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Grey model and DEA to form virtual strategic alliance: The application for ASEAN aviation industry

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ABSTRACT

The demand to travel by air and airlines services becomes higher and higher as the economic growth throughout the World. The South East Asian area is considered to be a dynamic place with many economic factors e.g., cheap labors, tourism, and then the low-cost carriers are established to serve those targeted groups of customers. Choosing a partner is a key to success in the competitive market, although criteria for partner selection vary between markets. This study aims to develop effective methods to assist enterprise to measure the firms 'operation efficiency, and find out a potential candidate based on inputs and outputs realistic data, and forecast the values of those variables in the future as well. The methodologies are constructed by Data Envelopment Analysis (DEA) and grey model (GM). Realistic data in four consecutive years (2013–2016) a total of 11 public companies of ASEAN aviation industry are completely collected. This paper tries to help "Target Company" to find the right alliance partners.

1. Introduction

Aviation, also known as Air Transport has been an importance industry in achieving economic growth and development for every region and countries. Aviation facilitates integration into the global economy and provides vital connectivity on a national, regional, and international scale. According to the International Air Transport Association (IATA), world airline passenger traffic grew by 8.8% year-on-year in December, and by 6.3% in 2016 as a whole. The increasing in air traffic demanding is creating challenges for airline corporation itself in management the operation and provide proper service. As a result, government also needs to work with the industry to meet that demand within infrastructure that can accommodate the growth.

As ASEAN is pursuing regional integration as a single bloc economic development, expanding in region's aviation industry is an essential approach to push the economic connectivity and tourism's growth up. Due to geographical location and region's population that accounts for half of the world number, ASEAN has become a transportation hub not only for tourist attraction but also for accessing the growing economic opportunities.

The opening of the skies under the ASEAN passenger carriage liberalization agreement signed on November 12, 2010 has come into effect among the 10 ratifying countries. Although the policy implementation meets several hurdles including reluctance among members, it is likely to boost the region's connectivity and will be fully carried out soon. The "Open Skies" removes restrictions on airspace freedoms for airlines based in ASEAN member states with the main content of creating a single aviation market (ASEAN-SAM), creating a free business environment for air transport enterprises, minimizing direct intervention of state toward business in the direction of free competition.

In addition, eliminating restriction may encourage competition, drive down ticket prices, and bring opportunities for principally domestic airlines to become regional players. However, the gap in overall economic development and in particular the gap in aviation development among ASEAN Member States is the biggest obstacle faced by ASEAN in establishing the single aviation market. Countries with low levels developed

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aviation are likely to have difficulty in integrating and implementing air freight liberalization within fear their domestic airlines will not have enough ability to compete on an open market.

The purpose of this study is to provide an essential model based on Data Analysis Development (DEA) and Grey Theory GM (1, 1) to help target aviation Vietnam Airline making a prudent decision in finding appropriate partner. Concurrently, the research provides past-present performance evaluations as well as predictions toward selected aviation's future business that can be taken as a reference consideration in coming-up-plan and whether they should put more effort in investment and expanding business or not.

2. Literature review

2.1. Strategic alliance

"A strategic alliance is a relationship between two or more entities that agree to share resources to achieve a mutually beneficial objective" (Nguyen and Tran, 2017). Strategic alliances are among the various options including inflow and linking resources which companies can use to achieve their goals (Parkhe, 1991). These definitions emphasize the strategic alliance's essential need in term of common business goal.

Angwin and Sammut-Bonnici (2015) stated hat alliance strategy for corporation in accessing market, exchanging technology, defensing shareholding blocs, entering third market, prohibiting expensive technology and production facilities. Therefore, forming an alliance is a facilitator of gaining advantage in operation rather than running enterprise itself.

In a study of global strategic alliance in telecommunications industry, Oh points out the global marketplace is demanding an increasingly sophisticated, seamless worldwide communications network along with one inexpensive contract for every service. To meet these needs in limited available resources condition, Global Strategic Alliances is a reasonable resolution.

2.2. DEA model and grey theory system

Model Data Envelopment Analysis (DEA) was first described in a 1978 paper by Charnes, Copper, and Rhodes (CCR). DEA is a method used to estimate the efficiency of homogeneous organizational units, called DMUs that use the same inputs to produce the same outputs. DEA takes the observed input and output values to form a production possibility space, against which the individual units are compared to determine their efficiencies.

Grey system theory, developed originally in early 1980s by JuLong. It is developed quickly and applied extensively in the field of forecasting science such as in industry, economy, natural phenomenon, etc. A grey model has some advantages, including: insufficient information requirement; reduced minimum data to four observations; independence from statistical methods to approximate a time-series, and no assumption about an original dataset.

A wide range of methods is used for ranking and evaluating efficiency. However, most of them provide no projection of Pareto efficiency. Hence, calculating the super efficiency becomes a significant issue (Zanboori et al., 2014). Throughout, Super SBM-I-V and grey model are integrated to resolve the problem with the super efficiency and choosing alliance partner.

Wang and Lee (2008) focused on global strategic alliances in the hi-tech industries in Taiwan. By combining grey model and DEA, the researcher develops an effective method to help Taiwan's TFT-LCD industry to evaluate the operation efficiency and find the right candidate for alliances. The results of the study could assist companies' managers in making decisions in business extension.

3. Methodology

3.1. Research process

Fig. 1 shows step-by-step details of this study about how to integrate DEA and GM approach. Step 1 and step 2 are matters of setting stage, which is mentioned earlier. Throughout step 3 and 4, Grey Prediction that has been based on Grey Model GM (1,1) is used to predict the input and output data on 2017 and 2018. However, it is difficult to expect that forecasts will effectively be right most of time. Therefore, the MAPE (Mean Absolute Percent Error) is employed to measure the prediction accuracy. If the forecasting error is too high, the study has to reselect the inputs and outputs.

In this study, software DEA-solver is employed to calculate super SBM-I-V model. Hence, after choosing the DEA model in step 5, the efficiency is measured by ranking all DMUs' performances. The formulation of DEA is to measure the efficiency of each decision making unit by constructing a relative efficiency score via the transformation of the multiple inputs and outputs into a ratio of a single virtual output to a single virtual input. In step 6, it is essential need to test whether the relationship between selected inputs and outputs is positive or not according to DEA methodology basic assumption. In this study, we employ the Pearson Correlation Coefficient Test. If the coefficients are negative, the corresponding variable must to be removed and the process need to be back from step 2 until the condition is satisfied.

In addition, step 7 aims to rank the efficiency off all decision making units via realistic data of the period from 2013 to 2016. By looking at the ranking, the researcher is able to aware of the target DMU's position comparing to other competitors as well as its ranking changes year by year. The result of step 7 is a facilitator of analysis of step 9, in which the researcher side to the effective cooperation between candidate companies and target company.

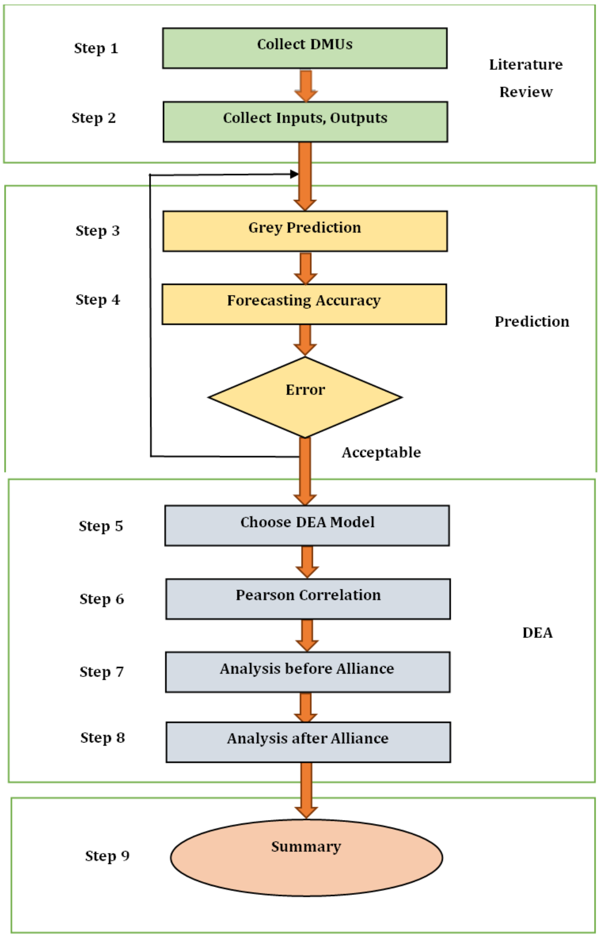

Fig. 1: Step-by-step details of this study

3.2. Collecting DMUs

This paper only conducted on 11 aviation companies including Full Service Carriers (FFCs) and Low Cost Carriers (LLCs) of most 6 developed economies over 11 ASEAN countries. These companies are holding and operate their national airlines and top LLC brands of domestic as well as the region.

Therefore, they play a major role in the ASEAN aviation stock market and are considered represent the whole industry (Table 1). Apart from it, they are stable and able to provide an obvious annual financial data within 4-year-schedule (2013-2016) in Wall Street Journal week news and Vietstock.vn. In this study, DMU_8 is set as the target company, which located in Hanoi, Vietnam. Within the upcoming region single aviation market, beside other approaches, strategic alliance could be one of the most effective recommended way to enhance its competitive ability as well as market share.

3.3. Choosing Input and output

The choice of input and output factors will affect the efficiency value evaluated, thus they need to be concerned thoroughly. Three input factors which are all considered as the key financial indicators those directly contributing to the performance of the industry including total asset, total liabilities and total equity were chosen. Concurrently, selling, general and administrative expenses (SG&A expenses), and revenue are chosen as outputs because they are the important indexes to measure the performance of enterprises both in current and future situation (see Tables 2 and 3).

3.4. Non-radial super efficiency model (Super-SBM)

In this paper, DEA model "Slack-based measure of super-efficiency" (super SBM) that developed based on super SBM of Tone was employed. In this model within n DMUs toward input and output matrices $X = (x_{ij}) \in R^{m \times n}$ and $Y = (y_{ij}) \in R^{s \times n}$ respectively, λ is a non-negative vector in R^n.

The vectors $s^- \in R^m$ and $s^+ \in R^s$ are called slacks and denote corresponding to the input excess and output shortfall.

The model formulation provides a constant return to scale as below:

$$\min \rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} S_i^-/x_{i0}}{1+\frac{1}{s}\sum_{i=1}^{s} S_i^-/y_{i0}} \tag{1}$$

$$\text{s.t} \quad x_0 = X\lambda + s^-$$

$$y_0 = Y\lambda - s^+ \tag{2}$$

$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

The variables s^- and s^+ evaluate the distances of inputs Xλ and output Yλ of a virtual unit from those of the unit evaluated. The numerator and the denominator of the objective function of model (1) measure respectively the average distance of inputs and outputs, from the efficiency threshold Let an optimal solution for SBM denote $(p^*, \lambda^*, s^{-^*}, s^{+^*})$. A DMU (x_0, y_0) is SBM-efficient, if $p^* = 1$. This condition is equivalent $s^{-^*} = 0$ and $s^{+^*} = 0$, i.e., to no input excesses and no output shortfalls in any optimal solution. SBM is non-radial and deals with input/output slacks directly. The SBM returns an efficiency measures are between 0 and 1.

The best performers have the full efficient status as denoted by unity. The super SBM model is based on the SBM model. Tone (2001) discriminated between these efficient DMUs and ranked the efficient DMUs by using the super-SBM model. By assuming that the DMU (x_0, y_0) is SBM-efficient, $p^* = 1$, super-SBM model is as follows:

$$\min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x_\iota}/x_{i0}}{\frac{1}{s}\sum_{r=1}^{m} \overline{y_r}/y_{r0}} \tag{3}$$

$$\text{s.t} \quad \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j x_j$$

$$\bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j x_j \tag{4}$$

$$\bar{y} \geq x_0, \bar{y} \leq y_0, \bar{y}\bar{y} \geq y_0, \lambda \geq 0$$

The input-oriented super SBM model is derived from model (3) with the denominator set to 1. The super SBM model returns a value of the objective function which is greater or equal to one. The higher the value implies a more efficient unit.

As in many DEA models, exactly how to deal with negative outputs must be considered when evaluating the efficiency in SBM models too.

However, negative data should also measure efficiency. Therefore, in this work, a new scheme was introduced in DEA-Solver pro 4.1 Manuel and the scheme was changed as follows:

Assume $y_{r0} \leq 0$ is defined $\overline{y_r^+}$ and y_{-r}^+ by

$$\overline{y_r^+} = \max_{j=1,\dots,n}\{y_{rj}|y_{rj} > 0\} \quad (5)$$

$$\overline{y_r^+} = \min_{j=1,\dots,n}\{y_{rj}|y_{rj} > 0\} \quad (6)$$

If output r has no positive elements, then it is defined as $\overline{y_r^+} = y_{-r}^+ = 1$. The term is replaced s_r^+/y_{r0} in the objective function as follows way. The value y_{r0} is never changed in the constraints $\overline{y_r^+} = y_{-r}^+ = 1$, the term is replaced by:

$$\frac{s_r^+}{y_{-r}^+(\overline{y_r^+} - y_{-r}^+)/(\overline{y_r^+} - y_{r0})} \quad (7)$$

$$\frac{s_r^+}{(y_{-r}^+)^2/\mathrm{B}(\overline{y_r^+} - y_{r0})} \quad (8)$$

where B is a large positive number, (in DEA-Solver B=100).

Table 1: List of collected aviation companies

Number order	DMUs	Companies	Headquarter addresses
1	DMU_1	Thai Airways International PCL	Bangkok, Thailand
2	DMU_2	Bangkok Airways PCL	Bangkok, Thailand
3	DMU_3	Nok Airlines PCL	Bangkok, Thailand
4	DMU_4	Asia Aviation PCL	Bangkok, Thailand
5	DMU_5	Malaysia Airports Holdings Bhd.	Sepang, Malaysia
6	DMU_6	AirAsia Bhd.	Sepang, Malaysia
7	DMU_7	Singapore Airline Ltd.	Singapore
8	DMU_8	Vietnam Airline JSC	Hanoi, Vietnam
9	DMU_9	Vietjet Aviation JSC	Hanoi, Vietnam
10	DMU_{10}	Cebu Air Inc.	Cebu, Philippine
11	DMU_{11}	PT. Garuda Indonesia (Persero) Tbk	Jakarta, Indonesia

Table 2: Inputs and outputs data of all DMUs in 2016

DMUs	Inputs (by million U.S dollars)			Outputs (by million U.S dollars)	
	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
DMU_1	8,178.05	7,207.57	970.19	418.75	5,150.58
DMU_2	1,741.45	817.45	924.00	107.94	713.23
DMU_3	173.34	183.16	-9.82	28.54	468.69
DMU_4	1,689.02	818.98	870.02	76.14	935.90
DMU_5	4,794.82	3,060.81	1,734.01	337.84	939.86
DMU_6	4,932.88	3,443.24	1,489.64	76.58	1,559.46
DMU_7	17,059.57	7,745.39	9,314.18	499.29	10,800.71
DMU_8	4,256.91	3,540.17	716.75	295.66	3.,092.47
DMU_9	885.21	676.33	208.87	31.18	1,213.33
DMU_{10}	2,077.03	1,404.36	672.66	36.40	1,242.70
DMU_{11}	3.773,11	2.753,61	1.019,50	494,20	3.850,84

Table 3: Inputs and outputs data of DMU_1 in period of 2013-2016

DMU_1	Inputs (by million U.S dollars)			Outputs (by million U.S dollars)	
	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
2013	8870.16	7226.05	1644.11	495.44	5960.02
2014	8875.42	7682.58	1192.84	432.87	5441.02
2015	8736.89	7785.82	951.07	466.32	5278.02
2016	8178.05	7207.57	970.19	418.75	5150.58

Nevertheless, the denominator is positive and strictly less than y_{-r}^+. Furthermore, it is inversely proportional to the distance $\overline{y_r^+} - y_{r0}$. This scheme, therefore, concerns the magnitude of the non-positive output positively. The score obtained is unit invariant, i.e., it is independent of the units of measurement used.

3.5. Grey forecasting model

Although it is not necessary to employ all the data from the original series to construct theGM (1, 1), the potency of the series must be more than 4. In addition, the data must be taken at equal intervals and in consecutive order without bypassing any data. The GM (1, 1) model constructing process is described as follows

Denote the variable primitive series $X^{(0)}$as formula

$$X^{(0)} = \left(X^{(0)}(1), X^{(0)}(2), \dots, X^{(0)}(n)\right), n \geq 4 \quad (9)$$

where $X^{(0)}$ is a nonnegative sequence. n is the number of data observed.

Accumulating Generation Operator (AGO) is one of the most important characteristics of grey theory with the aim at eliminating the uncertainty of the primitive data and smoothing the randomness. The accumulated generating operation (AGO) formation of $X^{(0)}$ is defined as:

$$X^{(1)} = \left(X^{(1)}(1), X^{(1)}(2), \dots, X^{(1)}(n)\right), n \geq 4 \quad (10)$$

where

$$X^{(0)}(1) = X^{(1)}(1) \quad (11)$$
$$X^{(1)}(k) = \textstyle\sum_{i=1}^{k} X^{(0)}(i), k = 1, 2, 3, \dots, n$$

The generated mean sequence $Z^{(1)}$ of $X^{(1)}$ is defined as:

$$Z^{(0)} = \left(Z^{(0)}(1), Z^{(0)}(2), \dots, Z^{(0)}(n)\right) \quad (12)$$

where Z is the mean value of adjacent data; that is:

$$Z^{(1)}(k) = \frac{1}{2}(X^1(k) - X^1(k-1)), k = 2,3,\dots,n \quad (13)$$

From the AGO sequence X^1,a GM(1, 1) model which corresponds to the first order different equation $X^1(k)$ can be constructed as follows:

$$\frac{dX^{(1)}(k)}{dk} + aX^{(1)}(k) = b \quad (14)$$

where parameters a and b are called the developing coefficient and grey input, respectively. In practice, parameters a and b are not calculated directly from (14). Hence, the solution of above equation can be obtained using the least squares method. That is:

$$\hat{X}^1(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} \quad (15)$$

where $X^1(k+1)$ denotes the prediction X at time point k+1and the coefficients $[a,b]^T$ can be obtained by the Ordinary Least Squares (OLS) method.

$$[a,b]^T = (B^TB)^{-1}B^TY$$

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \vdots \\ x^{(0)}(n) \end{bmatrix}, \qquad B = \begin{bmatrix} -z^{(0)}(2) & 1 \\ -z^{(0)}(3) & 1 \\ \vdots & \vdots \\ -z^{(0)}(n) & 1 \end{bmatrix} \quad (16)$$

where Y is called data series, $B$is called data matrix, and is called parameter series.

We obtained from (15). Let be the fitted and predicted series.

$$\hat{X}^{(0)} = X^{(0)}(1), \hat{X}^{(0)}(2), \dots, \hat{X}^{(0)}(n) \quad (17)$$

where

$$\hat{X}^{(0)} = X^{(0)}(1)$$

Applying the inverse accumulated generation operation (IAGO), namely,

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + (1 - e^{a}). \quad (18)$$

The grey model prediction is a local curve fitting extrapolation scheme. At least four data sets are required by the predictor (15) to obtain a reasonably accurate prediction

4. Empirical results and analysis

4.1. Forecasting results

GM (1, 1) model was used to predict the realistic input and output factors for the next two years 2017 and 2018. The study takes company DMU1 (Table 4) as an example to understand how to compute in GM (1, 1) model in period 2013–2016, for instance the total assets of DMU1. The other variables were calculated at the same manner within the following steps below:

Table 4: Inputs and outputs factors of DMU1 in period of 2013-2016

DMU_1	Inputs (by million U.S dollars)			Outputs (by million U.S dollars)	
	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
2013	8870.16	7226.05	1644.11	495.44	5960.02
2014	8875.42	7682.58	1192.84	432.87	5441.02
2015	8736.89	7785.82	951.07	466.32	5278.02
2016	8178.05	7207.57	970.19	418.75	5150.58

First, the variance of primitive series forecasted by using the GM (1,1) model.

1st: Create the primitive series:

$X^{(0)}$ = (8,870.16; 8,875.42; 8,736.89; 8,178.05)

2nd: Perform the accumulated generating operation (AGO):

$X^{(1)}$ = (8,870.16; 17,745.58; 26,482.47; 34,660.51)
$x^{(1)}(1) = x^{(0)}(1)$ =8,870.16
$x^{(1)}(2) = x^{(0)}(1) + x^{(0)}(2)$ = 17,745.58
$x^{(1)}(3) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3)$ = 26,482.47
$x^{(1)}(4) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4)$ = 34,660.51

3rd: Create the different equations of GM (1, 1). To find $X^{(1)}$ series, the following mean obtained by the mean equation is:

$z^{(1)}(2) = \frac{1}{2}$(8,870.16 + 17,745.58) = 13,307.87
$z^{(1)}(3) = \frac{1}{2}$(17,745.58 + 26,482.47) = 22,114.02
$z^{(1)}(4) = \frac{1}{2}$(26,482.47 + 34,660.51) = 30,571.49

4th: Solve the equations: To obtain a and b, the primitive series values are incorporated into the Grey differential equation to obtain:

$$\begin{cases} 8{,}875.42 + a \times 13{,}307.87 = b \\ 8{,}736.89 + a \times 22{,}114.02 = b \\ 8{,}178.05 + a \times 30{,}571.49 = b \end{cases}$$

The linear equations are then converted into the following matrix:

$$\text{Let } B = \begin{bmatrix} -13{,}307.87 & 1 \\ -22{,}114.02 & 1 \\ -30{,}571.49 & 1 \end{bmatrix}, \hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix}, y_N = \begin{bmatrix} 8{,}875.42 \\ 8{,}736.89 \\ 8{,}178.05 \end{bmatrix}$$

next, a and b are derived by using the least square method

$$\begin{bmatrix} a \\ b \end{bmatrix} = \hat{\theta} = (B^TB)^{-1}B^Ty_N = \begin{bmatrix} 0.040226054 \\ 9481.668632 \end{bmatrix}$$

additionally, the whitening equation of the differential equation is generated using the two coefficients a and b:

$$\frac{dX^{(1)}(k)}{dk} + 0.040226054\, X^{(1)} = 9481.668632$$

moreover, the prediction model is determined from the following equation:

$$X^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}$$
$$x^{(1)}(k+1) = \left[8{,}870.16 - \frac{9481.668632}{0.040226054}\right] e^{-0.040226054k} + \frac{9481.668632}{0.040226054}$$
$$= -226839.4748\, e^{-0.040226054k} + 235709.6365$$

furthermore, different values of k are incorporated into the following equation:

k=0, $X^{(1)}(1) = 8{,}870.16$
k=1, $X^{(1)}(2) = 17{,}813.93$
k=2, $X^{(1)}(3) = 26{,}405.06$
k=3, $X^{(1)}(4) = 34{,}657.46$
k=4, $X^{(1)}(5) = 42{,}584.49$
k=5, $X^{(1)}(6) = 50{,}198.98$

Also, the predicted value of the original series is derived based on the accumulated generating operation and subsequently yielding:

$\hat{x}^{(0)}(1) = x^{(1)}(1)$ =8,870.16 – for the year 2013
$\hat{x}^{(0)}(2) = x^{(1)}(2) + x^{(1)}(1) =$ 8,943.76 – forecast for 2014
$\hat{x}^{(0)}(3) = x^{(1)}(3) + x^{(1)}(2) = 8{,}591.13$ – forecast for 2015
$\hat{x}^{(0)}(4) = x^{(1)}(4) + x^{(1)}(3) = 8{,}252.40$ – forecast for 2016
$\hat{x}^{(0)}(5) = x^{(1)}(5) + x^{(1)}(4) = 7{,}927.03$ – forecast for 2017
$\hat{x}^{(0)}(6) = x^{(1)}(6) + x^{(1)}(5) = 7{,}614.49$ – forecast for 2018

In the same with above computation process, the study could get the forecasting result of all DMUs in 2017 and 2018 the detail numbers are shown in Tables 5 and 6.

Table 5: Forecasted input and output of all DMUs in 2017

DMUs	Inputs (by million U.S dollars)			Outputs (by million U.S dollars)	
	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
DMU_1	7927.03	7102.18	825.69	425.78	5005.41
DMU_2	1958.23	905.21	1052.88	122.96	774.79
DMU_3	174.27	289.18	69.23	32.16	538.22
DMU_4	1808.96	894.69	914.63	89.53	1061.77
DMU_5	4669.67	2759.05	459.18	405.97	1055.86
DMU_6	4985.75	3373.67	1752.13	91.64	1769.25
DMU_7	17727.99	8691.30	9209.68	259.51	10873.37
DMU_8	4961.85	4111.31	882.88	323.80	2821.48
DMU_9	1361.22	988.19	382.25	44.45	1965.81
DMU_{10}	2375.83	1559.25	828.30	36.61	1353.48
DMU_{11}	4328.85	3176.03	1155.06	496.08	4088.07

Table 6: Forecasted input and output of all DMUs in 2018

DMUs	Inputs (by million U.S dollars)			Outputs (by million U.S dollars)	
	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
DMU_1	7614.49	6885.72	738.38	419.20	4869.72
DMU_2	2173.21	999.99	1173.04	139.41	838.82
DMU_3	167.18	467.53	57.77	35.07	622.83
DMU_4	1939.96	975.07	966.28	104.17	1197.25
DMU_5	4494.33	2490.16	296.97	479.03	1176.32
DMU_6	5026.68	3209.04	2166.22	111.21	1995.60
DMU_7	18216.62	9415.75	9055.28	172.09	10868.09
DMU_8	5698.09	4664.92	1111.52	377.24	2848.21
DMU_9	2199.87	1494.30	812.04	63.76	3170.81
DMU_{10}	2741.74	1735.49	1043.27	43.30	1476.97
DMU_{11}	4930.92	3652.94	1283.86	498.71	4284.15

4.2. Forecasting accuracy

Accuracy is controversial and concerned whenever a forecasting is produced since there is always exist an error. Therefore, this study measured the accuracy by using mean absolute percent error (MAPE), which is applied commonly in many prediction studies. MAPE is the average absolute percent error which measures the accuracy in a fitted time series value in statistics, specifically trending (Stevenson, 2009).

$$MAPE = \frac{1}{n}\sum \frac{|Actual - Forecast|}{Actual} \times 100$$

n is forecasting number of steps.

The parameters of MAPE state the forecasting ability as follows:

MAPE < 10% "Excellent"
10% < MAPE < 20% "Good"
20% < MAPE < 50% "Reasonable"
MAPE > 50% "Poor

According to the results of MAPE in Table 7, all 11 average MAPEs of DMUs is smaller than 10% and average of all MAPEs is only accounted for 4.35%. It infers that the forecasting of GM (1,1) model has an excellent capability within high prediction accuracy.

4.3. Pearson correlation

When employing DEA approach, the researcher concerns about ensuring not merely that the relationship between input and output indicators is isotonic, but also that the linear relation determines an efficiency measure of position relative to the frontier toward each DMU. In this paper, Pearson correlation is conducted to define level of alignment between two variables whereas higher correlation coefficient implies a closer relation and vice versa (Table 8). The correlation coefficient always has a value within the range of -1 and +1, in which -1 and +1 are representative of the perfect linear relationship.

Table 7: Average MAPE of all DMUs

DMUs	Average MAPEs
DMU_1	2,91%
DMU_2	1,66%
DMU_3	5,61%
DMU_4	0,98%
DMU_5	9,11%
DMU_6	3,33%
DMU_7	5,91%
DMU_8	7,58%
DMU_9	6,50%
DMU_{10}	4,10%
DMU_{11}	1,54%
Average of all MAPEs	4.35%

Table 8: Pearson correlation coefficient.

Correlation coefficient	Degree of correlation
>0.8	Very high
0.6-0.8	High
0.4-0.6	Medium
0.2-0.4	Low
<0.2	Very low

The results of Table 9, 10, 11, and 12 showing strong correlation coefficient indicate a positive association among variables of DEA model. Apart from it, the appropriate initial inputs and outputs choice of researcher is proved. Therefore, all variables are acceptable and no need to be remove.

4.4. Analysis before alliance

Table 13 shows the consolidated DEA super-SBM efficiency scores for the last-4-year data and rankings of DMUs by their scores. This indicates that the ranking of the industries is tending to change slightly on yearly basis. Table 14 summarizes the empirical result based on GM (1,1) data in 2017 and 2018 in same manor.

The target DMU_8 achieves the efficient score about 0.65 at the position 7th over 11 companies, at where considered unsatisfactory. The raking obviously demonstrates again that the target should engage in strategic alliance to enhance its performance.

4.5. Analysis after alliance

In this work, empirical research is performed by first forming a virtual alliance and then executing DEA calculations. By combining DMU_8 with the remaining DMUs, the new catalog gains 21 virtual DMUs.

Again, 21 virtual DMUs are calculated using the Super-SBM-I-V model. Table 15 summarizes the score and ranking results of virtual alliance in 2017 and 2018.

Table 9: Correlation of input and output data in 2013

	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
Total Assets	1	0.906106	0.897149	0.779456	0.973223
Total Liabilities	0.906106	1	0.6285	0.843073	0.880018
Total Equity	0.897149	0.6285	1	0.553202	0.870909
SGandA Expenses	0.779456	0.843073	0.553202	1	0.850194
Revenue	0.973223	0.880018	0.870909	0.850194	1

Table 10: Correlation of input and output data in 2014

	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
Total Assets	1	0.88314	0.899341	0.891377	0.928014
Total Liabilities	0.88314	1	0.589233	0.757392	0.770929
Total Equity	0.899341	0.589233	1	0.831019	0.880679
SGandA Expenses	0.891377	0.757392	0.831019	1	0.956955
Revenue	0.928014	0.770929	0.880679	0.956955	1

Table 11: Correlation of input and output data in 2015

	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
Total Assets	1	0.918515	0.906464	0.673324	0.941801
Total Liabilities	0.918515	1	0.665726	0.765212	0.837005
Total Equity	0.906464	0.665726	1	0.455806	0.884832
SGandA Expenses	0.673324	0.765212	0.455806	1	0.718786
Revenue	0.941801	0.837005	0.884832	0.718786	1

Table 12: Correlation of input and output data in 2016

	Total Assets	Total Liabilities	Total Equity	SGandA Expenses	Revenue
Total Assets	1	0.916741	0.920731	0.705311	0.947371
Total Liabilities	0.916741	1	0.688289	0.802774	0.868309
Total Equity	0.920731	0.688289	1	0.497626	0.873261
SGandA Expenses	0.705311	0.802774	0.497626	1	0.749218
Revenue	0.947371	0.868309	0.873261	0.749218	1

According to the result, changing from the original target DMU_8 to a virtual alliance definitely create differences, which can be split into two groups: positive and negative. Positive results demonstrate the judiciousness of virtual alliance that achieve a better performance compared to original DMUs in terms of efficiency scale. A larger difference implies a more efficient alliance. In contrast, a negative outcome implies an ineffective alliance.

Table 16, and 17 reveals that 8 companies (i.e., DMU1, DMU4, DMU5, DMU7, DMU11, DMU9, DMU10, and DMU2) have the desired features, which correlate with the desire of the partners to do business. The virtual companies (DMU8 + DMU1; DMU8 + DMU4; DMU8 + DMU5; and DMU8+DMU7) have the greatest number of opportunities to achieve the highest and best efficiency when using a strategic alliance business model (score =1) toward both 2 years. Thus, those 4 candidates are highly appreciated when considering a strategic alliance.

Table 13: Past-present period scores and rankings

DMUs	2013		2014		2015		2016	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank
DMU_1	1	1	1	1	1	1	1	1
DMU_2	0.4019	9	0.3473	9	0.2893	10	0.2727	10
DMU_3	1	1	1	1	1	1	1	1
DMU_4	0.4414	8	0.4046	8	0.3679	8	0.391	9
DMU_5	0.3611	10	0.2338	10	0.3613	9	0.4627	7
DMU_6	0.2547	11	0.219	11	0.2258	11	0.2478	11
DMU_7	1	1	1	1	1	1	1	1
DMU_8	1	1	1	1	0.5813	6	0.8692	6
DMU_9	1	1	1	1	1	1	1	1
DMU_{10}	0.5194	7	0.5442	7	0.4259	7	0.4213	8
DMU_{11}	1	1	1	1	1	1	1	1

Table 14: Efficiency and ranking before strategic alliances

2017			2018		
Rank	DMUs	Score	Rank	DMUs	Score
1	DMU1	1	1	DMU1	1
1	DMU3	1	1	DMU3	1
1	DMU5	1	1	DMU5	1
1	DMU7	1	1	DMU7	1
1	DMU9	1	1	DMU9	1
1	DMU11	1	1	DMU11	1
7	DMU8	0.6505	7	DMU8	0.6462
8	DMU2	0.5718	8	DMU4	0.5659
9	DMU4	0.4756	9	DMU2	0.5471
10	DMU10	0.3665	10	DMU10	0.3583
11	DMU6	0.2612	11	DMU6	0.3074

Table 15: Efficiency and ranking after strategic alliances

2017			2018		
Rank	DMUs	Score	Rank	DMUs	Score
1	DMU1	1	1	DMU1	1
1	DMU3	1	1	DMU3	1
1	DMU5	1	1	DMU5	1
1	DMU7	1	1	DMU7	1
1	DMU9	1	1	DMU9	1
1	DMU11	1	1	DMU11	1
1	DMU8+DMU1	1	1	DMU8+DMU1	1
1	DMU8+DMU4	1	1	DMU8+DMU4	1
1	DMU8+DMU5	1	1	DMU8+DMU5	1
1	DMU8+DMU7	1	1	DMU8+DMU7	1
1	DMU8+DMU11	1	1	DMU8+DMU9	1
12	DMU8+DMU9	0.9501	1	DMU8+DMU10	1
13	DMU8+DMU10	0.8431	13	DMU8+DMU2	0.9999
14	DMU8+DMU2	0.7144	14	DMU8+DMU11	0.9624
15	DMU8	0.6505	15	DMU8+DMU6	0.7927
16	DMU8+DMU6	0.583	16	DMU8	0.6462
17	DMU2	0.5718	17	DMU4	0.5659
18	DMU8+DMU3	0.505	18	DMU2	0.5471
19	DMU4	0.4756	19	DMU8+DMU3	0.4972
20	DMU10	0.3665	20	DMU10	0.3583
21	DMU6	0.2612	21	DMU6	0.3074

Table 18 clearly reveals that 2 companies (i.e. DMU6 and DMU3) perform worse after strategic alliances in 2017. Table 16 infers again DMU3 in 2018 as well. Restated, ranking of the DMUs significantly decline. Those companies are not the preferred ones, owing to non-benefits for the target company.

4.6. Partner selection

After setting the process of making an alliance for DMU1, all DMUs in the list of Good Alliance Partnership as shown in Table 16 and 17 are ranked to determine their current position, which attempts to identify the most appropriate one for the target company. Two companies DMU4 and DMU11 in Table 18 and Table 19 decline in their ranking scores after the alliance, reflecting their inability to form good alliances with the target company. Restated, the performances of DMU6 and DMU3 are sufficient to decline a partnership with DMU8.Therefore, these 4 companies are not likely to form an alliance with the target company because of decline collaboration performance (see Tables 20 and 21).

This work also evaluates the effectiveness of DMU10 and DMU2 before and after forming an alliance. Before the alliance, although the efficiency of DMU10 and DMU2 is lower than that of the DEA frontier, these companies improves in its ranking after the alliance with DMU8. This finding suggests that the alliance can increase the productivity efficiency of both side of partners. Restated, implementing the alliance may enable DMU8, and DMU10 and DMU2 to manage their resource more effectively. Furthermore, the performances of 4 companies (DMU1, DMU4, DMU5 and DMU7) before and after engaging in alliance are remained in 2 coming years. However, the efficient of DMU8 is increased significant. It infers the negative alliance with no damage for both sides. Thus collaborating with these companies might be reasonable suggestions.

Table 16: The good alliance partnership in 2017

Virtual Alliance	Target DMU_8 Ranking (1)	Virtual Alliance Ranking(2)	Difference: (1)-(2)
DMU8+DMU1	15	1	14
DMU8+DMU4	15	1	14
DMU8+DMU5	15	1	14
DMU8+DMU7	15	1	14
DMU8+DMU11	15	1	14
DMU8+DMU9	15	12	3
DMU8+DMU10	15	13	2
DMU8+DMU2	15	14	1

Table 17: The good alliance partnership in 2018

Virtual Alliance	Target DMU_8 Ranking (1)	Virtual Alliance Ranking(2)	Difference: (1)-(2)
DMU8+DMU1	16	1	15
DMU8+DMU4	16	1	15
DMU8+DMU5	16	1	15
DMU8+DMU7	16	1	15
DMU8+DMU9	16	1	15
DMU8+DMU10	16	1	15
DMU8+DMU2	16	13	3
DMU8+DMU11	16	14	2
DMU8+DMU6	16	15	1

Table 18: The unqualified alliance partnership in 2017

Virtual Alliance	Target DMU_8 Ranking (1)	Virtual Alliance Ranking(2)	Difference: (1)-(2)
DMU8+DMU6	15	16	-1
DMU8+DMU3	15	18	-3

Table 19: The unqualified alliance partnership in 2018

Virtual Alliance	Target DMU_8 Ranking (1)	Virtual Alliance Ranking(2)	Difference: (1)-(2)
DMU8+DMU3	15	19	-4

Table 20: The impossible partners in 2017

DMUs	Rank Before Alliance	Rank After Alliance
DMU_4	1	12

Table 21: The impossible partners in 2018

DMUs	Rank Before Alliance	Rank After Alliance
DMU_{11}	1	14

As the recommendations of the strategic alliance conducted in this study, the target company DMU8 would aware of the right direction for selecting alliance partner and improving its business efficiency. The recommendation outlined in the above section elucidates the case of alliance formation. Above analytical results indicate that DMU1, DMU4, DMU5, and DMU7 is selected as the most improved partner for the target DMU8. Furthermore, DMU10 and DMU2 is efficient in performance for both DMU8 and them because this choice improves their business performances.

5. Conclusion

The competition among region aviation companies would become more intense due to higher demand for fight and service, especially after the Open Skies implementation. The burden of how to enhance the efficiency, competitiveness and expand business scale is put on the enterprises managers' shoulders. That is the reason to raise an integrated method based on the Grey theory and the Super-SBM model. Throughout this approach, essential index business indicators for the ASEAN aviation industry are forecasted, and an appropriate evaluation among selected objects is performed as well. Analysis of this study provides a valuable reference in details for upper managers in the industry in order to provide wiser and simpler decision making when establishing a business alliance strategy. Toward other industries, this study is also applicable in attempting to select the appropriate alliance partner and enhance business efficiency. Concurrently, the result of this approach contain restrictions for further study since the information of non-listed companies is complicated to obtain and the number of conducted companies is limited. The input and output variables are unable to reflect the whole performance measurement scale of a business as well as the industry. In real-life alliances or union, the enterprises may have different considerations, such as the code trade, technology acquisition, and market development. As long as adjusting properly the input and output factors through the method applied and the process established, management can still get variety other results for reference purposes.

References

Angwin D and Sammut-Bonnici T (2015). Strategic alliance. In: Cooper CL (ed.), Wiley encyclopedia of management. John

Wiley & Sons Ltd., Hoboken, USA. https://doi.org/10.1002/9781118785317

Nguyen NT and Tran TT (2017). Optimizing mathematical parameters of Grey system theory: an empirical forecasting case of Vietnamese tourism. Neural Computing and Applications: 1-15. https://doi.org/10.1007/s00521-017-3058-9

Parkhe A (1991). Interfirm diversity, organizational learning, and longevity in global strategic alliances. Journal of International Business Studies, 22(4): 579-601.

Stevenson JW (2009). Operations management. 10th Edition, McGraw-Hill, London, UK.

Tone K (2001). A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130(3): 498-509.

Wang CN and Lee YR (2008). GM (1, 1) and DEA application model for strategic alliance in taiwan. In the 8th International Conference on Intelligent Systems Design and Applications, IEEE, Kaohsiung, Taiwan, 2: 454-459. https://doi.org/10.1109/ISDA.2008.274

Zanboori E, Rostamy-Malkhalifeh M, Jahanshahloo GR, and Shoja N (2014). Calculating super efficiency of DMUs for ranking units in data envelopment analysis based on SBM model. The Scientific World Journal, 2014: Article ID 382390, 7 pages. https://doi.org/10.1155/2014/382390