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Automobile Industry Strategic Alliance Partner Selection: The Application of a Hybrid DEA and Grey Theory Model

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Abstract: Finding the right strategic alliance partner is a critical success factor for many enterprises. Therefore, the purpose of this study is to propose an effective approach based on grey theory and data envelopment analysis (DEA) for selecting better partners for alliance. This study used grey forecasting to predict future business performances and used DEA for the partner selection of alliances. This research was implemented with realistic public data in four consecutive financial years (2009–2012) of the world's 20 biggest automobile enterprises. Nissan Motor Co., Ltd was set to be the target decision making unit (DMU). The empirical results showed that, among 19 candidate DMUs, Renault (DMU10) and Daimler (DMU11) were the two feasible beneficial alliance partners for Nissan. Although this research is specifically applied to the automobile industry, the proposed method could also be applied to other manufacturing industries.

Keywords: strategic alliance; data envelopment analysis; grey prediction; automobile industry

1. Introduction

The automobile industry is a pillar of the global economy and a main driver of macroeconomic growth and innovation. Its cycle intertwines with all major business cycles [1]. Since it has strong linkages with other parts of the economy, this industry has been severely affected by the economic recession starting in 2008. In spite of manufacturers trying various strategies, production is still below its pre-crisis level.

This research investigation began with the top 50 automobile enterprises, by using the World Ranking OICAs' survey of 2012 [2]. However, the study was obliged to focus on the top 20, due to a lack of public data. These enterprises played major roles and could fully represent the automobile industry. Among them, Nissan Motor Company was ranked sixth by production volume. Established in Japan in 1933, Nissan manufactures vehicles in 20 countries now. It also provides products and services in more than 160 countries. Figure 1 shows Nissan's global retail sales volume and market share. Except for 2008, the enterprise had increased its sale volume and market share year by year (3,569,000–5,650,000 units and 5.6%–6.7% from 2005 to 2014) [3].

Renault-Nissan Alliance chairman, Carlos Ghosn, said: "Renault-Nissan Alliance is deeply committed to the twin goals of zero emissions and zero fatalities. That's why we are developing autonomous driving and connectivity for mass-market, mainstream vehicles on three continents". This alliance will launch more than 10 vehicles with autonomous drive technology in the next four years in the US, Europe, Japan and China. The years 2016 and 2018 will mark the debut of vehicles with "single-lane control", and "multiple-lane control". The year 2020 will see the launch of "intersection autonomy", which can allow cars to navigate city intersections and heavy urban traffic without driver intervention. In addition, the alliance will launch a suite of new connectivity applications (APPs), including for mobile devices, and the first "alliance multimedia system" in later years. Renault-Nissan alliance is already the industry's zero-emission leader with 300,000 all-electric vehicles sold since December 2010. They have proven their ability to provide safe and efficient vehicles over time [4].

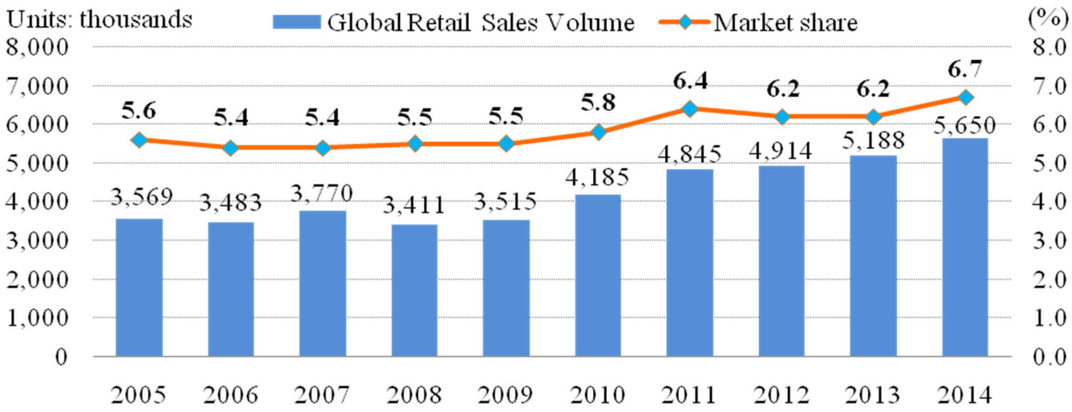

Figure 1. Global retail sales volume/market share.

However, the enterprise is faced with many difficulties, such as product recall (1.56 million vehicles from 2008 to 2015, with about 25 million vehicles recalled with Takata airbags among 10 different carmakers worldwide since 2008) [5]. Moreover, Nissan's 2013 annual report stated that they aimed to increase their global market share to 8% by the end of the fiscal year 2016, up from the current level of 6.2% [6]. The company is counting on expansion in big emerging markets such as Brazil, Russia, India and China (BRIC) to drive sales and profit growth.

The tight competition among automakers leads to the continuous improvement of science and technology, and especially their ability to meet the customer's wishes. Important questions are raised for the future of the automobile industry and Nissan. How will Nissan create value for the customers, societies and for Nissan itself in the pursuit of perfection? How will it maintain its competitiveness in fierce markets, expand its scale, produce high quality products while maintaining low-costs and protecting the environment? The purpose of this study is to propose an effective approach based on grey forecasting and data envelopment analysis (DEA) to find the best partners of alliance. The model predicts future business and measures operation efficiency by using critical input and output variables. From that, the enterprises can find their suitable candidates when setting international business strategies. For this purpose, this study sets Nissan as a target decision making unit (DMU) in order to conduct empirical research. The study's results can be referenced for worldwide automobile manufactures.

James *et al.* stated that "Alliances are fueling the success of a wide range of firms, including British Petroleum, Eli Lilly, General Electric, Corning Glass, Federal Express, IBM, Starbucks, Cisco Systems, Millennium Pharmaceuticals, and Siebel Systems" [7]. However, many enterprises have failed with alliances or have not met the conditions of their partner. In this section, the research helps to define strategic alliances and provides a literature review.

Mockler difined "Strategic alliances are agreements between companies (partners) to reach objectives of common interest" [8]. International strategic alliances (ISAs) are voluntary, long-term, contractual, cross-border relationships between two firms, designed to achieve specific objectives [9]. These definitions emphasize the importance of common business goals with the involved companies. Cravens *et al.*, distinguished strategic alliance as a horizontal collaborative relationship that does not include any kind of equity exchange or creation of a new entity as in joint ventures [10]. Chan *et al.* stated that: Strategic alliance is a cooperative agreement between different organizations. The purpose of action aims at achieving the competitive advantages and sharing resources in product design, production, marketing and/or distribution [11]. The types of alliances range from simple agreements with no equity ties to more formal arrangements involving equity ownership and shared managerial control over joint activities. The alliance activities can be supplier–buyer partnerships, outsourcing agreements, technical collaboration, joint research projects, shared new product development, shared manufacturing arrangements, common distribution agreements, and cross-selling arrangements. The type that should be applied depends on the structures or objectives of each enterprise.

Besides that, the alliance should conform to competition laws, with the world's largest and most influential anti-trust law systems existing in the United States and European Union. However, business cooperation could be seen as one kind of alliance as well. This research focuses on the selection of business partners, so anti-trust law issues are not major focus of this study.

Candace *et al.* had investigated 89 high technology alliances and suggested that direct-competitor alliances might be an inefficient means for innovating [12]. Cho *et al.* observed the trend of world telecommunication and sought to answer whether alliance strategies needed to be regulated by the government. By reviewing global alliance strategies in some countries, the research pointed towards some reasonable recommendations for regulation of telecommunication enterprises [13]. Kauser and Shaw investigated strategic alliance agreements among UK firms and their European, Japanese and US partners. The results indicated that the majority of UK firms engaged in international partnerships for marketing of relevant activities and for entering a foreign market. The findings had also indicated that the majority of UK managers were satisfied with the overall performance of their international strategic alliances [14]. Those papers had investigated alliances in various type of firms, however, the lack of focus on the automobile industry is one of the impetuses for this research.

Forecast time series have been used quite regularly by researchers. There are various forecasting models which have different mathematical backgrounds such as fuzzy predictors, neural networks, trend extrapolation, and grey prediction. Grey system theory as an interdisciplinary scientific area was first introduced in the early 1980s by Deng in 1982 [15].From then on, the theory has become a quite popular method to deal with the uncertainty problems under partially unknown parameters and poor or missing information. Superior to conventional statistical models, grey models claim only a limited amount of data to evaluate the action of unknown systems [16].

The techniques of frontier analysis had been described by Farrel in 1957 [17], but a mathematical framework to handle frontier analysis was established only after two decades. The DEA was introduced by Charnes *et al.* [18]. They proposed a "data oriented" approach for measuring the performance of multiple DMUs, by converting multiple input into multiple output. DMU could include manufacturing units, schools, universities, bank branches, hospitals, power plants, *etc.* Recently, there have been various DEA applications in private and public sectors of different countries.

Martín and Roman used DEA to analyze the technical efficiency and performance of each individual Spanish airport. They used the results to put forward some policy considerations in preparation for the process of privatization of the Spanish airport system [19]. Wang *et al.* applied data envelopment analysis and the heuristic technique approach to help department stores find the most proper partners for strategic alliances. The results indicated that candidate selection of strategic alliances could be an effective strategy for enterprises to find out the right partners for cooperation [20]. Wang *et al.* used Grey and DEA techniques to measure production and marketing efficiencies of 23 companies in the printing circuit board industry. The results showed that 15 companies require improvements in both production and marketing efficiency, while four companies had their production efficiency improved and the remaining four firms experienced both improvement in production and marketing efficiency [21]. Yuan and Tian applied the two-stage method of the DEA model to analyze the science and technology resources efficiency of industrial enterprises and its influencing factors. The results reflected the independence of the input element and the concentration of the output element [22].

For the above reasons, the integrating model of Grey and DEA in alliance decision making is a new effective approach in this research. The model predicts future business and measures operation efficiency by using critical input and output variables. From that, automobile manufacturers can find feasible candidates for alliance strategies.

2. Methodologies

2.1. Research Development

In this study, the researchers use GM(1,1) [16] and DEA models to construct a systematic forecast and assessment approach. Figure 2 provides an overview of how to combine GM and DEA through detailed steps. The study uses future data (prediction data by grey forecasting) as the inputs and outputs of DEA. Then, the DEA method is used to compare alliance combinations. The research uses GM(1,1) to develop a forecast approach through the use of time series data with four inputs and three outputs. The prediction results are continuously put in the DEA model to measure the efficiency of all DMUs before and after alliance. The steps involved in data collection and inputs-outputs selection constitute the initial work of this study. Step 3 involves forecast work by using grey model GM(1,1) to predict the data values in future years. In order to ensure that the forecasting error is reliable, MAPE is employed to measure the prediction accuracy in Step 4. The researcher has to reselect input and output factors if there is a high level of error.

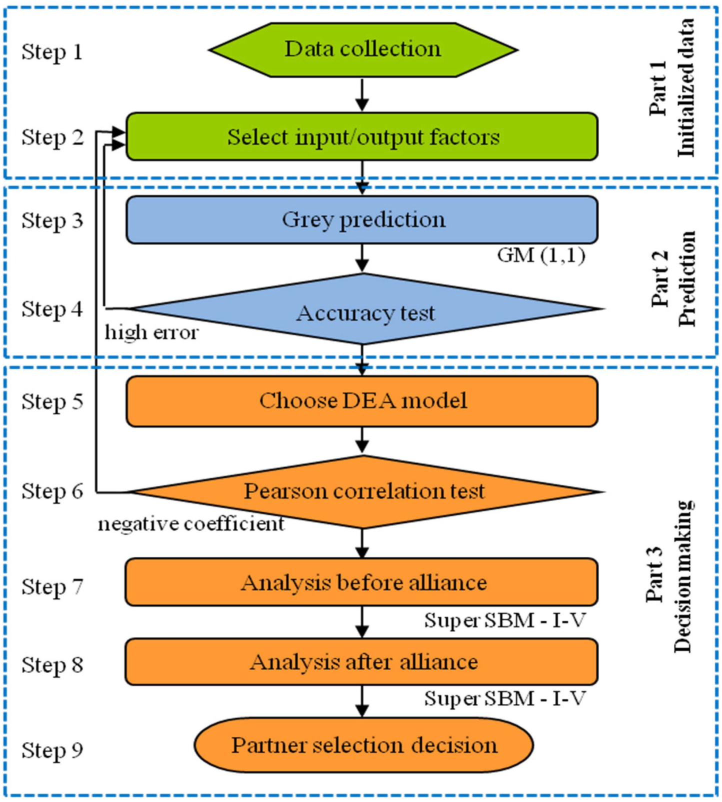

Figure 2. Research development.

DEA is a linear programming methodology. It measures the efficiency of multiple DMUs with a structure of multiple inputs and outputs. Hence, the super SBM-I-V model of DEA-Solver software is applied for the calculations in Step 5. Step 6 employs the Pearson Correlation Coefficient Test to check correlation values between inputs and outputs and whether they are positive or not. If the variables have a negative coefficient, we remove them and go back to Step 2 to rebuild a new variable until it can meet our requirements.

The aim of Step 7 is to find out the target company's position in comparison with the other 19 automobiles competitors via ranking the efficiency of each decision making unit, by applying the Super-SBM-I-V model in the realistic data. Step 8 is performed to establish new virtual alliances by combining the target DMU6 with the other 19 DMUs, respectively. After consolidation, the Super-SBM-I-V model is used to evaluate and rank new companies in comparison with existing ones. Suggestions will be provided based on the analysis results of this step, but they do not necessarily presume feasibility until further analysis in Step 9. In this step, the researcher looks more closely at the candidate firms to determine possible approaches for forming alliances.

2.2. Collecting the DMUs

This research was only conducted examining the 20 companies in the World Ranking of Manufacturing [2]. They have demonstrated a steady performance and can provide complete data for four consecutive financial years (2009–2012) as reported in Bloomberg Business Week [23]. Furthermore, these enterprises are representative of the entire auto industry in the global market (Table 1). DMU6 Nissan is set as the target company. Recently, this auto maker has faced great challenges with regards to globalization and competition. Hence, a strategic alliance could be part of an effective strategy for DMU6 to acquire resources and build business relationships.

Table 1. List of Automobile Manufacturing Companies.

Number Order	Code DMUs	Companies Name	Headquarter Address	Founded Year
1	DMU1	Toyota Motor Corporation	Japan	1937
2	DMU2	General Motors Company	U.S	1908
3	DMU3	Volkswagen Group AG	Germany	1937
4	DMU4	Hyundai Motor Company	Korea	1967
5	DMU5	Ford Motor Co.	U.S	1903
6	DMU6	Nissan Motor Co. Ltd.	Japan	1933
7	DMU7	Fiat Automobiles S.p.A	Italy	1899
8	DMU8	Honda Motor Co., Ltd.	Japan	1948
9	DMU9	Suzuki Motor Corporation	Japan	1909
10	DMU10	Renault S.A	France	1899
11	DMU11	Daimler AG	Germany	1926
12	DMU12	Bayerische Motoren Werke AG(BMW)	Germany	1916
13	DMU13	Mazda Motor Corporation	Japan	1920
14	DMU14	DongFeng Motor Corporation	China	1969
15	DMU15	Mitsubishi Motors Corporation	Japan	1970
16	DMU16	Chang An Automobile (Group) Co. Ltd.	China	1862
17	DMU17	Tata Motors Ltd. (TTMT)	India	1945
18	DMU18	Geely Automobile Holdings Ltd.	China	1986
19	DMU19	Isuzu Motors Ltd.	Japan	1916
20	DMU20	Daihatsu Motor Co. Ltd.	Japan	1907

Source: World Ranking of Manufacturers [2].

2.3. Grey Forecasting Model

GM(1,1) model of this study is built based on two basic operations. Accumulated generation operation (AGO) is applied to reduce the randomization of the raw data, and inverse accumulated generation (IAGO) is used to find the predicted values of initial data. The data series must be more than four, taking equal intervals and in consecutive order without neglecting any data [16]. The GM(1,1) model establishment process in this study is summarized as follows:

Establish the initial series $X^{(0)}$ by

$$X^{(0)} = \left(X^{(0)}(1), X^{(0)}(2), \ldots, X^{(0)}(n)\right),\ n \geqslant 4 \tag{1}$$

where $X^{(0)}$ is a non-negative sequence and n is the number of years observed.

Based on initial series $X^{(0)}$, a new sequence $X^{(1)}$ is set up through the AGO, which is

$$X^{(1)} = \left(X^{(1)}(1),\ X^{(1)}(2), \ldots, X^{(1)}(n)\right),\ n \geqslant 4 \tag{2}$$

$$\text{where } X^{(1)}(1) = X^{(0)}(1) \text{ and } X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}_{(\mathrm{i})}, k = 1,\ 2,\ 3, \ldots, n \tag{3}$$

Define mean value series $Z^{(1)}$ of adjacent data $X^{(1)}$ as:

$$Z^{(1)} = \left(Z^{(1)}(1),\ Z^{(1)}(2), \ldots, Z^{(1)}(n)\right) \tag{4}$$

where $Z^{(1)}(\mathrm{k})$ is calculated as follow:

$$Z^{(1)}(k) = 0.5 \times \left(X^{(1)}(k) + X^{(1)}(k-1)\right),\ k = 2,\ 3,\ \ldots,\ n \tag{5}$$

The GM(1,1) model can be built by establishing first order differential equation for $X^{(1)}(k)$.

$$\frac{dX^{(1)}(k)}{dk} + aX^{(1)}k = b \tag{6}$$

where parameter a is developing coefficient and b is grey input.

The solution to Equation (6) can be found by using the least square method to find parameters a and b:

$$\begin{bmatrix} a \\ b \end{bmatrix}^T = \left(B^T B\right)^{-1} B^T \overline{Y}_N \tag{7}$$

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \cdots\cdots\cdots & \cdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \tag{8}$$

and

$$Y_N = \begin{bmatrix} X^{(0)}(2) \\ \cdots\cdots\cdots \\ X^{(0)}(n) \end{bmatrix} \tag{9}$$

(B is called data matrix, Y is called data series, and $[a,\ b]^T$ is called parameter series).

According to Equation (6), the solution of $X^{(1)}(\mathrm{k})$ at time k:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak} + \frac{b}{a}\ (k = 1,\ 2,\ 3,\ \ldots) \tag{10}$$

We acquired $\hat{X}^{(1)}$ from Equation (10). Let $\hat{X}^{(0)}$ be the GM(1,1) fitted and predicted series

$$\hat{X}^{(0)} = \left(\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \ldots, \hat{X}^{(0)}(n), \ldots\right),\ where\ \hat{X}^{(0)}(1) = X^{(0)}(1) \tag{11}$$

Finally, to obtain the predicted value of the primitive data at time (k + 1), the inverse accumulated generating operation (IAGO) is used to establish the following grey model:

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}\left(1 - e^{a}\right)\ (k = 1,\ 2,\ 3,\ \ldots) \tag{12}$$

In general, the grey forecasting model uses this operation to construct differential Equations.

2.4. Non-Radial Super Efficiency Model (Super-SBM)

The super SBM was developed on a non-radial model called SBM "Slacks-based measure of efficiency" introduced by Tone in 2001 [24], which directly deals with input and output slacks and return efficiency scores between 0 and 1. SBM deals with n DMUs, each DMU having input/output matrices $X = \left(x_{ij}\right) \in R^{m\times n}$ and $Y = \left(Y_{ij}\right) \in R^{s\times n}$, respectively. λ is a non-negative vector in R^{n}. Vectors $S^{-} \in R^{m}$ and $S^{+} \in R^{s}$ are the input excess and output shortfalls, respectively [25]. To estimate the efficiency of (x_0, y_0), the SBM programwas formulated as follows [24]:

$$\min \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} S_i^{-}/x_{i0}}{1 + \frac{1}{s}\sum_{i=1}^{s} S_i^{+}/y_{i0}} \tag{13}$$

$$\text{st.} x_0 = X\lambda + S^{-},\ y_0 = Y\lambda - S^{+},\ \lambda \geqslant 0,\ S^{-} \geqslant 0,\ S^{+} \geqslant 0 \tag{14}$$

Let an optimal solution for SBM be $(p^{*},\ \lambda^{*}, S^{-*},\ S^{+*})$. A DMU$(x_0, y_0)$ is SBM-efficient, if $p^{*} = 1$. That means $S^{-*} = 0,\ and\ S^{+*} = 0$ (or no input excesses and no output shortfalls). Based on this assumption, Tone has proposed a super-efficiency model for ranking DMUs and it was identified as following program [26]:

$$\min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \overline{x}_i/x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \overline{y}_r/y_{r0}} \tag{15}$$

$$\text{st.}\overline{x} \geqslant \sum_{j=1,\neq 0}^{n}\lambda_j x_j,\ \overline{y} \leqslant \sum_{j=1,\neq 0}^{n}\lambda_j x_j,\ \overline{x} \geqslant\ x_0,\ and\ \overline{y} \leqslant\ y_0,\ \overline{y}\ \geqslant 0,\ \lambda \geqslant 0 \tag{16}$$

If the denominator is equal to 1, the objective function will become the input-oriented of the super SBM model and it returns a value for the objective function which is greater or equal to one.

By the nature of things, inputs should be positive, but outputs may be negative. Nevertheless, many DEA models including SBM models cannot handle non-positive outputs, until a new scheme was introduced in DEA-Solver pro 4.1 Manual [25].

Suppose that $y_{r0} \leqslant\ 0$. It has defined $\overline{y}_r^{+}\ and\ \overline{y}_{-r}^{+}$ by

$$\overline{y}_r^{+}\ =\ \max_{j=1,\ldots,n}\left\{y_{rj}\middle|y_{rj} > 0\right\}, \tag{17}$$

$$\overline{y}_r^{+}\ =\ \min_{j=1,\ldots,n}\left\{y_{rj}\middle|y_{rj} > 0\right\}, \tag{18}$$

In the objective function, if the output r has no positive elements, then it is defined as $\overline{y}_r^{+}\ =\ y_{-r}^{+}\ =\ 1$. The term s_r^{+}/y_{r0} will be replaced in the following way. (The value y_{r0} of in the constraints has never changed).

If $\overline{y}_r^+ > y_{-r}^+$ the term is replaced by:

$$s_r^+ / \frac{y_{-r}^+ \left(\overline{y}_r^+ - y_{-r}^+\right)}{\overline{y}_r^+ - y_{r0}} \tag{19}$$

If $\overline{y}_r^+ = y_{-r}^+$ the term is replaced by:

$$s_r^+ / \frac{\left(y_{-r}^+\right)^2}{B\left(\overline{y}_r^+ - y_{r0}\right)} \tag{20}$$

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

Furthermore, the denominator is positive and strictly less than y_{-r}^+. Moreover, it isinverse to the distance $\overline{y}_r^+ - y_{r0}$. Hence, this scheme concerns the magnitude of the nonpositive output positively. The score obtained is units invariant; it is independent of the units of measurement used [25].

2.5. EstablishingInput/Output Variables

In order to adequately measure the efficiency of a DEA model and simultaneously help the target DMU to find the right alliance partners, the selection of input and output elements should be carefully considered. Based on literature reviews of DEA, automobile operations, the International Accounting Standard (IAS) [27], and also the suitable correlation between input and output, in this research we decided to select four inputs factors, including fixed assets (Fix.as), cost of goods sold (Cogs), operating expenses (O.exp) and long-term investment (L.inv). Revenues (Rev), total equity (T.eq) and net incomes (Net.in) are chosen as output factors. These indicators provide a signal to measure the health of a firm and the benefit it could bring through a strategic alliance to all owners and investors. In the interest of length, the researcher only shows the data from 2012. Detailed data are shown in Table 2.

Table 2. Inputs and outputs data of all DMUs in 2012.

DMUs	Inputs (1,000,000 U.S Dollars)				Outputs (1,000,000 U.S Dollars)		
	(I) Fix.as	(I) Cogs	(I) O.exp	(I) L.inv	(O) Rev	(O) T.eq	(O) Net.in
DMU1	65,703.40	172,721.40	19,298.00	71,530.40	211,595.60	122,619.40	9227.10
DMU2	24,196.00	135,963.00	12,231.00	7062.00	152,256.00	37,000.00	6188.00
DMU3	73,415.80	193,658.50	29,135.30	18,222.00	262,873.60	111,594.60	16,412.90
DMU4	26,870.00	61,106.30	10,402.50	13,809.10	79,443.80	45,066.50	8052.40
DMU5	26,228.00	112,578.00	12,175.00	3133.00	134,252.00	16,311.00	5665.00
DMU6	41,837.50	76,937.30	10,389.50	5825.40	92,347.60	39,069.60	3284.10
DMU7	25,559.20	96,989.80	11,667.40	2693.50	114,181.50	17,919.60	473.30
DMU8	22,987.50	70,440.10	19,220.80	6370.80	94,729.50	49,794.40	3521.00
DMU9	5829.00	18,386.10	4935.10	2602.20	24,700.30	12,440.10	770.10
DMU10	15,687.20	46,373.30	8772.20	22,333.90	56,137.10	33,385.90	2410.30
DMU11	60,398.20	120,679.40	24,397.90	9401.60	155,483.90	61,910.90	8291.30
DMU12	14,607.30	63,896.00	8537.50	4367.10	104,556.30	41,360.70	6933.40
DMU13	7522.30	16,583.90	4047.30	1299.80	21,148.50	4921.80	329.00
DMU14	4264.70	16,536.50	2503.80	316.40	20,484.50	9518.10	1501.50
DMU15	3714.30	14,161.40	2616.90	929.40	17,425.10	3371.80	364.60
DMU16	2383.40	3970.00	1004.00	1292.70	4865.50	2541.50	238.90
DMU17	5970.30	21,734.80	6206.30	246.60	30,701.70	6183.90	1608.50
DMU18	1157.00	3313.40	475.70	32.80	4066.10	2180.00	336.80
DMU19	4799.80	13,420.40	1187.20	1369.50	15,860.50	5948.80	924.80
DMU20	4267.20	13,378.20	2582.20	5787.30	17,261.50	15,512.00	796.20

Sources: Bloomberg news [23].

3. Results and Discussion

3.1. Prediction Results

This research applies the GM(1,1) model to predict the input/output factors for future years. The fixed assets of DMU_6 were selected as an example to condcut the experiment (Table 3), and other variables are computed in line with the following steps:

Table 3. Inputs and outputs factors of DMU6 in the period of 2009–2012.

	Inputs (1,000,000 U.S dollars)				Outputs (1,000,000 U.S dollars)		
DMU6	(I) Fix.as	(I) Cogs	(I) O.exp	(I) L.inv	(O) Rev	(O) T.eq	(O) Net.in
2009	36,999.50	55,140.60	10,264.70	2548.20	72,090.70	28,914.90	406.50
2010	34,879.20	68,617.40	10,362.20	5113.30	84,134.00	31,395.60	3061.30
2011	35,782.60	74,541.50	10,456.50	4916.10	90,232.60	33,085.50	3274.30
2012	41,837.50	76,937.30	10,389.50	5825.40	92,347.60	39,069.60	3284.10

Sources: Bloomberg news [23].

1st: establish the original series:

$$X^{(0)} = (36,999.50; 34,879.20; 35,782.60; 41,837.50)$$

2nd: create $X^{(1)}$ series by executing the accumulated generating operation (AGO):

$$X^{(1)} = (36,999.50; 71,878.70; 107,661.30; 149,498.80)$$

3rd: calculate mean sequence $Z^{(1)}$ of $X^{(1)}$ by the mean equation:

$$Z^{(1)}(k) = (54,439.10; 89,770.00; 128,580.05),\ k = 2,\ 3,\ 4$$

4th: solve equations:
To find a and b, the original series are substituted into the Grey differential equation:

$$\begin{cases} 34,879.20 + & \mathrm{a} \times & 54,439.10 = \mathrm{b} \\ 35,782.60 + & \mathrm{a} \times & 89,770.00 = \mathrm{b} \\ 41,837.50 + & \mathrm{a} \times & 128,580.05 = \mathrm{b} \end{cases}$$

and convert the linear equations into the form of a matrix:

$$\text{Let } B = \begin{bmatrix} -54,439.10 & 1 \\ -89,770.00 & 1 \\ -128,580.05 & 1 \end{bmatrix},\ \hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix}, Y_N = \begin{bmatrix} 34,879.20 \\ 35,782.60 \\ 41,837.50 \end{bmatrix}$$

Before using the least square method to find a and b

$$\hat{\theta} = \left(B^T B\right)^{-1} B^T \overline{Y}_N = \begin{bmatrix} -0.094869531 \\ 28,873.31 \end{bmatrix}$$

use the two coefficients a and b to generate the whitening equation of the differential equation:

$$\frac{dX^{(1)}}{dk} - 0.09486531 \times X^{(1)} = 28,873.31$$

Find the prediction model from equation:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} = 341,347.05 \ * \ e^{0.094869531 \text{ k}} - 304,347.56$$

Finding $X^{(1)}$ series by substituting different values of k into above equation:

$$\text{K} = 0 \quad X^{(1)}(1) = 36,999.50$$

$$\text{K} = 1 \quad X^{(1)}(2) = 70,968.78$$

$$\text{K} = 2 \quad X^{(1)}(3) = 108,318.53$$

$$\text{K} = 3 \quad X^{(1)}(4) = 149,385.16$$

$$\text{K} = 4 \quad X^{(1)}(5) = 194,538.55$$

$$\text{K} = 5 \quad X^{(1)}(6) = 244,185.39$$

$$\text{K} = 6 \quad X^{(1)}(7) = 298,772.86$$

$$\text{K} = 7 \quad X^{(1)}(8) = 358,792.60$$

$$\text{K} = 8 \quad X^{(1)}(9) = 424,785.30$$

Originate the predicted value of the original series according to the IAGO and obtain:

$$\hat{X}^{(0)}(1) = \hat{X}^{(1)}(1) = 36,999.50$$

$$\hat{X}^{(0)}(2) = \hat{X}^{(1)}(2) - \hat{X}^{(1)}(1) = 33,969.28$$

$$\hat{X}^{(0)}(3) = \hat{X}^{(1)}(3) - \hat{X}^{(1)}(2) = 37,349.75$$

$$\hat{X}^{(0)}(4) = \hat{X}^{(1)}(4) - \hat{X}^{(1)}(3) = 41,066.63$$

$$\hat{X}^{(0)}(5) = \hat{X}^{(1)}(5) - \hat{X}^{(1)}(4) = 45,153.39$$

$$\hat{X}^{(0)}(6) = \hat{X}^{(1)}(6) - \hat{X}^{(1)}(5) = 49,646.84$$

$$\hat{X}^{(0)}(7) = \hat{X}^{(1)}(7) - \hat{X}^{(1)}(6) = 54,587.47 \ \text{(predicted value of 2015)}$$

$$\hat{X}^{(0)}(8) = \hat{X}^{(1)}(8) - \hat{X}^{(1)}(7) = 60,019.76 \ \text{(predicted value of 2016)}$$

$$\hat{X}^{(0)}(9) = \hat{X}^{(1)}(9) - \hat{X}^{(1)}(8) = 65,992.65 \ \text{(predicted value of 2017)}$$

Using the above computation process, this research could obtain the forecasting result of all DMUs for subsequent years; the detailed data is shown in the following Table 4:

Table 4. Predicted inputs and outputs value of all DMUs in 2016 and 2017 (calculated by GM).

DMUs	Inputs (1,000,000 U.S Dollars)								Outputs (1,000,000 U.S Dollars)					
	(I) Fixed Assets		(I) Cost of Goods Sold		(I) Operating Expenses		(I) Long-Term Investments		(O) Revenues		(O) Total Equity		(O) Net Income	
	2016	2017	2016	2017	2016	2017	2016	2017	2016	2017	2016	2017	2016	2017
1	76,687.0	80,030.2	217,158.9	231,159.2	21,093.2	21,674.4	124,614.0	143,671.4	283,274.9	306,795.8	166,888.2	181,102.1	86,510.6	163,021.6
2	38,145.7	42,570.8	178,534.5	190,828.1	13,791.7	14,196.5	4366.8	3925.1	193,191.1	204,363.3	37,327.8	37,250.5	7218.4	7225.4
3	175,325.5	218,068.3	440,708.4	541,512.0	70,484.0	88,446.5	13,915.8	12,926.1	597,532.6	733,901.5	309,703.8	400,581.0	39,379.8	48,592.5
4	48,927.6	56,836.7	97,854.3	109,970.5	13,680.6	14,598.0	30,158.2	36,413.7	125,928.4	141,029.0	94,663.7	113,980.0	18,263.2	22,307.3
5	30,115.6	31,336.1	132,009.9	136,898.3	12,647.2	12,809.7	4785.4	5321.4	146,889.9	149,806.7	255,175.4	480,692.6	9401.7	9142.5
6	60,019.8	65,992.7	97,057.8	102,672.3	10,471.0	10,484.7	7474.2	8014.2	111,709.3	116,949.5	60,499.7	67,763.5	3806.0	3939.1
7	90,406.1	122,177.9	467,417.7	694,650.7	48,355.5	69,039.4	4189.9	4586.4	553,201.8	823,165.7	19,817.2	20,392.2	666.2	614.5
8	35,211.1	39,412.1	88,989.2	95,371.2	22,491.6	23,502.5	7113.9	7335.8	112,881.3	119,350.7	63,448.4	67,790.1	840.9	634.9
9	7800.2	8453.0	17,034.6	16,740.1	4814.0	4813.7	3,808.5	4288.3	23,871.2	23,731.1	17,023.6	18,511.6	2539.4	3452.4
10	15,696.1	15,716.8	58,170.3	61,220.3	8950.3	8957.0	26,398.2	27,397.1	63,902.8	65,684.6	39,160.3	40,631.7	517.4	360.8
11	93,944.0	104,884.2	168,675.6	183,521.6	30,441.0	32,120.4	11,399.9	11,929.0	212,500.5	229,667.8	88,905.4	97,380.6	15,001.0	17,320.3
12	14,614.5	14,620.7	111,821.0	128,629.1	11,900.1	12,919.7	8890.3	10,659.5	168,383.5	189,641.2	66,600.4	75,028.9	16,066.7	19,633.6
13	7483.8	7475.0	13,790.7	13,258.6	3682.3	3611.6	2085.2	2361.6	18,188.0	17,676.6	6989.7	7626.8	(26.9)	(15.5)
14	8247.3	9742.0	18,320.8	18,691.4	2980.0	3107.2	584.8	677.3	21,475.1	21,612.5	18,359.5	21,633.1	1061.7	969.0
15	3752.8	3769.3	12,944.6	12,671.4	3134.7	3283.5	195.9	139.7	17,123.7	17,060.5	6888.1	8292.9	2053.7	3194.6
16	10,976.2	16,122.6	2782.9	2577.6	1169.5	1228.2	2212.4	2512.8	3431.6	3193.3	5032.9	5927.1	72.9	57.5
17	12,773.6	15,467.8	48,191.7	58,533.9	18,354.1	24,129.1	315.3	336.3	70,654.4	86,707.7	20,429.5	27,357.7	2009.5	2060.9
18	1887.2	2120.0	4968.6	5520.2	691.8	763.2	569.9	1214.5	6098.0	6776.8	4676.1	5689.8	761.0	938.4
19	5078.6	5165.0	17,717.1	19,116.2	1424.2	1495.0	2995.5	3645.7	21,553.3	23,418.1	15,263.3	19,376.8	2746.9	3565.4
20	4868.4	5042.3	16,840.6	17,860.6	3156.8	3324.7	10,075.6	11,595.4	22,055.2	23,479.8	40,887.8	52,126.0	1894.9	2357.8

Source: Calculated by researcher.

3.2. Forecasting Accuracy

Forecasting method is implemented to predict future results using the present uncompleted information, so we do not introduce new errors. Hence, the MAPE (Mean absolute percent error) is employed to measure the accuracy values in statistics. The smaller values of MAPE demonstrate that the forecasting values are more reasonable [28]. The results of MAPE are shown in Table 5:

Table 5. Average MAPE of DMUs.

DMUs	Average MAPE	DMUs	Average MAPE
DMU1	5.84809%	DMU11	0.79240%
DMU2	3.52436%	DMU12	1.30784%
DMU3	1.90186%	DMU13	10.8717%
DMU4	1.71334%	DMU14	1.65806%
DMU5	45.3331%	DMU15	3.07850%
DMU6	1.51432%	DMU16	6.56818%
DMU7	11.4944%	DMU17	3.83133%
DMU8	6.64905%	DMU18	3.48085%
DMU9	3.99930%	DMU19	2.67108%
DMU10	2.22754%	DMU20	0.68057%
Average MAPE of 20 DMUs		*5.95730%*	

Most of the MAPE values are good and qualified, being smaller than 10%. The average of all MAPE reaches 5.95730%.This affirms that the GM(1,1) model offers a high accurate prediction. DMU5 obtains a 45% higher MAPE value because it is strongly affected by the 2008 crisis. However, based on the MAPE accuracy standards, only this value is qualified.

3.3. Pearson Correlation

The homogeneity and isotonicity are two major basic DEA data assumptions. The basic DEA assumption between input data and output data needs to be isotonic. The means the input data and output data need to have a positive correlation. Correlation test is an important step in applying the DEA technique to ensure the relationship between input and output factors is isotonic (*i.e.*, an increase in any input should not result in a decrease in any output) [29]. This study employs a simple correlation test—Pearson correlation—to measure the strength of the linear relationship of normal distributed variables [30]. If the correlation coefficient is positive, these factors are isotonically related and will be put into the DEA model; when the factor demonstrates a weak isotonic relationship, it will be reexamined [31]. The correlation coefficient is always between −1 and +1.

The results of correlation coefficients between input and output variables in Tables 6–9 show strong positive associations and comply with the precondition of the DEA model. Hence, these positive correlations also prove that the selection of input and output variables is appropriate. This means those data are proper for DEA assumption and can be used for the analysis for DEA calculations.

Table 6. Correlation of input and output data in 2009.

	Fix.as	Cogs	O.exp	L.inv	Rev	T.eq	Net.in
Fix.as	1	0.900516	0.902008	0.770458	0.924567	0.868580	0.010851
Cogs	0.900516	1	0.916182	0.750937	0.989125	0.788681	0.334254
O.exp	0.902008	0.916182	1	0.666827	0.938334	0.799956	0.140062
L.inv	0.770454	0.750937	0.666827	1	0.745437	0.887277	0.090390
Rev	0.924567	0.989125	0.938334	0.745437	1	0.812591	0.225816
T.eq	0.868580	0.788681	0.799956	0.887277	0.812591	1	0.078414
Net.in	0.010851	0.334254	0.140062	0.090390	0.225816	0.078414	1

Table 7. Correlation of input and output data in 2010.

	Fix.as	Cogs	O.exp	L.inv	Rev	T.eq	Net.in
Fix.as	1	0.908011	0.901304	0.760279	0.915191	0.888756	0.712517
Cogs	0.908011	1	0.884399	0.701945	0.991911	0.821255	0.810075
O.exp	0.901304	0.884399	1	0.598485	0.907604	0.826895	0.827244
L.inv	0.760279	0.701945	0.598485	1	0.680493	0.878784	0.421430
Rev	0.915191	0.991911	0.907604	0.680493	1	0.831531	0.851679
T.eq	0.888756	0.821255	0.826895	0.878784	0.831531	1	0.626496
Net.in	0.712517	0.810075	0.827244	0.421430	0.851679	0.626496	1

Table 8. Correlation of input and output data in 2011.

	Fix.as	Cogs	O.exp	L.inv	Rev	T.eq	Net.in
Fix.as	1	0.908680	0.911810	0.691419	0.915207	0.909611	0.535213
Cogs	0.908680	1	0.872887	0.627072	0.991641	0.853222	0.728935
O.exp	0.911810	0.872887	1	0.547521	0.893166	0.855927	0.586748
L.inv	0.691419	0.627072	0.547521	1	0.600729	0.846506	0.142137
Rev	0.915207	0.991641	0.893166	0.600729	1	0.867635	0.750202
T.eq	0.909612	0.853222	0.855927	0.846506	0.867635	1	0.413475
Net.in	0.535214	0.728935	0.586748	0.142137	0.750202	0.413475	1

Table 9. Correlation of input and output data in 2012.

	Fix.as	Cogs	O.exp	L.inv	Rev	T.eq	Net.in
Fix.as	1	0.916378	0.921629	0.632545	0.925523	0.913111	0.85602
Cogs	0.916377	1	0.898532	0.594043	0.992487	0.861108	0.857803
O.exp	0.921629	0.898532	1	0.481858	0.919848	0.860337	0.84896
L.inv	0.632545	0.594043	0.481858	1	0.580518	0.796618	0.50826
Rev	0.925523	0.992487	0.919848	0.580518	1	0.886316	0.897967
T.eq	0.913110	0.861108	0.860337	0.796617	0.886316	1	0.874886
Net.in	0.856015	0.857803	0.84896	0.508260	0.897967	0.874886	1

Remark: Fixed assets (Fix.as), Cost of goods sold (Cogs), Operating expenses (O.exp); Long-term investment (L.inv). Revenues (Rev), Total equity (T.eq) and Net incomes (Net.in).

3.4. Analysis before Alliance

In this research, the efficiency of 20 DMUs and their ranking before alliances was measured by the Super-SBM-I-V model, with the realistic data of 2012. The empirical results of Table 10 indicated that DMU18 has the best efficiency (the first ranking with the score = 5.8965750), followed by DMU12 and DMU14 ranking second and third place. The target DMU6 is in the 18th ranking, being part of the last group. This ranking emphasizes again that it is necessary for the target company to form strategic alliances to improve its performance.

Table 10. Efficiency and ranking before alliances.

Rank	DMU	Score
1	DMU18	5.8965750
2	DMU12	1.5655136
3	DMU14	1.3982037
4	DMU17	1.3777954
5	DMU20	1.3447020
6	DMU5	1.2097953
7	DMU2	1.1359231
8	DMU4	1.0876949

Table 10. *Cont.*

Rank	DMU	Score
9	DMU19	1.0484095
10	DMU8	1.0307413
11	DMU7	1.0133168
12	DMU1	1
12	DMU3	1
14	DMU11	0.7448770
15	DMU9	0.7176400
16	DMU15	0.7105391
17	DMU10	0.7104498
18	DMU6	0.6492883
19	DMU13	0.5816934
20	DMU16	0.5283717

3.5. Analysis after Alliance

The low inefficiency score (0.6492883 < 1) and low rank (18th/20) of target DMU6 suggests that the enterprise should enhance its operating efficiency and seek advantages from cooperative partners by building a creative alliance strategy. To implement the empirical results, this research combines DMU6 with the remaining DMUs to form 39 virtual DMUs (19 alliances and 20 original cases) in total. The software of DEA-Solver Pro 8.0–Super-SBM-I-V model built by Saitech Company was employed to compute efficiency for all new DMUs. Table 11 shows the ranking results and scores of the virtual alliances.

Table 11. Performance ranking of virtual DMUs.

Rank	DMU	Score	Rank	DMU	Score
1	DMU18	5.8965750	21	DMU6 + DMU4	0.9011136
2	DMU12	1.5655136	22	DMU6 + DMU11	0.8376827
3	DMU14	1.3982037	23	DMU6 + DMU20	0.7731485
4	DMU17	1.3777954	24	DMU6 + DMU14	0.7545630
5	DMU20	1.3447020	25	DMU6 + DMU10	0.7462483
6	DMU5	1.1714878	26	DMU11	0.7229771
7	DMU3	1.1161306	27	DMU9	0.7176400
8	DMU1	1.1140650	28	DMU6 + DMU9	0.7113479
9	DMU2	1.1058616	29	DMU15	0.7105391
10	DMU4	1.0876949	30	DMU10	0.7104498
11	DMU6 + DMU5	1.0655124	31	DMU6 + DMU17	0.7013426
12	DMU19	1.0484095	32	DMU6 + DMU19	0.6720799
13	DMU6 + DMU12	1.0443239	33	DMU6 + DMU18	0.6649845
14	DMU6 + DMU2	1.0400331	34	DMU6	0.6492883
15	DMU8	1.0282731	35	DMU6 + DMU15	0.6279972
16	DMU7	1.0133168	36	DMU6 + DMU16	0.6265420
17	DMU6 + DMU8	1.0117510	37	DMU6 + DMU13	0.6219810
18	DMU6 + DMU7	1.0002026	38	DMU13	0.5816934
19	DMU6 + DMU3	1	39	DMU16	0.5283717
19	DMU6 + DMU1	1			

The results of Table 11 indicate clearly the change from original DMUs to a virtual alliance at different rates. The target DMU6 shows the highest efficiency scores in a relationship with DMU1, DMU3, DMU7, DMU8, DMU2, DMU12 and DMU5. The researcher can compare the efficiency between them by separating them into two groups (see Table 12). The fact that the group has positive results proves these alliances are better than original DMUs. A higher difference value the increased efficiency of an alliance. In contrast, the negative value of the second group means the alliance is worse.

Table 12. The good & bad alliance partnership.

Number Order	Virtual Alliance	Target DMU6 Ranking (1)	Virtual alliance Ranking (2)	Difference (1)–(2)
1st group		Good alliance		
1	DMU6 + DMU5	34	11	23
2	DMU6 + DMU12	34	13	21
3	DMU6 + DMU2	34	14	20
4	DMU6 + DMU8	34	17	17
5	DMU6 + DMU7	34	18	16
6	DMU6 + DMU3	34	19	15
7	DMU6 + DMU1	34	19	15
8	DMU6 + DMU4	34	21	13
9	DMU6 + DMU11	34	22	12
10	DMU6 + DMU20	34	23	11
11	DMU6 + DMU14	34	24	10
12	DMU6 + DMU10	34	25	9
13	DMU6 + DMU9	34	28	6
14	DMU6 + DMU17	34	31	3
15	DMU6 + DMU19	34	32	2
16	DMU6 + DMU18	34	33	1
2nd group		Bad Alliance		
1	DMU6 + DMU15	34	35	−1
2	DMU6 + DMU16	34	36	−2
3	DMU6 + DMU13	34	37	−3

In the first group, the ranking of target DMU is improved after an alliance with another 16 enterprises (DMU1, DMU2, DMU3, DMU4, DMU5, DMU7, DMU8, DMU9, DMU10, DMU11, DMU12, DMU14, DMU17, DMU18, DMU19 and DMU20). This demonstrates that target DMU can take advantages from alliance. The alliance of DMU6 + DMU5, DMU6 + DMU12, DMU6 + DMU2, DMU6 + DMU8 and DMU6 + DMU7 gets the highest efficiency (score >1). Hence, those five candidates will be firstly priority when considering alliance partners. Especially, DMU5 is one of the best potential candidates because of its largest difference value (23). The second group has three enterprises including (DMU15, DMU16, and DMU13) of which DMU6 is worse off after strategic alliances (DMUs' ranking reduced). Thus, those firms would not be chosen by a target DMU because they do not help the enterprise in its vision.

3.6. Partner Selection

In the previous section, the best alliance partnerships are identified based on the position of the target DMU6. Nevertheless, we must further analyze the feasibility of alliance partnerships and compare situations before and after alliances. It can be seen clearly, as shown in the results in Table 12, that there are 16 good partners. However, they will not cooperate with the target DMU, because, the DMU's ranking is lower. In other words, the performance of DMU1, DMU2, DMU3, DMU4, DMU5, DMU7, DMU8, DMU9, DMU12, DMU14, DMU17, DMU18, DMU19 and DMU20 are already good; if there are no special circumstances, they currently have no incentive to form an alliance partnership with the DMU6.

Figure 3 shows more clearly the change in ranking of the above DMUs before and after alliance with target DMU6. The blue line is nearer to the center-point than the red line in most DMUs. This indicates that most of the DMUs have a high efficiency before alliance, but some of them are lower before the alliance relationship (DMU6 + DMU10, DMU6 + DMU11, DMU6 + DMU13, DMU6 + DMU16).

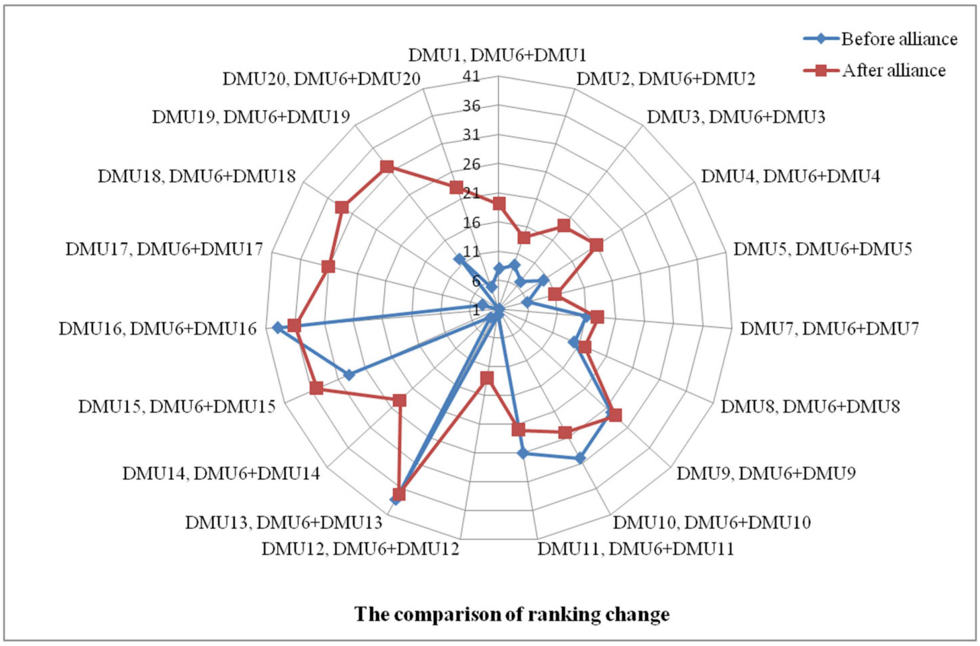

Figure 3. The comparison of changes in ranking.

Combined with Tables 10–12 the efficiency and ranking of all DMUs before and after alliance are reviewed again in Figure 3. Those points which are more close to the center are ranked higher. The points clearly point to an alliance with Renault and Daimler with the target company. Renault and Daimler are not at the level of DEA before alliance; however, their rankings improved after cooperating with Nissan. It means the alliance can bring benefits not only for Nissan but also for Renault and Daimler. In other words, through the alliance, both of Nissan–Renault and Nissan–Daimler AG, opportunities to manage their resource more effectively may arise. Hence, Renault and Daimler should have a strong desire to form an alliance.

In fact, Nissan–Renault has maintained an alliance relationship since 1999. These enterprises now are developing a three-party alliance between Renault–Nissan–Daimler AG. This once again proves the results of this paper are correct and have practical feasibility. However, Nissan should continue to cooperate to effectively utilize the resources of both parties. This will be entailing an intersection between Eastern and Western culture, in line with current globalization trends. The alliance can help to build a production system, which can reduce waste, create value for the customer and achieve perfection. Besides that, the company also needs to enhance common understanding, seeking potential cooperation opportunities from less feasible alliance partners.

In a word, the results and findings of this case study also lead to new recommendations for strategic alliances. The readers can clearly recognize the noticeable candidates for an alliance strategy are Ford Motor (DMU5, the best efficiency improvement for the target company), Renault and Daimler (the efficiency improvement for both target DMU6 and partners DMU10, DMU11).

4. Conclusions

Nowadays, the automobile industry as well as many other industries faces numerous challenges such as: How to achieve competitive advantage and enter new markets? How to obtain new technology and resources and how to reduce risk and share costs of research and development? For solving these problems, this research proposed a decision making model by using a hybrid of Grey theory and DEA. This study focused on the relationship between strategic alliances and the performance of the top 20 enterprises in the automobile industry.

Based on the realistic public data of automobile enterprises from 2009 to 2012, this study used GM(1,1) model to predict the future change in value of the specific input/output variables. The accuracy forecast value had been tested by average MAPE and a reliable percentage of 5.9573% was obtained.

Nissan was used as a case study to determine the potential benefits of strategic alliances between firms. The DEA-Super SBM model was applied to evaluate efficiency all real DMUs and virtual DMUs. The empirical results showed that 16 candidates are suitable for Nissan to form strategic alliances with, of which Ford, BMW, General Motors, Honda, and Fiat are strongly recommended. However, only two partnerships are feasible for Nissan (Nissan–Renault and Nissan–Daimler). If a firm decides to form an alliance, it is necessary to conduct extensive an assessment of performance before and after the alliance in terms of many aspects.

In conclusion, by combining Grey theory and the Super SBM model, this research proposed a new accurate and appropriate approach to forecast and evaluate automobile firms. This model provides a reference for decision making for automaker strategists when developing alliance strategies.

The DEA is one kind of sensitive method for factor selection. The selection of input/output variables could be different, and the results would be impacted. Therefore, robust checking is necessary. The different input/output variables and removing outlierd from DMUs should be re-calculated and re-discussed.

For future study, sensitive analysis for different inputs or outputs of DMUs or data of different years can be discussed further. Moreover, the methodology should be further developed by using qualitative data and should be applied in different industries.

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