derived by Equation (11) as follows.

$$
\begin{aligned}
Z^{(1)}(2) &= \tfrac{1}{2}(197 + 402) = 299.5 \\
Z^{(1)}(3) &= \tfrac{1}{2}(402 + 619) = 510.5 \\
Z^{(1)}(4) &= \tfrac{1}{2}(619 + 855) = 737 \\
Z^{(1)}(5) &= \tfrac{1}{2}(855 + 1099) = 977
\end{aligned}
$$

Stage 4: Based on Equation (14) the B and Y can be derived as follows.

$$
B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ -Z^{(1)}(3) & 1 \\ -Z^{(1)}(4) & 1 \\ -Z^{(1)}(5) & 1 \end{bmatrix} = \begin{bmatrix} -2995 & 1 \\ -5105 & 1 \\ -737 & 1 \\ -977 & 1 \end{bmatrix} \qquad Y = \begin{bmatrix} X^{(0)}(2) \\ X^{(0)}(3) \\ X^{(0)}(4) \\ X^{(0)}(5) \end{bmatrix} = \begin{bmatrix} 205 \\ 217 \\ 236 \\ 244 \end{bmatrix}
$$

Consequently, the coefficients a and b can be derived by Equation (13) as follows.

$$
\begin{bmatrix} a \\ b \end{bmatrix} = \left(B^{T} B\right)^{-1} B^{T} Y = \begin{bmatrix} -0.06005 \\ 187.61 \end{bmatrix}
$$

Stage 5: Generate the series of predictive values.

The $\ddot{X}^{(1)}(k)$ of the "fleet" column for the DMU-Emirates can be derived by Equation (15). Table 9 lists the derived results. The predictive values $\ddot{X}^{(0)}(k)$ of the "fleet" column for the DMU-Emirates can be derived by Equation (16) and listed in the 5th column.

Table 9. Predictive values $\ddot{X}^{(0)}(k)$ for the DMU-Emirates from 2017 to 2021.

k (year)	$\ddot{X}^{(1)}(k)$	Value	$\ddot{X}^{(0)}(k)$	Value
0 (2012)	$\ddot{X}^{(1)}(0)$	197	$\ddot{X}^{(0)}(0)$	197
1 (2013)	$\ddot{X}^{(1)}(1)$	402.549	$\ddot{X}^{(0)}(1)$	205.549
2 (2014)	$\ddot{X}^{(1)}(2)$	620.8188	$\ddot{X}^{(0)}(2)$	218.2698
3 (2015)	$\ddot{X}^{(1)}(3)$	852.5966	$\ddot{X}^{(0)}(3)$	231.7778
4 (2016)	$\ddot{X}^{(1)}(4)$	1098.718	$\ddot{X}^{(0)}(4)$	246.1219
5 (2017)	$\ddot{X}^{(1)}(5)$	1360.072	$\ddot{X}^{(0)}(5)$	261.3536
6 (2018)	$\ddot{X}^{(1)}(6)$	1637.6	$\ddot{X}^{(0)}(6)$	277.528
7 (2019)	$\ddot{X}^{(1)}(7)$	1932.303	$\ddot{X}^{(0)}(7)$	294.7034
8 (2020)	$\ddot{X}^{(1)}(8)$	2245.245	$\ddot{X}^{(0)}(8)$	312.9417
9 (2021)	$\ddot{X}^{(1)}(9)$	2577.554	$\ddot{X}^{(0)}(9)$	332.3087

Following the same procedure, the predicted values of other variables for all DMUs in the same time period can be derived.

4.4. Evaluation of the Forecast Accuracy

Based on Equation (17), Table 10 lists the average MAPEs of predicative values obtained from the GM(1,1) for the 16 DMUs.

Table 10. Average mean absolute percentage error (MAPE) of 16 DMUs.

DMU	Average MAPE	DMU	Average MAPE
DMU	0.264%	DMU9	0.370%
DMU2	0.202%	DMU10	0.161%
DMU3	0.136%	DMU11	0.393%
DMU4	0.295%	DMU12	0.256%
DMU5	0.266%	DMU13	0.454%
DMU6	0.263%	DMU14	0.327%
DMU7	0.341%	DMU15	0.318%
DMU8	0.261%	DMU16	0.350%

Table 10 shows that all average MAPEs are within the range of 0.161 to 0.393%. As these values are ≤10%, the forecasting accuracy of the GM(1,1) is found to be excellent.

4.5. DEA Window Analysis

The DEA Window model was used to measure the efficiency of DMUs for the time period of 2012 to 2016. Firstly, Window DEA of the whole time period was conducted, which helps the researcher establish a whole view of DMUs' efficiency. Then, three widows of the 3-year period were used to investigate the performance of these DMUs.

4.5.1. DEA Window of the Whole Time Period

Table 11 shows the efficiency scores of the 16 DMUs obtained from the DEA Window for the whole time period (2012–2016). It is found that DMU14–Sri Lankan Airlines ranks No. 1, with the best efficiency score of 0.99106 in the whole time period, while the DMU8-All Nippon Airways ranks No. 16, with the worst efficiency score of 0.42.

Table 11. The results of DEA Window of the whole time period (2012–2016).

DMU	2012	2013	2014	2015	2016	Average	Rank
DMU	0.86087	0.93750	0.96418	0.99010	1	0.95053	3
DMU2	0.71509	0.75317	0.72810	0.83631	0.92865	0.79226	8
DMU3	0.63944	0.64499	0.66169	0.77884	0.80489	0.70597	13
DMU4	0.60787	0.65282	0.75102	0.97636	1	0.79761	6
DMU5	0.66655	0.69015	0.73300	0.88035	0.99459	0.79293	7
DMU6	0.69301	0.69677	0.73283	0.90591	1	0.80570	4
DMU7	0.63906	0.63079	0.66623	0.80734	0.93072	0.73483	11
DMU8	0.34404	0.37457	0.41181	0.49835	0.48914	0.42358	16
DMU9	0.99999	0.99999	0.88483	1	1	0.97696	2
DMU10	0.40257	0.42807	0.44737	0.51833	0.49747	0.45876	15
DMU11	0.71147	0.71166	0.67782	0.76469	0.79001	0.73113	12
DMU12	0.74181	0.70856	0.67111	0.78235	0.83201	0.74717	10
DMU13	0.83861	0.75311	0.71826	0.79151	0.82447	0.78519	9
DMU14	0.95531	0.99999	1	1	1	0.99106	1
DMU15	0.67835	0.72651	0.76804	0.87253	0.96227	0.80154	5
DMU16	0.73829	0.71510	0.67015	0.67498	0.68741	0.69719	14

4.5.2. DEA Window of 3-Year Period

To have a further investigation, Table 12 defines three widows for DEA Window analysis.

Table 12. The three windows of 3-year period.

Windows	Years
1st Window	2012–2014
2nd Window	2013–2015
3rd Window	2014—2016

Based on Equations (6)–(8), Table 13 shows the efficiency scores of 16 DMUs obtained from the DEA Window model for a 3-year period. It is found that the rankings of these DMUs have a slight change between Tables 11 and 13. This table provides a higher resolution on the efficiency scores for each DMU.

Table 13. The results of DEA Window for a 3-year period.

DMU	2012	2013	2014	2015	2016	Average	Rank
	0.94	1.00	1.00				
Emirates		0.98	1.00	1.00			
			0.96	0.99	1.00		
Average	**0.94**	**0.99**	**0.99**	**1.00**	**1.00**	**0.98**	**3**

Table 13. *Cont.*

DMU	2012	2013	2014	2015	2016	Average	Rank
Thai Airways	0.86	0.92	0.89				
		0.79	0.76	0.87			
			0.73	0.84	0.93		
Average	**0.86**	**0.85**	**0.79**	**0.85**	**0.93**	**0.86**	**8**
Cathay Pacific Group	0.77	0.78	0.80				
		0.66	0.67	0.79			
			0.66	0.78	0.80		
Average	**0.77**	**0.72**	**0.71**	**0.79**	**0.80**	**0.76**	**11**
Jet Airways	0.78	0.86	1.00				
		0.73	0.83	1.00			
			0.75	0.98	1.00		
Average	**0.78**	**0.79**	**0.86**	**0.99**	**1.00**	**0.88**	**5**
Air China	0.84	0.87	0.92				
		0.73	0.78	0.95			
			0.73	0.88	0.99		
Average	**0.84**	**0.80**	**0.81**	**0.92**	**0.99**	**0.87**	**7**
China Southern Airlines	0.83	0.87	0.93				
		0.73	0.78	0.98			
			0.73	0.91	1.00		
Average	**0.83**	**0.80**	**0.81**	**0.94**	**1.00**	**0.88**	**6**
China Eastern Airlines	0.77	0.77	0.85				
		0.65	0.71	0.88			
			0.67	0.81	0.93		
Average	**0.77**	**0.71**	**0.74**	**0.84**	**0.93**	**0.80**	**10**
All Nippon Airways	0.42	0.46	0.51				
		0.39	0.43	0.52			
			0.41	0.50	0.49		
Average	**0.42**	**0.43**	**0.45**	**0.51**	**0.49**	**0.46**	**16**
Cebu Pacific	1.00	1.00	1.00				
		1.00	0.89	1.00			
			0.91	1.00	1.00		
Average	**1.00**	**1.00**	**0.93**	**1.00**	**1.00**	**0.99**	**2**
Japan Airlines	0.49	0.53	0.55				
		0.47	0.47	0.54			
			0.45	0.52	0.50		
Average	**0.49**	**0.50**	**0.49**	**0.53**	**0.50**	**0.50**	**15**
Eva Air	0.73	0.72	0.75				
		0.72	0.69	0.77			
			0.68	0.76	0.79		
Average	**0.73**	**0.72**	**0.71**	**0.77**	**0.79**	**0.74**	**13**
China Airlines	0.77	0.74	0.79				
		0.73	0.68	0.79			
			0.67	0.78	0.83		
Average	**0.77**	**0.74**	**0.71**	**0.79**	**0.83**	**0.77**	**12**
Oman Air	0.93	0.84	0.80				
		0.76	0.72	0.80			
			0.73	0.79	0.82		
Average	**0.93**	**0.80**	**0.75**	**0.80**	**0.82**	**0.82**	**9**
SriLankan Airlines	0.96	1.00	1.00				
		1.00	1.00	1.00			
			1.00	1.00	1.00		
Average	**0.96**	**1.00**	**1.00**	**1.00**	**1.00**	**0.99**	**1**
Garuda Indonesia Airways	0.88	0.95	1.00				
		0.78	0.93	0.93			
			0.77	0.87	0.96		
Average	**0.88**	**0.86**	**0.90**	**0.90**	**0.96**	**0.90**	**4**
Singapore Airlines	0.77	0.75	0.73				
		0.74	0.69	0.70			
			0.67	0.67	0.69		
Average	**0.77**	**0.74**	**0.70**	**0.69**	**0.69**	**0.72**	**14**

Figure 2 shows the average efficiency rankings of these DMUs listed in Table 13. According to their rankings, these DMUs can be separated into three groups. The 1st and 3rd groups include the top best and worst three companies. The 2nd group includes the rest companies.
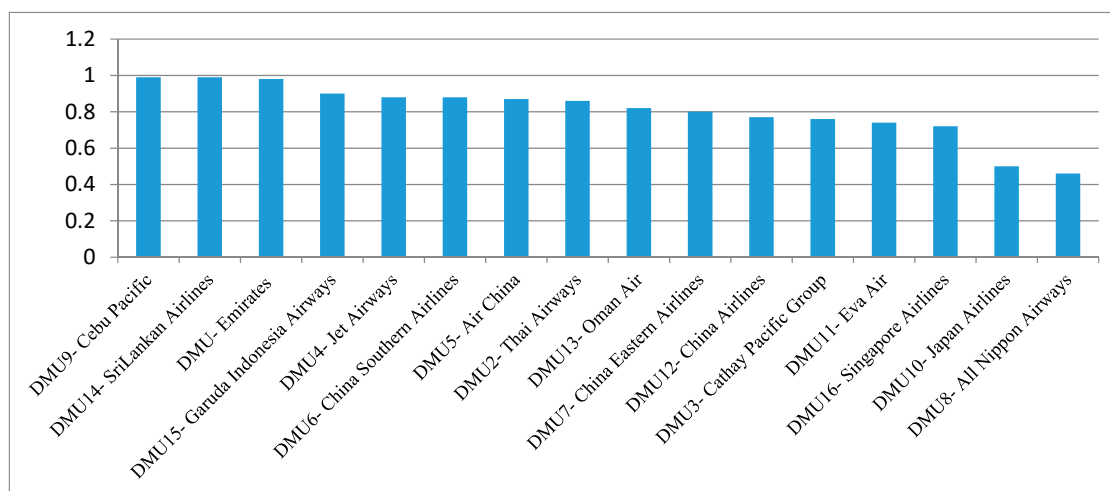

Figure 2. Average efficiency ranking of DMUs from 2012 to 2016.

The 1st group includes Cebu Pacific, Sri Lankan Airlines, and Emirates. Cebu Pacific is a privately owned low cost carrier while Sri Lankan Airlines and Emirates are two state owned flag carriers. The efficiency scores of Sri Lankan Airlines increased steadily from 0.96 in 2012 to 1.00 in 2013, and then remained stable in the last three years. Meanwhile, Emirates' efficiency has improved year-by-year as the score had been increased from 0.94 in 2012 to 1.00 in 2016. On the contrary, Cebu Pacific witnessed a favorable initial efficiency of 1.00 in 2012 then the efficiency reduced to 0.93 in 2014 and then increased back to 1.00 in 2015 and 2016.

The 2nd group includes Garuda Indonesia Airway, Jet Airway, China Southern Airlines, Air China, Thai Airways, Oman Air, China Eastern Airlines, China Airlines, Cathy Pacific Group, and Eva Air. It was found that China's commercial airline industry surged over the last 20 years. For instance, Air China has a fleet of over 600 planes that fly to 200 destinations worldwide. Table 16 shows that the efficiency scores of Air China, China Eastern, and China Southern Airlines had improved significantly from 0.84, 0.77, and 0.83 to 0.99, 0.93, and 1.00, respectively.

The 3rd group includes Singapore Airlines, Japan Airlines, and All Nippon Airways. These airline companies used to perform well in the Asia aviation, but they performed poorly throughout the whole time period.

Singapore Airlines and Cathay Pacific Group were forerunners in terms of long-haul air transportation. However, Figure 2 shows the turndown of the two companies. To survive, Cathay Pacific Group will need to dismiss employees and execute a large reassessment, while Singapore Airlines also has the same dilemma [30]. For Japan Airlines (JAL), investors wonder whether it can better survive after the process of liquidation and rearrangement [31]. Today, these airline companies are lagging behind their opponents such as China Southern Airlines, China Eastern Airlines, Air China, and Emirates [30].

4.6. Performance Evaluation

4.6.1. Efficiency Change Index

Based on Equation (3), Table 14 and Figure 3 show the efficiency change indexes (catch-up effects) of 16 DMUs for the time period of 2012 to 2016. The efficiency of each DMU changes year-by-year. DMU5-Air China, DMU6-China Southern Airlines, DMU7-China Eastern Airlines, DMU11-Eva Air, DMU12-China Airlines, and DMU13-Oman Air improved during that time period. Practically, a

DMU5-Air China, DMU6-China, DMU7-China Eastern Airlines, DMU11-Eva Air, DMU12-China Airlines, and DMU13-Oman Air achieved a noticeable improvement, with their efficiency change indexes increasing from 0.96, 0.93, 0.93, 1, 0.98, and 0.81 to 1.44, 1.47, 1.14, 1.03, 1.04, and 1.16, respectively.

Table 14. The efficiency change indexes of DMU (2012–2016).

DMU	2012–2013	2013–2014	2014–2015	2015–2016	Average
DMU	1	1	1	1	1
DMU2	1.022144	0.945607	1.015684	1.068443	1.01296
DMU3	0.920699	1.018862	1.047909	0.982322	0.99244
DMU4	1.121351	1.379235	1.082651	1.084630	1.16696
DMU5	0.960345	1.036379	1.065577	1.444541	1.12671
DMU6	0.933864	1.020124	1.111289	1.456444	1.13043
DMU7	0.933364	0.990430	1.025294	1.142754	1.02296
DMU8	1.052998	1.058232	1.042745	0.945054	1.02475
DMU9	1.011201	0.996441	1.057971	1.022223	1.02195
DMU10	0.992907	1.014996	1.000655	0.932986	0.98538
DMU11	1.006890	1.029436	1.004832	1.028759	1.01747
DMU12	0.971682	1.012760	1.030212	1.059947	1.01865
DMU13	0.817895	0.929828	1.088509	1.155010	0.99781
DMU14	1.147281	1.005244	1.396500	1.039999	1.14725
DMU15	0.993408	1.010125	0.768008	0.984767	0.93907
DMU16	0.939675	1.018399	0.974501	0.979387	0.97799
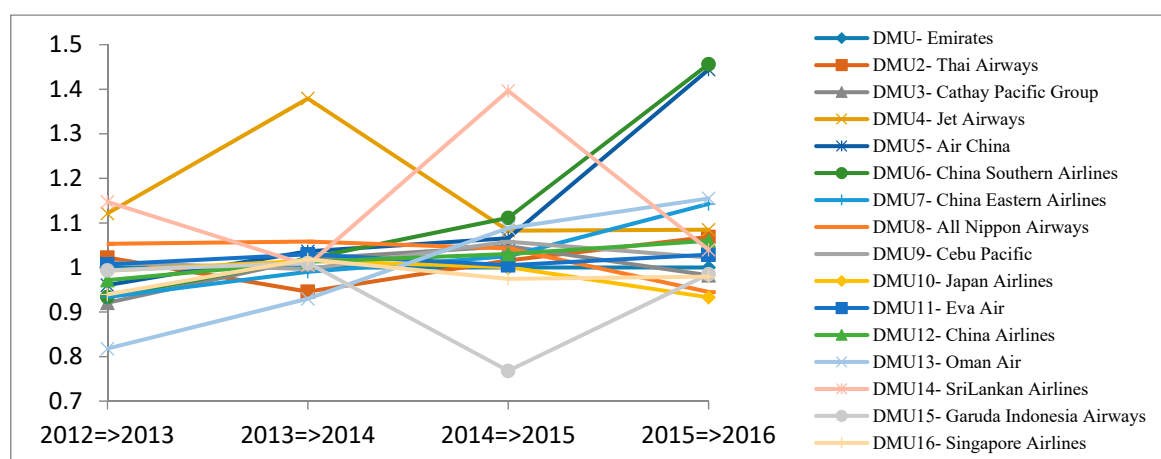
Figure 3. The efficiency change indexes of DMUs (2012–2016).

Meanwhile, DMU8-All Nippon Airways and DMU10-Japan Airlines experienced a decline in efficiency change index, with their efficiency change indexes decreasing to 0.95 and 0.3 (in 2016) from 1.05 and 1.00 (in 2013), respectively.

Figure 4 shows the forecasted efficiency change indexes of 16 DMUs for the time period of 2017 to 2021. Most of the efficiency changes of the 16 DMUs are expected to decline. Especially, DMU14-SriLankan Airlines and DMU7-China Eastern Airlines are expected to have a dramatic dip.
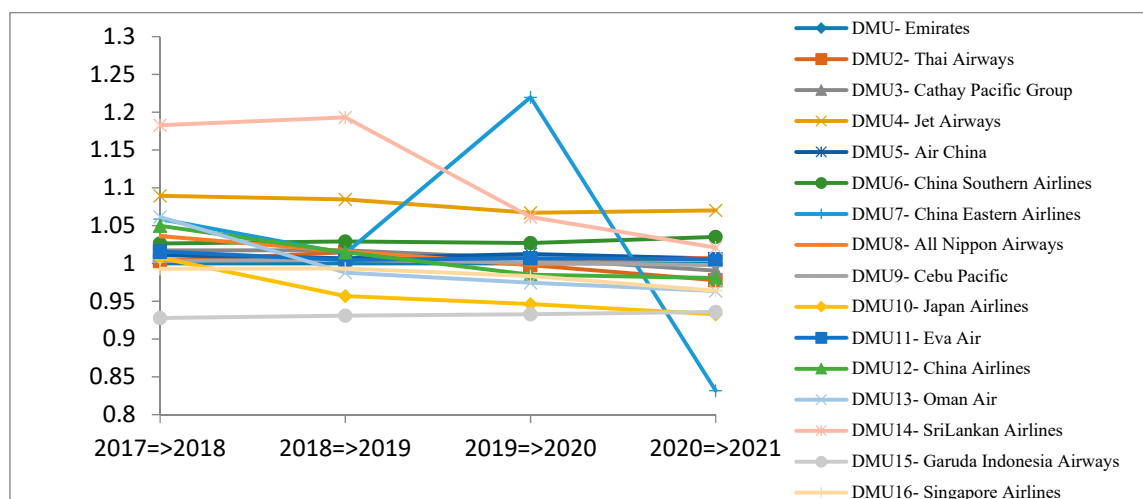
Figure 4. The efficiency change indexes of DMUs (2017–2021).

4.6.2. Technological Change Index

Table 15 and Figure 5 show the technological change indexes (frontier-shift effects) of the 16 Asia airline companies for the time period of 2012 to 2016. Figure 6 shows the trends of the technological change indexes for the 16 DMUs. Many of the DMUs have a fluctuating trend.

Table 15. The technological change indexes of DMUs (2012–2016).

DMU	2012–2013	2013–2014	2014–2015	2015–2016	Average
DMU	1.030308	1.005838	0.998817	1.018876	1.01345
DMU2	1.112939	1.018684	1.168310	1.042989	1.08573
DMU3	1.056719	1.021641	1.069319	1.027652	1.04383
DMU4	1.183521	1.029377	1.186115	1.059748	1.11469
DMU5	1.049983	1.022626	1.337322	1.075550	1.12137
DMU6	1.053584	1.018625	1.279385	1.022795	1.09359
DMU7	1.053960	1.018991	1.375833	1.247085	1.17396
DMU8	1.060404	1.018654	1.109026	1.043595	1.05792
DMU9	1.008379	0.997715	1.236168	1.002991	1.06131
DMU10	1.060398	1.017276	1.113167	1.031216	1.05551
DMU11	1.057101	1.017305	1.074853	0.996026	1.03632
DMU12	1.056490	1.020859	1.098148	0.998859	1.04358
DMU13	1.053349	0.992803	1.167868	0.972591	1.04665
DMU14	0.985295	0.984564	0.943874	0.942748	0.96412
DMU15	1.143990	1.102972	1.341016	1.173203	1.19029
DMU16	1.064881	1.020747	1.060730	1.028048	1.04360

Almost all the technological change indexes of these DMUs dropped for the time period of 2013 to 2014 and then surged dramatically for the time period of 2014 to 2015. This recovery, however, was short-lived as there was a dramatic dip for the time period of 2105 to 2016. Thus, it is concluded that the technological capabilities of these DMUs had not improved over recent years.

Table 15 shows that DMU15-Garuda Indonesia Airways, DMU7-China Eastern Airlines, and DMU5-Air China had the best average technological change indexes of 1.19, 1.17, and 1.12, respectively. On the contrary, DMU11-Eva Air, DMU-Emirates, and DMU14-Sri Lankan Airlines are the three worst companies, in which DMU14-Sri Lankan Airlines had the lowest score (with an overall average score of $0.96 \leq 1$).

Figure 6 shows the technological change indexes for the 16 DMUs for the time period of 2017 to 2021. During this time period most of the DMUs are expected to have a stable technological change index. However, DMU7-China Eastern Airlines is expected to have a declined index in 2017–2020 and then recover in 2021.
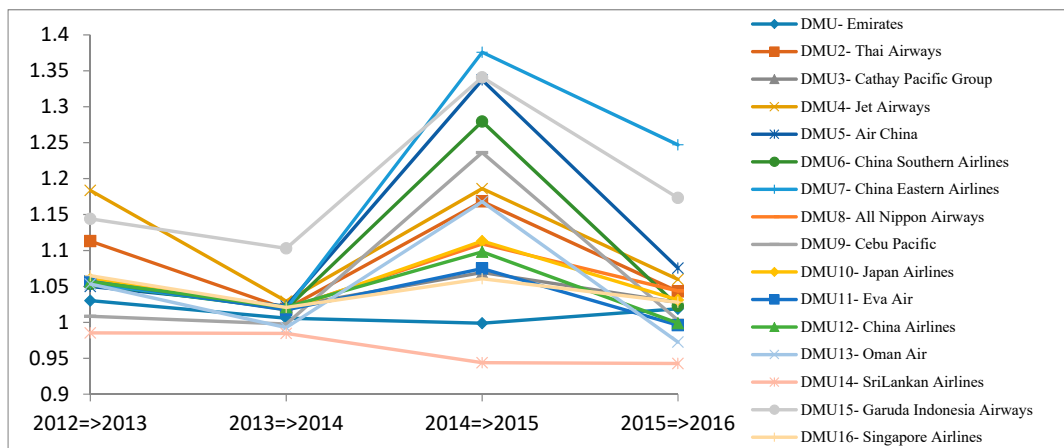
Figure 5. The technological change indexes of DMUs (2012–2016).
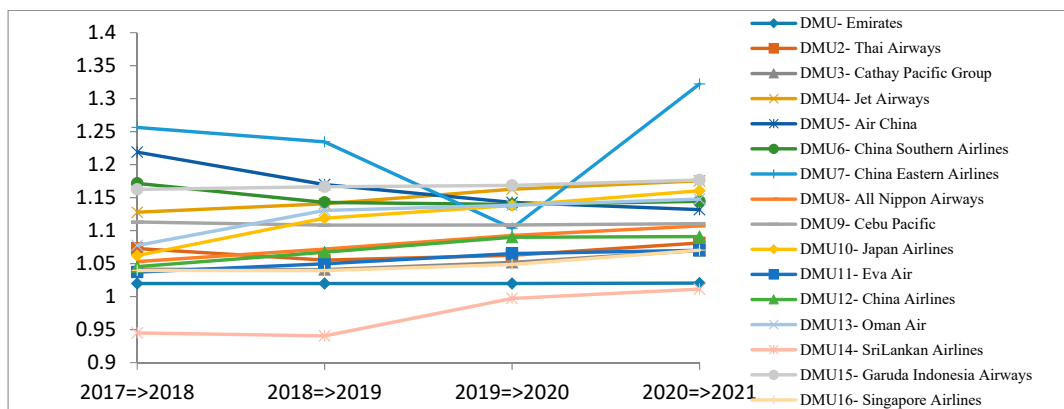

Figure 6. The technological change indexes of DMUs (2017–2021).

4.6.3. Malmquist Productivity Index

Based on Equation (2), Table 16 and Figure 7 show the MPIs of DMUs for the time period of 2012 to 2016. In the first time period (2012–2013) airline companies, including DMU3-Cathay Pacific Group, DMU6-China Southern Airlines, DMU7-China Eastern Airlines, and DMU13-Oman Air, had poor productivity (with MPIs of 0.97, 0.98, 0.98, and 0.86, respectively). Nevertheless, these airline companies had improved their performance for the time period of 2013 to 2016. In 2016, DMU6-China Southern Airlines, DMU7-China Eastern Airlines, and DMU13-Oman Air had increased their MPIs to 1.49, 1.43, and 1.12, respectively, which helps raise their average MPI scores.
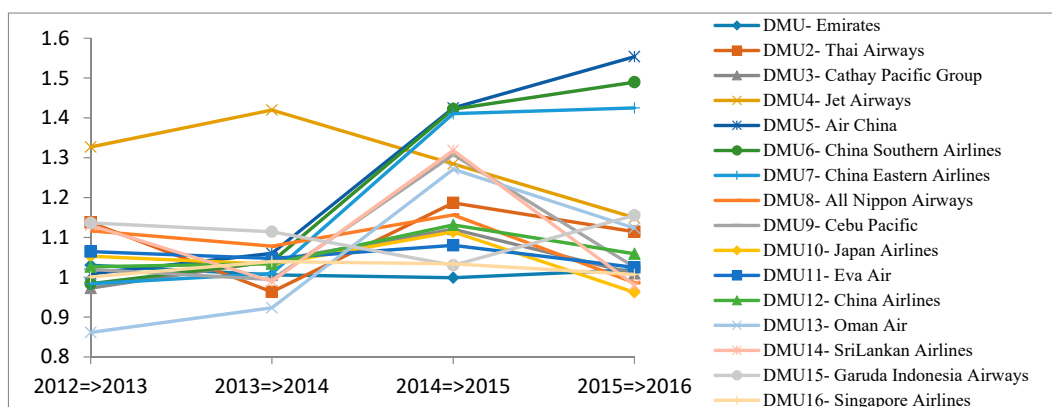
Figure 7. Malmquist productivity index (2012–2016).

Table 16. The MPIs of DMUs (2012–2016).

DMU	2012–2013	2013–2014	2014–2015	2015–2016	Average
DMU	1.030308	1.005838	0.998817	1.018876	1.01345
DMU2	1.137584	0.963275	1.186634	1.114373	1.10046
DMU3	0.972920	1.040911	1.120549	1.009486	1.03596
DMU4	1.327143	1.419753	1.284148	1.149435	1.29512
DMU5	1.008346	1.059828	1.425019	1.553675	1.26171
DMU6	0.983904	1.039124	1.421766	1.489644	1.23360
DMU7	0.983728	1.009239	1.410633	1.425112	1.20717
DMU8	1.116603	1.077972	1.156431	0.986254	1.08431
DMU9	1.019674	0.994165	1.307830	1.025280	1.08673
DMU10	1.052876	1.032531	1.113897	0.962110	1.04035
DMU11	1.064385	1.047250	1.080047	1.024671	1.05408
DMU12	1.026573	1.033884	1.131325	1.058738	1.06263
DMU13	0.861529	0.923136	1.271235	1.123352	1.04481
DMU14	1.130409	0.989726	1.318121	0.980457	1.10467
DMU15	1.136449	1.114140	1.029911	1.155331	1.10895
DMU16	1.000641	1.039527	1.033682	1.006857	1.02017
Average	1.053317	1.049394	1.205628	1.130228	1.10964

Airline companies, including DMU8-All Nippon Airways, DMU10-Japan Airlines, and DMU14-SriLankan Airlines, failed to improve their productivity as their MPIs are down from 1.12, 1.05, and 1.13 in 2012 to their lowest points at 0.98, 0.96, and 0.98, respectively, in 2016.

Table 17 shows the forecasted MPIs of all 16 DMUs in the time period 2017–2021. Though with some fluctuations, all these DMUs are found with improved productivity as their MPIs >1.

Table 17. The forecasted MPIs of DMUs (2017–2021).

DMU	2017–2018	2018–2019	2019–2020	2020–2021	Average
DMU	1.019948	1.019883	1.019828	1.020415	1.020019
DMU2	1.076143	1.070901	1.060145	1.057297	1.066121
DMU3	1.059506	1.059120	1.058745	1.059874	1.059311
DMU4	1.228791	1.237375	1.240584	1.257866	1.241154
DMU5	1.232024	1.177755	1.157005	1.139002	1.176446
DMU6	1.202669	1.175979	1.170434	1.184397	1.183370
DMU7	1.330209	1.251003	1.346116	1.099687	1.256754
DMU8	1.091076	1.089263	1.090702	1.115797	1.096709
DMU9	1.116606	1.113391	1.109818	1.108030	1.111961
DMU10	1.070202	1.070493	1.076761	1.082520	1.074994
DMU11	1.053492	1.054542	1.072725	1.076058	1.064204
DMU12	1.097660	1.083014	1.073699	1.070021	1.081098
DMU13	1.143971	1.116903	1.109269	1.105917	1.119015
DMU14	1.117836	1.122267	1.058430	1.032547	1.082770
DMU15	1.078566	1.085943	1.090054	1.101419	1.088996
DMU16	1.032213	1.032688	1.031053	1.031685	1.031910
Average	1.121932	1.110032	1.110335	1.096408	1.109677

5. Conclusions and Future Research Direction

This research proposes a hybrid model combining GM(1,1) with DEA Window model as a means to evaluate the current performance (2012–2016) and future performance (2017–2021) of 16 Asia airline companies. Their performance in different time periods was measured by measurements including the Efficiency Change Index, Technological Change Index, and MPI. The main results are summarized as follows.

1. The DEA Window analysis showed that DMUs performed differently for the time period of 2012 to 2016. Specifically, airline companies, including Emirates, Cebu Pacific, and Sri Lankan Airlines, are in the 1st group with leading performance. Airline companies Thai Airways, Jet Airways, Air China, China Southern Airlines, China Eastern Airlines, Oman Air, Garuda Indonesia, and

Cathay Pacific are in the 2nd group, followed by the 3rd group that includes Singapore Airlines, Japan Airlines, and All Nippon Airway. Singapore Airlines and Cathay Pacific used to perform well in the Asia air transport industry, but they have lost their leading positions.

2. The Efficiency change indexes (catch-up effect) showed that Air China, China Southern Airlines, China Eastern Airlines, Eva Air, China Airlines, and Oman Air improved their efficiency for the time period 2012 to 2016. Especially, Air China, China, China Eastern Airlines, Eva Air, China Airlines, and Oman Air had a noticeable improvement. Meanwhile, All Nippon Airways and Japan Airlines had declined efficiency. In the time period 2017 to 2021 most airline companies are expected to have declined efficiency; especially China Eastern Airlines and Sir Lanka Airlines, which will experience a dramatic dip on their efficiency.

3. The Technological change indexes (Frontier-shift effect) showed that these DMUs failed to improve their technological capabilities in the time period 2012 to 2016. In the time period 2017 to 2021 most of the DMUs are expected to have a stable Technological Change Index, excluding China Eastern Airlines that will have a declined Technological change index in the time period 2017 to 2020, which then recovers in 2021.

4. The MPIs showed that Cathay Pacific Group, China Southern Airlines, China Eastern Airlines and Oman Air performed poorly in the first time period 2012 to 2013, but improved their performance in following years from 2013 to 2016. In 2016, airline companies China Southern Airlines, China Eastern Airlines, and Oman Air had greatly improved their MPIs in 2016, while airline companies All Nippon Airways, Japan Airlines, and Sri Lankan Airlines had a declined MPI. In the time period 2017 to 2021, all airline companies are expected to improve their productivity as their MPIs ≥1.

This paper proposed a novel approach and applied it to investigate the performance of Asia airline companies. To our best knowledge, in past studies this novel approach has never been proposed and used for this purpose. However, this research still has some limitations. First, due to the lack of annual reports, only some of the Asia airline companies have been included in this research: including more Asia airline companies can give a more detailed overall view. Second, this research only includes specific input and output variables. The use of other input and output variables may lead to different results. As one study cannot complete all these tasks, relaxing these limitations can be considered for future research.

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