

## A strategic alliance study by performance evaluation and forecasting techniques: A case in the petroleum industry



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### ABSTRACT

Petroleum is vital to many industries, and is of importance to the maintenance of industrial civilization in its current configuration. Moreover, the current trend in the World is to form strategic alliance to strengthen the business which is still considering due to uncountable heuristic reasons behind. Thus, this study seems to be a new method and point of view to form strategic alliance. We selected the companies can present for this industry according to Forbes. They also play important roles in the energy industry and global economic. Hence, the selection of these 15 candidates is qualified. We use the data approved and published recently belonging to the petroleum companies, then we analyzed the sequences of data and proposed one of advanced methods in evaluation: DEA – data development analysis. After that, we employed the forecasting technique: grey system theory. We set up one targeted Company to form alliance and final results can fulfill all requirements in their performance both in present and in the future.

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### 1. Introduction

The petroleum industry includes the global processes of exploration, extraction, refining, transporting (often by oil tankers and pipelines), and marketing petroleum products (Jafarinejad, 2016). The largest volume products of the industry are fuel oil and gasoline (petrol). Petroleum (oil) is also the raw material for many chemical products, including pharmaceuticals, solvents, fertilizers, pesticides, and plastics. The industry is usually divided into three major components: upstream, midstream and downstream. Midstream operations are usually included in the downstream category (Wei et al., 2009). Petroleum is vital to many industries, and is of importance to the maintenance of industrial civilization in its current configuration, and thus is a critical concern for many nations. Oil accounts for a large percentage of the world's energy consumption, ranging from as low of 32% for Europe and Asia, up to a high of 53% for the Middle East.

The Middle Eastern region is abundantly endowed with oil and gas resources. Of the 1,050 billion barrels of proven crude oil reserves the MENA region accounted for about 69 percent. In

contrast, the region accounted for just about 31 percent of total world production, and about 50 percent of exports, which clearly demonstrates the centrality of the region to the present and future of the global oil market (Bere, 2010). Although new oil reserves continue to be discovered and developed in various countries, such as in the countries of the former Soviet Union and in offshore West Africa, most forecasts indicate that dependence on Middle Eastern oil will increase in the coming years, as production starts to decline in the key North Sea basin and elsewhere (Klare and Volman, 2006).

From Dubai, Shell now provides a full suite of world-class, environmentally-sound, sustainable exploration and production services from the UAE, to the UAE and the world. Leveraging the logistical and technological synergies available from our Dubai-based sister company Shell Gas & Power, we can transfer our wealth of expertise and innovation to our strategic upstream joint ventures in the UAE, and beyond.

Both Abu Dhabi Company for Onshore Oil Operations (Adco) - in which Shell holds a 9.5 per cent share and which produces one million barrels per day of oil - and Abu Dhabi Gas Industries Company (Gasco), in which Shell holds a 15 per cent share and which extracts four million tons per year of natural gas liquids from the associated gas produced by Adco - benefit from our next-generation digital field capabilities, including enhanced oil recovery (EOR) techniques (Butt, 2001).

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After doing the survey the oil and gas industry, the study finds out 15 enterprises which are in the World's Largest Oil and Gas Companies. Although fifty Leading Oil and Gas Companies around the World were published in 2013, the analysis was only conducted on the 15 companies which are stable in market and can provide the completely data for 4 consecutive years (2010-2013) in their financial statements. We try to propose a new approach of DEA model based on grey forecasting and neural network in helping the target company to make a well-considered decision in finding the right partners (Nguyen et al., 2015). SuperSBM model is evaluated as a necessary approach for any enterprise to get the accuracy information about business performance, to rank business efficiency score, and to know where it is in the current market (Nguyen and Tran, 2017a). At the same time, the study also provides the prediction about business performance in the future – GM(1,1) and neural network, which is relevant for them when setting strategies for production capacity planning and for investment decision making whether should expand their business in international market or not (Nguyen and Tran, 2017b). The authors hope that this study would make several important contributions to the practical field of alliance partner selection

**2. Methodology**

**2.1. Grey forecasting model**

Grey system theory was initiated in 1982 by Deng (1982). The main task of grey system theory is to extract realistic governing laws of the system using available data. This process is known as the generation of the grey sequence. Grey model is suitable for forecasting the competitive environment where decision makers can refer only to a limited historical data (Nguyen and Tran, 2015).

Although various existing types of grey models can be applied for forecasting, the most frequently used grey forecasting model is GM (1,1) due to its computational efficiency (Chen and Huang, 2013). In this study, GM (1,1) was used to get the predicting results. This model is a time series forecasting model, encompassing a group of differential equations adapted for parameter variance, rather than a first order differential equation. Its difference equations have structures that vary with time rather than being general difference equations. Although it is not necessary to employ all the data from the original series to construct the GM (1, 1), the potency of the series must be more than four (Wang et al., 2015). 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 following.

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

$$X^{(0)}=(X^{(0)}(1),X^{(0)}(2),...,X^{(0)}(n)), n \geq 4 \tag{1}$$

where;  $X^{(0)}$ : a non-negative sequence and  $n$ : 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  $X^{(0)}$  defined as:

$$X^{(1)}=(X^{(1)}(1),X^{(1)}(2),...,X^{(1)}(n)), n \geq 4 \tag{2}$$

where;  $X^{(1)}(1)=X^{(0)}(1)$

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

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

$$Z^{(1)}=(Z^{(1)}(1),Z^{(1)}(2),...,Z^{(1)}(n)), \tag{4}$$

where  $Z^{(1)}(k)$  is the mean value of adjacent data, i.e.,

$$Z^{(1)}(k) = \frac{1}{2} (X^{(1)}(k) + X^{(1)}(k + 1)), k = 2,3, \dots, n \tag{5}$$

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:

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

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 Eq. 6. Hence, the solution of above equation can be obtained using the least square method. That is

$$X^{(1)}(k + 1) = \left( X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} \frac{b}{a} \tag{7}$$

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

$$\begin{bmatrix} a \\ b \end{bmatrix} = \hat{\theta} = (B^T B)^{-1} B^T Y_N \tag{8}$$

and

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \dots \dots \dots \\ x^{(0)}(n) \end{bmatrix} \tag{9}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \dots \dots \dots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{10}$$

where: Y is called data series, B is called data matrix, and  $[a, b]^T$  is called parameter series.

We obtained  $\hat{x}^{(1)}$  from Eq. 7. Let  $\hat{x}^{(0)}$  be the fitted and predicted series

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

where  $\hat{x}^{(0)}(1) = \hat{x}^{(0)}(1)$

Applying the inverse accumulated generation operation (IAGO). Namely

$$X^{(0)}(k + 1) = \left( X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} (1 - e^a) \quad (11)$$

The grey model prediction is a local curve fitting extrapolation scheme. At least four data sets are required by the predictor (Eq. 7) to obtain a reasonably accurate prediction and all the process of Grey prediction was showed in Fig. 1.

### 2.2. Non-radial super efficiency model (Super-SBM)

In the present study, a DEA model “Slack-based measure of super-efficiency” (super SBM) was used. This model was developed on “Slacks-based measure of efficiency” (SBM) introduced by Tone (2002).

In this model with  $n$  DMUs with the input and output matrices  $X = (x_{ij}) \in R^{m \times n}$  and  $Y = (y_{ij}) \in R^{s \times n}$  respectively  $\lambda$  is a non-negative vector in  $R^n$ . The vectors  $S^- \in R^m$  and  $S^+ \in R^s$

$R^n$  indicate the input excess and output shortfall respectively.

The model formulation provides a constant return to scale is as follows (Tone, 2002):

$$\min \rho = \frac{1 - \frac{1}{m} \sum_{i=1}^m \frac{S_i^-}{x_{i0}}}{1 + \frac{1}{s} \sum_{i=1}^s \frac{S_i^+}{y_{i0}}} \quad (12)$$

Subject to (s.t)

$$x_0 = X\lambda + s^-, y_0 = Y\lambda - s^+, \lambda \geq 0, s^- \geq 0, s^+ \geq 0 \quad (13)$$

The variables  $S^+$  and  $S^-$  measure the distance of inputs  $X\lambda$  and output  $Y\lambda$  of a virtual unit from those of the unit evaluated. The numerator and the denominator of the objective function of model (Eq. 12) measures the average distance of inputs and outputs, respectively, from the efficiency threshold. Let an optimal solution for SBM be  $p^*, \lambda^*, s^{-*}, s^{+*}$ .

A DMU  $(x_0, y_0)$  is SBM-efficient, if  $p^* = 1$ . This condition is equivalent to  $s^{-*} = 0$  and  $s^{+*} = 0$ , 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 measure between 0 and 1.

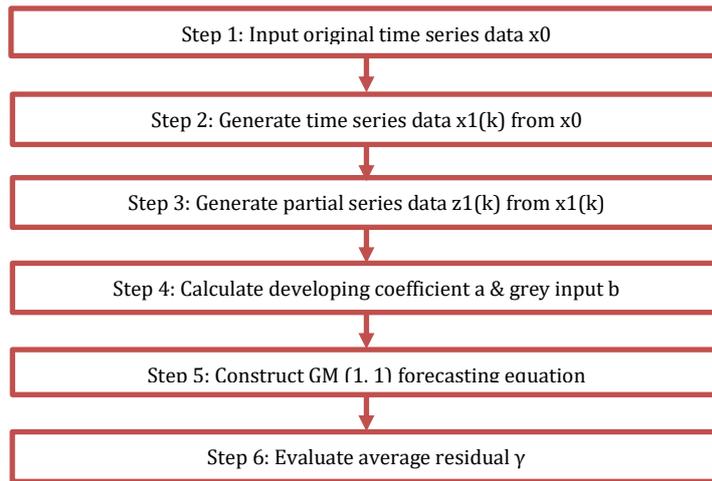


Fig. 1: The process of grey prediction

The best performers have the full efficient status denoted by unity. The super SBM model is based on the SBM model Tone (2002) discriminated these efficient DMUs and ranked the efficient DMUs by super-SBM model. Assuming that the DMU  $(x_0, y_0)$  is SBM-efficient,  $p^* = 1$ , super-SBM model is as follows:

$$\min \delta = \frac{\frac{1}{m} \sum_{i=1}^m \frac{\bar{x}_i}{x_{i0}}}{\frac{1}{s} \sum_{r=1}^s \frac{\bar{y}_r}{y_{r0}}} \quad (14)$$

$$\text{s.t } \bar{x} \geq \sum_{j=1, \neq 0}^n \lambda_j x_j, \bar{y} \leq \sum_{j=1, \neq 0}^n \lambda_j y_j, \bar{y} \geq x_0 \text{ and } \bar{y} \leq y_0, \bar{y} \geq x y_0, \lambda \geq 0 \quad (15)$$

The input-oriented super SBM model is derived from model (Eq. 14) 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 is, the more efficient the unit is.

As in many DEA models, it is crucial to consider how to deal with negative outputs in the evaluation

of efficiency in SBM models too. However, negative data should have their duly role in measuring efficiency, hence a new scheme was introduced in DEA-Solver pro 4.1 Manuel and the scheme was changed as follows:

Let us suppose  $y_{r0} \leq 0$  it is defined by  $\bar{y}_r^+$  and  $\bar{y}_r^-$

$$\bar{y}_r^+ = \max_{j=1, \dots, n} \{y_{rj} | y_{rj} > 0\}, \quad (16)$$

$$\bar{y}_r^- = \min_{j=1, \dots, n} \{y_{rj} | y_{rj} > 0\} \quad (17)$$

If the output  $r$  has no positive elements, then it is defined as  $\bar{y}_r^+ = \bar{y}_r^- = 1$ . The term is replaced  $\{s_r^+ | y_{r0}\}$  in the objective function in the following way. The value  $y_{r0}$  is never changed in the constraints.

$$(1) \bar{y}_r^+ = \bar{y}_r^- = 1,$$

the term is replaced by

$$s_r^+ / \frac{y_r^+ (\bar{y}_r^+ - y_r^+)}{\bar{y}_r^+ - y_{r0}} \tag{18}$$

$$(2) s_r^+ / \frac{(y_r^+)^2}{B(\bar{y}_r^+ - y_{r0})} \tag{19}$$

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

In any case, the denominator is positive and strictly less than  $y_r^+$ . Furthermore, it is inverse proportion to the distance  $\bar{y}_r^+ - y_{r0}$ . This scheme, therefore, concerns the magnitude of the non-positive output positively. The score obtained is units invariant, i.e., it is independent of the units of measurement used.

### 3. Research development

This study uses GM (1,1) and DEA model as the foundation of a set of forecasting and selecting alliance partner models. The research development in this paper is implemented in EMS industry and also selects all related documentations as references. Then after confirming the subject and proceeding industrial analysis.

#### 3.1. Step 1: Collect the data of EMS companies

Referring to domestic and foreign related literatures on DEA, Grey theory and then the researcher determined the subject and which approach this paper will use.

The researcher investigated Petroleum related enterprises to find all potential candidates to be DMUs list. 15 manufacturers in the World's Largest Oil and Gas Companies list, 2013 in which firms published their financial statement during the period 2010 to 2013. This study selects CPC Corporation (Taiwan Chinese Petroleum) as Target Company to incorporate with the rest of other DMUs to simulate the efficiency by applying the strategic alliance.

#### 3.2. Step 2: Choose input/output variables

It is said that DEA is a sensitive tool. Therefore, before using it, choosing inputs and outputs very thoroughly is necessary because the selection of input and output variables will influence on the correction of final efficiency or not. It is better to have wider range of input and output variables to analyze, but too many variables will dilute the variation among DMUs, leading to insensitivity of benefit analysis. Therefore, this paper considers the following critical factors in selecting input and output items: related literature discussion or necessary variables selected in factor analysis method; Pearson correlation coefficient for testing the correlation and significant level between inputs and outputs. Input/output items must correspond to units to evaluate; the data has public trust and each variable can be quantified for analysis.

### 3.3. Step 3: Grey prediction

Grey Prediction has based on grey model GM (1, 1) to predict the data values on 2014 and 2015. However, the forecast always exist error. Therefore, in this study the MAPE is applied to measure the forecasting error.

### 3.4. Step 4: Forecasting accuracy

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.

### 3.5. Step 5: Choose the DEA model

In this paper, the software of DEA-Solver is employed to calculate super-SBM- O-V model. The efficiency measuring by ranking DMUs' performance is then achieved.

### 3.6. Step 6: Pearson correlation

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. Therefore, to test the data whether match with the basic assumptions of DEA methodology or not, correlation analysis of variables is calculated to verify for positive relationship between the selected inputs and outputs. If the variables with the negative coefficient, they need to be removed, then we will go back to step 2 of the selection process to re-do the variable selection until they can satisfy our condition. In this study, we employ the Pearson Correlation Coefficient Test.

### 3.7. Step 7: Analysis before alliance

The purpose of this step is to rank the efficiency of each decision making unit by applying the super-SBM- O-V model in the realistic data in 2012. Especially, by this way the researcher also can find out the target company's position in comparison with other 14 EMS competitors.

### 3.8. Step 8: Analysis after alliance

The researcher conducted combining the target DMU with the rest 14 DMUs. By adding the values of all variables respectively, virtual alliances are established. It means that two DMUs (target DMU and another DMUs) are formed together to be a new one.

After consolidation, we get 29 virtual DMUs for comparing, then using the supper-SBM-O-V model to evaluate and rank 29 companies in comparison with

original ones. The result will be dressed clearly in the next chapter. Finally, based on the analysis result, suggestions are provided.

If virtual alliances get better results in comparison with target DMU, then the study recommends strategic alliance is a good choice, helping the target company improve its performance. Contrarily, if virtual alliances cannot improve ranking, (even reduce ranking) in comparison with target DMU, it means that target company cannot get any advantage from alliances. Obviously, the study does not recommend strategic alliance in this case.

**3.9. Step 9: Partner selection**

Strategic alliances are not a one-way working relationship, the analysis of efficiencies of the decision making units before and after alliance is based on the stand of the target company in previous step. In this step, the researcher has to stand on the side of the candidate companies which are selected for the target company’s alliance to find the possible way of cooperation.

**4. Application and result analysis**

**4.1. Collect the DMUs**

Petroleum is vital to many industries, and is of importance to the maintenance of industrial civilization in its current configuration, and thus is a critical concern for many nations. Oil accounts for a large percentage of the world’s energy consumption, ranging from a low of 32% for Europe and Asia, to a high of 53% for the Middle East (Coady et al., 2015).

Oil companies used to be classified by sales as "supermajors" (BP, Chevron, ExxonMobil, ConocoPhillips, Shell, Eni and Total S.A.), National Oil Companies (NOC, as opposed to IOC, International Oil Companies) have come to control the rights over the largest oil reserves; Aside from the NOCs which dominate the Upstream sector, there are many international companies that have a market share such as BG Group, Chevron, ExxonMobil. After doing the survey the oil and gas industry, the study finds out 15 enterprises which are in the World's Largest Oil and Gas Companies. Although fifty Leading Oil and Gas Companies around the World were published in 2013, the analysis was only conducted on the 15 companies which are stable in market and can provide the completely data for 4 consecutive years (2010-2013) in their financial statements. Moreover, these collected companies are World's Largest Oil and Gas Companies with a lot of famous brand, play important roles in the energy industry and global economic. Hence, the selection of these 15 candidates is qualified.

In this study, DMU14 is set as the target company. As mentioned in the first chapter, DMU14 is a realistic oil and Gas company with the headquarter located in Taipei City, Republic of China. In the globalization and competition environment, strategic alliance could be a great way for DMU14 to require resources and extend its business map. The study ultimately aims to help the company to find the right partners to cooperate. All information of DMUs were taken from the financial statement with USD millions currency unit. Table 1 lists the EMS companies covered in the analysis.

**Table 1:** List of EMS companies

Number order	CodeDMUs	Companies	Headquarter address	Website
1	DMU <sub>1</sub>	Chevron Corporation	San Ramon, California, U.S.	Chevron.com
2	DMU <sub>2</sub>	China National Offshore Oil Corporation	Beijing, China	www.cnooc.com.cn
3	DMU <sub>3</sub>	ExxonMobil	Irving, Texas, United States	ExxonMobil.com
4	DMU <sub>4</sub>	Gazprom	Moskva, Russia	www.gazprom.com
5	DMU <sub>5</sub>	Kuwait National Petroleum	Al Ahmadi	http://www.knpc.com
6	DMU <sub>6</sub>	Lukoil	Moscow, Russia	www.lukoil.com
7	DMU <sub>7</sub>	Occidental Petroleum Corporation (Oxy)	10889 Wilshire Boulevard Los Angeles, California	www.oxy.com
8	DMU <sub>8</sub>	Pertamina	Jakarta, Indonesia	www.pertamina.com
9	DMU <sub>9</sub>	Petróleo Brasileiro S.A. or Petrobras	Rio de Janeiro, RJ, Brazil	www.petrobras.com/en
10	DMU <sub>10</sub>	Petro China Company Limited	Dongcheng District, Beijing,China	petrochina.com.cn/ptr/
11	DMU <sub>11</sub>	Petronas	Petronas Twin Towers Kuala Lumpur,	www.petronas.com.my
12	DMU <sub>12</sub>	Rosneft	Moscow, Russia	www.rosneft.com
13	DMU <sub>13</sub>	Royal Dutch Shell ( Shell )	The Hague, Netherlands	Shell.com
14	DMU <sub>14</sub>	CPC Corporation	CPC Corporation	www.cpc.com.tw
15	DMU <sub>15</sub>	Total S.A.	Tour Total, Paris, France	www.total.com

**4.2. Establish input/output variables**

In order to apply DEA model, it is particularly vital that inputs and outputs considered for the study be specified. Besides that, using appropriate inputs and outputs should be considered carefully so that conclusions drawn may not be misleading. The main purpose of this research is to help the target

company finding right alliance partners by evaluating and ranking the operating performance of the petroleum industry. Therefore, the selection of our input and output factors is highly correlated with operating performance.

By investigating some DEA literature reviews and the elements of the operation for petroleum industry, the researcher decided to choose three

inputs factors which are all considered as the key financial indicators those directly contributing to the performance of the industry including Fixed Assets, Total Operating Expenses, Long-term Investments and Total Equity. The research selected the Revenues, Net income, Retained Earnings as output factors because they are the important indexes to

measure the performance of enterprises both in current and future situation (Table 2).

The study also applied DEA-based testing the correlation between input and output factors correlation, which will clearly show whether those variables are suitable or not.

**Table 2: Inputs and outputs data of all DMUs in 2013**

DMU	Inputs (Currency unit: Millions of US Dollars)				Outputs (Currency unit: Millions of US Dollars)		
	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
DMU <sub>1</sub>	164,829	192,943	25,502	150,427	228,848	21,597	173,677
DMU <sub>2</sub>	23627	80810	7083	93435	95703	11675	43489
DMU <sub>3</sub>	243,650	380,544	36,328	180,495	438,255	33,448	387,432
DMU <sub>4</sub>	240193	96746	14768	258846	141051	31319	244444
DMU <sub>5</sub>	38143	133296	1454	79396	141847	8835	8074
DMU <sub>6</sub>	78,466	131205	4,255	78,855	141,452	7,627	81,733
DMU <sub>7</sub>	55821	16454	1459	43372	24455	5903	41831
DMU <sub>8</sub>	9187	64103	685	17289	71102	3067	6773
DMU <sub>9</sub>	227,901	108,254	6,666	149,123	141,462	10,832	75,689
DMU <sub>10</sub>	267419	335645	18927	205968	366241	23075	108552
DMU <sub>11</sub>	75727	63676	4228	115766	98667	20394	104385
DMU <sub>12</sub>	146682	113905	8999	87101	129179	15164	73258
DMU <sub>13</sub>	191,897	353199	4,715	181,148	459,599	16526	183,474
DMU <sub>14</sub>	14827	38784	572	7570	39591	110	3270
DMU <sub>15</sub>	101315	207949	19789	100132	253361	11577	99516

Sources: Financial statements

**4.3. Grey forecasting model**

Predicting and analyzing the developing trend in future based on past facts is one of the great ways keeping enterprises competitive with other competitors. Various forecasting methods have been proposed in the last few decades. GM is suitable for forecasting the competitive environment where decision makers can refer only to a limited historical

data. Therefore, GM can be an ideal model to apply in this research because of the limitation of time series (from 2010 to 2013). The researcher uses GM (1,1) model to predict the realistic input/output factors for the next three years 2014, 2015, and 2016. In the Table 3, the study takes company DMU<sub>14</sub> as example to understand how to compute in GM (1,1) model in period 2010-2013.

**Table 3: Inputs and outputs factors of DMU<sub>14</sub> in period of 2010-2013**

DMU 14	Inputs (Currency unit: Millions of US Dollars)				Outputs (Currency unit: Millions of US Dollars)		
	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
2010	12047	29799	619	8933	31141	536	4209
2011	14324	34983	596	9120	34277	-1081	3129
2012	14704	38745	625	7403	38241	-1124	3142
2013	14827	38784	572	7570	39591	110	3270

This research selects the fixed assets of DMU<sub>14</sub> as example to explain for calculation procedure, other variables are calculated in the same way.

The procedure is carried out step by step as following:

First, the researcher uses the GM (1,1) model for trying to forecast the variance of primitive series:

1. Create the primitive series:

$$X^{(0)} = (12047; 14324; 14704; 14827)$$

2. Perform the accumulated generating operation (AGO):

$$X^{(1)} = (12047; 26372; 41076; 55903)$$

$$x^{(1)}(1) = x^{(0)}(1) = 12047$$

$$x^{(1)}(2) = x^{(0)}(1) + x^{(0)}(2) = 26372$$

$$x^{(1)}(3) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) = 41076$$

$$x^{(1)}(4) = x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) = 55903$$

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

$$Z^{(1)}(2) = \frac{1}{2}x^{(1)}(1) + x^{(1)}(2) = 19209.5$$

$$Z^{(1)}(3) = \frac{1}{2}x^{(1)}(2) + x^{(1)}(3) = 33724$$

$$Z^{(1)}(4) = \frac{1}{2}x^{(1)}(3) + x^{(1)}(4) = 48489.5$$

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

$$\begin{cases} 14324 + a \times 19209.5 = b \\ 14704 + a \times 33724 = b \\ 14827 + a \times 48489.5 = b \end{cases}$$

Convert the linear equations into the form of a matrix:

Let,

$$B = \begin{bmatrix} -19209.5 & 1 \\ -33724 & 1 \\ -48489.5 & 1 \end{bmatrix}, \hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix}, Y_N = \begin{bmatrix} 14324 \\ 14704 \\ 14827 \end{bmatrix}$$

$$\begin{aligned} k=2 & \quad x^{(1)}(3) = 41032.27 \\ k=3 & \quad x^{(1)}(4) = 55901.73 \\ k=4 & \quad x^{(1)}(5) = 71028.28 \\ k=5 & \quad x^{(1)}(6) = 86416.39 \end{aligned}$$

and then use the least square method to find a and b

$$\begin{bmatrix} a \\ b \end{bmatrix} = \hat{\theta} = (B^T B)^{-1} B^T Y_N = \begin{bmatrix} -0.0171428 \\ 14038.9581 \end{bmatrix}$$

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

$$\frac{dx^{(1)}}{dt} - 0.0171428 \times x^{(1)} = 14038.9581$$

Find the prediction model from Equation:

$$\begin{aligned} X^{(1)}(k+1) &= \left( X^{(0)}(1) - \frac{b}{a} \right) e^{-ak} \frac{b}{a} + X^{(1)}(k) + \frac{b}{a} \\ &= \left( 124047 - \frac{14038.9581}{-0.0171428} \right) e^{0.0171428 \times k} + \frac{14038.9581}{-0.0171428} \\ &= 830989.4496 \times e^{0.0171428 \times k} - 818942.1741 \end{aligned}$$

Substitute different values of k into the equation:

$$\begin{aligned} k=0 & \quad x^{(1)}(1) = 12047 \\ k=1 & \quad x^{(1)}(2) = 26415.55 \end{aligned}$$

Derive the predicted value of the original series according to the accumulated generating operation and obtain:

$$\begin{aligned} \hat{x}^{(0)}(1) &= x^{(1)}(1) = 12047 \\ \hat{x}^{(0)}(2) &= \hat{x}^{(1)}(2) - \hat{x}^{(1)}(1) = 14368.283 \\ \hat{x}^{(0)}(3) &= \hat{x}^{(1)}(3) - \hat{x}^{(1)}(2) = 14616.72 \\ \hat{x}^{(0)}(4) &= \hat{x}^{(1)}(4) - \hat{x}^{(1)}(3) = 14869.45 \\ \hat{x}^{(0)}(5) &= \hat{x}^{(1)}(5) - \hat{x}^{(1)}(4) = 15126.59 \\ \hat{x}^{(0)}(6) &= \hat{x}^{(1)}(6) - \hat{x}^{(1)}(5) = 15388.11 \end{aligned}$$

In the same with above computation process, the study could get the forecasting result of all DMU14 in 2014, 2015 and 2016; the detail number was shown in the two following tables, respectively (Table 4 and Table 5).

**Table 4:** Predicted input and output data of all DMUs in 2014 (calculated by GM)

DMU	Inputs (Currency unit: Millions of US Dollars)				Outputs (Currency unit: Millions of US Dollars)		
	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
DMU <sub>1</sub>	190417.52	185327.43	26796.61	167273.63	219356.67	20148.77	193806.31
DMU <sub>2</sub>	25891.38	91879.74	7167.05	104762.74	104686.32	10372.29	51599.15
DMU <sub>3</sub>	258973.85	367111.45	37178.39	191583.61	422808.72	33650.66	421013.31
DMU <sub>4</sub>	277510.80	108049.73	11997.53	286912.58	148737.68	29190.16	272473.45
DMU <sub>5</sub>	42152.11	161655.22	1515.87	88847.12	170681.05	9279.40	9261.65
DMU <sub>6</sub>	91932.67	136696.06	3217.82	85538.56	146068.03	7596.08	90006.01
DMU <sub>7</sub>	62033.28	18537.05	1286.15	46448.90	24613.67	4855.70	45508.21
DMU <sub>8</sub>	9887.98	66928.34	716.02	19692.27	73629.52	3468.91	9196.81
DMU <sub>9</sub>	254574.61	113967.20	6574.72	136528.34	139432.32	6368.13	84723.93
DMU <sub>10</sub>	399429.66	360898.30	24008.00	223296.58	391843.10	22028.06	118417.77
DMU <sub>11</sub>	82555.44	24626.27	4270.13	124277.96	34988.78	5515.83	112349.49
DMU <sub>12</sub>	218581.83	151221.96	14061.48	106013.81	166986.73	19587.43	86459.47
DMU <sub>13</sub>	215565.51	336378.47	9468.19	194405.87	451048.90	13833.76	196720.98
DMU <sub>14</sub>	15126.56	41392.02	574.28	6543.11	42918.48	-187.91	3325.05
DMU <sub>15</sub>	109584.03	220669.28	21069.67	104175.73	262288.02	9770.02	105160.53

**Table 5:** Predicted input and output data of all DMUs in 2015 (calculated by GM)

DMU	Inputs (Currency unit: Millions of US Dollars)				Outputs (Currency unit: Millions of US Dollars)		
	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
DMU <sub>1</sub>	220846.52	179250.84	28315.98	185375.79	212158.53	18134.54	215189.75
DMU <sub>2</sub>	28450.82	105004.38	7293.50	117244.47	115222.45	9421.31	61178.71
DMU <sub>3</sub>	275988.51	352451.28	38255.57	202948.89	401889.59	30497.05	455010.97
DMU <sub>4</sub>	319279.04	119127.07	10377.19	320085.54	158485.72	27203.17	305831.03
DMU <sub>5</sub>	46804.77	188191.57	1567.23	100217.58	197123.21	10688.24	10630.72
DMU <sub>6</sub>	107991.29	142661.34	2661.33	92392.16	150261.00	6821.08	98577.98
DMU <sub>7</sub>	68426.86	20198.27	1090.35	49892.42	24784.68	4466.53	49674.46
DMU <sub>8</sub>	10813.78	69182.85	749.72	22457.61	75647.55	3910.87	12699.09
DMU <sub>9</sub>	284377.59	118702.57	6646.40	125255.61	137292.55	4426.17	95058.79
DMU <sub>10</sub>	878997.19	382864.44	31566.75	241751.68	415436.32	21725.96	129986.62
DMU <sub>11</sub>	89802.88	19876.13	4326.21	134431.27	26544.70	3646.84	121703.39
DMU <sub>12</sub>	367956.72	208948.47	21277.92	133278.20	224992.66	26658.16	103398.52
DMU <sub>13</sub>	241954.93	307255.18	5790.47	206580.06	439469.43	10465.01	208377.46
DMU <sub>14</sub>	15388.10	43506.86	563.04	5918.61	46041.76	-101.73	3400.17
DMU <sub>15</sub>	118878.46	228064.97	22495.76	108226.27	265556.45	8140.42	111276.45

**4.4. Forecast accuracy**

It is undeniable that forecasting always exist some errors; they essentially predict the future in uncompleted information. Thus, in this paper, the

MAPE (Mean Absolute Percent Error) is employed to measure the accuracy of a method of constructing fitted time series values in statistics. The value of MAPE is small, that means the forecasting value is

typically close to the actual value. The result of MAPE was displayed as follows (Table 6):

**Table 6:** Average MAPE error of DMUs

DMU <sub>s</sub>	Average MAPE	DMU <sub>s</sub>	Average MAPE
DMU <sub>1</sub>	0.92733%	DMU <sub>9</sub>	2.08007%
DMU <sub>2</sub>	0.66836%	DMU <sub>10</sub>	4.77243%
DMU <sub>3</sub>	1.65981%	DMU <sub>11</sub>	0.96491%
DMU <sub>4</sub>	1.43773%	DMU <sub>12</sub>	6.87137%
DMU <sub>5</sub>	3.91913%	DMU <sub>13</sub>	11.51932%
DMU <sub>6</sub>	2.38523%	DMU <sub>14</sub>	18.16641%
DMU <sub>7</sub>	2.75001%	DMU <sub>15</sub>	0.97300%
DMU <sub>8</sub>	0.81190%	The average MAPE of 15 DMUs	3.99380%

The calculations of MAPE are almost smaller than 10%, especially the average MAPE of 15 DMUs reaches 3.99380% (below 10% as well), it strongly confirms that the GM (1, 1) model provides a highly accurate prediction (Table 6).

**4.5. Choose DEA model**

Science articles on DEA indicate that several potential models can be utilized to evaluate overall efficiencies of decision making units that are responsible to convert a set of inputs into a set of outputs. However, the efficient DMUs obtained in most DEA models like CCR and BCC (Banker et al., 1984) cannot be compared. Besides, the standard of conventional DEA models cannot be employed with negative data. In recent years, some models have been proposed to deal with negative data. However, all these models evaluate the number of DMUs as efficient and assign to them an efficiency amount of unity, but make no mention of the priority of one unit over the others. Super SBM Efficiency Model was developed to solve this problem.

In details, Tone (2002) developed a slacks-based measure (SBM) of efficiency in DEA, which takes account of scalar measure and slacks. Tone (2002) extended “Slack – based measure of super – efficiency” (Super – SBM) to distinguish the order when many DMU values are 1 simultaneously. Moreover, Super – SBM also can deal with positive and negative inputs and outputs.

Furthermore, in & output oriented models are two basic ways to maximize efficient of a firm, object of output oriented model is to maximize outputs while using no more than the observed amount of any input, on the other hand object of input oriented model is to minimize inputs while producing at least the given output levels (Nguyen and Tran, 2016).

In this study, suggestions about raising the output values to the maximum should be considered. Therefore, slacks-based super-efficiency (SBM-O-V) models are suitable for this study to show that an efficiency ranking can be provided for each efficient unit in comparison to other DMUs.

**4.6. Pearson correlation**

The important step in applying DEA technique is to make sure the relationship between input and output factors is isotonic, and ensure existing the linear relation to defines an efficiency measure of a

DMU by its position relative to the frontier or essentially call envelopment surface.

In this study, firstly, the researcher conducted a simple correlation test - Pearson correlation to measures the degree of association between two variables. Higher correlation coefficient means closer relation between two variables while lower correlation coefficient means that they are less correlated.

The interpretation of the correlation coefficient is explained in more detail as follows (Table 7):

**Table 7:** 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 correlation coefficient is always between -1 and +1. The closer the correlation is to +/-1, the closer to a perfect linear relationship. Its general meaning was shown in Table 7.

In this empirical study, the bellowing results (Tables 8-11) indicate that the correlation well complies with the prerequisite condition of the DEA model because their correlation coefficient shows strong positive associations. Therefore, these positive correlations also demonstrate very clearly the fact that the researcher’s choice of input and output variables at the beginning is appropriate. Obviously, none of variables removal is necessary.

**4.7. Analysis before alliance**

This research well carries out the Super-SBM-O-V software for the 2015 data to calculate all 15 DMUs efficiency and get their rankings before alliances. Because the input applied to DEA model were negative, so we have to modify the Net income input by make it add more \$200 million unit but their realistic value not change after modifying. So, it clearly show that the data applied to turn into positive value to calculate not effect on the empirical results, shown as the Table 12. The empirical results are shown as the Table 13.

The result clearly show that the DMU<sub>13</sub> has the best efficiency (the first ranking with the score = 1.6455203). 14 other companies including the target DMU<sub>14</sub> also have good operation efficiency. All this ranking proves definitely the target company in the 7<sup>th</sup> ranking and the result is also good, but it is

necessary for the target company to conduct strategic alliance to make its performance better.

**Table 8: Correlation of input and output data in 2010**

	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
Fixed assets	1	0.6568142	0.804203	0.8636472	0.7081191	0.8666902	0.8308808
Total Operating Expenses	0.6568142	1	0.8865738	0.5814777	0.994985	0.6680772	0.7511983
Long-term Investments	0.804203	0.8865738	1	0.6624733	0.9015024	0.789805	0.8958257
Total Equity	0.8636472	0.5814777	0.6624733	1	0.6355134	0.9244163	0.656437
Revenue	0.7081191	0.994985	0.9015024	0.6355134	1	0.7196197	0.7786874
Net income	0.8666902	0.6680772	0.789805	0.9244163	0.7196197	1	0.848707
Retained earnings	0.8308808	0.7511983	0.8958257	0.656437	0.7786874	0.848707	1

Source: Calculated by researcher

**Table 9: Correlation of input and output data in 2011**

	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
Fixed assets	1	0.6053022	0.7670929	0.8594481	0.66768	0.8812317	0.8485595
Total Operating Expenses	0.6053022	1	0.8815193	0.584248	0.9947367	0.7070494	0.7280758
Long-term Investments	0.7670929	0.8815193	1	0.6681929	0.9077157	0.8522075	0.8627774
Total Equity	0.8594481	0.584248	0.6681929	1	0.6357325	0.8924235	0.7075192
Revenue	0.66768	0.9947367	0.9077157	0.6357325	1	0.7613086	0.7731313
Net income	0.8812317	0.7070494	0.8522075	0.8924235	0.7613086	1	0.9247731
Retained earnings	0.8485595	0.7280758	0.8627774	0.7075192	0.7731313	0.9247731	1

Source: Calculated by researcher

**Table 10: Correlation of input and output data in 2012**

	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
Fixed assets	1	0.5611483	0.7144957	0.856139	0.6159036	0.8157897	0.8331102
Total Operating Expenses	0.5611483	1	0.8800625	0.6205915	0.9954944	0.6991129	0.6895499
Long-term Investments	0.7144957	0.8800625	1	0.6583347	0.9033608	0.8264864	0.8358796
Total Equity	0.856139	0.6205915	0.6583347	1	0.6543016	0.8211823	0.7313802
Revenue	0.6159036	0.9954944	0.9033608	0.6543016	1	0.7459345	0.7393245
Net income	0.8157897	0.6991129	0.8264864	0.8211823	0.7459345	1	0.9741864
Retained earnings	0.8331102	0.6895499	0.8358796	0.7313802	0.7393245	0.9741864	1

Source: Calculated by researcher

**Table 11: Correlation of input and output data in 2013**

	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
Fixed assets	1	0.6776093	0.6550916	0.8938314	0.6954092	0.7868619	0.7316729
Total Operating Expenses	0.6776093	1	0.6793239	0.6099892	0.9909178	0.5900059	0.6737194
Long-term Investments	0.6550916	0.6793239	1	0.5992778	0.6556205	0.7734239	0.8101136
Total Equity	0.8938314	0.6099892	0.5992778	1	0.6503666	0.8822939	0.7517638
Revenue	0.6954092	0.9909178	0.6556205	0.6503666	1	0.6119085	0.7042442
Net income	0.7868619	0.5900059	0.7734239	0.8822939	0.6119085	1	0.8861008
Retained earnings	0.7316729	0.6737194	0.8101136	0.7517638	0.7042442	0.8861008	1

Source: Calculated by researcher

**Table 12: Scanning results for positive value**

DMUs	Inputs (Currency unit: Millions of US Dollars)			Outputs (Currency unit: Millions of US Dollars)			
	Fixed assets	Total Operating Expenses	Long-term Investments	Total Equity	Revenue	Net income	Retained earnings
DMU <sub>1</sub>	220846.52	179250.84	28315.98	185375.79	212158.53	18334.54	215189.75
DMU <sub>2</sub>	28450.82	105004.38	7293.5	117244.47	115222.45	9621.31	61178.71
DMU <sub>3</sub>	275988.51	352451.28	38255.57	202948.89	401889.59	30697.05	455010.97
DMU <sub>4</sub>	319279.04	119127.07	10377.19	320085.54	158485.72	27403.17	306031.03
DMU <sub>5</sub>	46804.77	188191.57	1567.23	100217.58	197123.21	10888.24	10630.72
DMU <sub>6</sub>	107991.29	142661.34	2661.33	92392.16	150261	7021.08	98577.98
DMU <sub>7</sub>	68426.86	20198.27	1090.35	49892.42	24784.68	4666.53	49674.46
DMU <sub>8</sub>	10813.78	69182.85	749.72	22457.61	75647.55	4110.87	12699.09
DMU <sub>9</sub>	284377.59	118702.57	6646.4	125255.61	137292.55	4626.17	95058.79
DMU <sub>10</sub>	878997.19	382864.44	31566.75	241751.68	415436.32	21925.96	129986.62
DMU <sub>11</sub>	89802.88	19876.13	4326.21	134431.27	26544.7	3846.84	121703.39
DMU <sub>12</sub>	367956.72	208948.47	21277.92	133278.2	224992.66	26858.16	103398.52
DMU <sub>13</sub>	241954.93	307255.18	5790.47	206580.06	439469.43	10665.01	208377.46
DMU <sub>14</sub>	15388.1	43506.86	563.04	5918.61	46041.76	98.27	3400.17
DMU <sub>15</sub>	118878.46	228064.97	22495.76	108226.27	265556.45	8340.42	111276.45

**Table 13:** Efficiency and ranking before strategic alliances

Rank	DMUs	Score
1	DMU 13	1.6455203
2	DMU 3	1.5097543
3	DMU 11	1.4664743
4	DMU 2	1.4368527
5	DMU 4	1.3677916
6	DMU 5	1.1710513
7	DMU 14	1
7	DMU 7	1
7	DMU 8	1
10	DMU 15	0.9519363
11	DMU 1	0.8425923
12	DMU 6	0.8182457
13	DMU 12	0.8014017
14	DMU 10	0.6308455
15	DMU 9	0.5992751

Source: Calculated by researcher

**4.8. Analysis after alliance**

Company DMU14 - CPC Corporation (Taiwan Chinese Petroleum) is a state-owned petroleum, natural gas, and gasoline company in Taiwan and is the core of the Taiwanese petrochemicals industry. According to the above calculated result before alliance, the target company got the score equal to 1, interpreting correctly that its business in 2013 was good. However, the target company only is in the 7th ranking in total of 15 companies. Guided by the business philosophy of developing constantly, this company should dramatically improve its production efficiency and obtain advantages which it cannot get on by its own but through the entering into the alliance group.

To implement the empirical research, the study starts to form virtual alliance and then executes DEA calculation. By combining the DMU14 with the rest of DMUs, the research gets 29 virtual alliances totally.

Here, the software of DEA-Solver Pro 5.0 built by Saitech Company is used to calculate Super-SBM-O-V model for 29 DMUs. Table 14 shows the score and ranking results of virtual alliance in 2014.

The considerably change from original target DMU14 to virtual alliance in efficient frontiers indicate clearly the deference.

This research suggests an equation of – Difference|| = the ranking of Target company – the ranking of virtual alliance. The difference can be split into two groups. Positive results in difference demonstrate the alliance is better than original DMUs. The difference value number more lager shows the most efficient of alliance group. In contrast, the negative result means the alliance is worse.

Table 15 presents the concrete result of two groups. The first group includes the companies who can help the target company get better result in improving its operation efficiency after strategic alliance and the second group includes the companies in the category of the bad alliance partnership:

The results in first group show that the target DMUs’ ranking increase after alliance. This all

demonstrates this company can take advantages from alliance. The Table 14 shows that there are 07 companies including DMU2, DMU3, DMU4, DMU5, DMU8, DMU11, and DMU13 have the good characteristics and necessarily match with candidates’ desire in doing business.

**Table 14:** Performance ranking of virtual alliance

Rank	DMU	Score
1	DMU 2	1.3604941
2	DMU 11	1.2920844
3	DMU 4	1.2110413
4	DMU 5	1.1210354
5	DMU 13	1.0797198
6	DMU14+DMU8	1.0664329
7	DMU 3	1.039652
8	DMU14+DMU3	1.0325221
9	DMU14+DMU13	1.0269264
10	DMU14+DMU5	1.0153257
11	DMU14+DMU2	1.0129052
12	DMU14+DMU4	1.0095901
13	DMU14+DMU11	1.0035977
14	DMU 7	1
14	DMU 14	1
14	DMU 8	1
17	DMU14+DMU15	0.9532896
18	DMU 15	0.9448241
19	DMU14+DMU7	0.86771
20	DMU 1	0.8425923
21	DMU 6	0.8182457
22	DMU14+DMU6	0.8084471
23	DMU 12	0.8014017
24	DMU14+DMU1	0.7897955
25	DMU14+DMU12	0.7794872
26	DMU14+DMU10	0.638657
27	DMU 10	0.6276864
28	DMU 9	0.5992751
29	DMU14+DMU9	0.5913397

Source: Calculated by researcher

The virtual companies (DMU14+DMU2, DMU14+DMU3, DMU14+DMU4, DMU14+DMU5, DMU14+DMU8, DMU14+DMU11, DMU14+DMU13) all have the highest opportunities to have the best efficiency in applying strategic alliance business model (score >1). Thus, those 07 candidates will be highly appreciated in considering about strategic alliance. Especially, DMU8 is the best potential candidate for strategic alliance because the difference is the biggest (8). Therefore, DMU8 is the first priority for this strategy.

Through the second group it is absolutely clear that there are also 07 companies including (DMU1, DMU6, DMU7, DMU9, DMU10, DMU12, DMU15) which make DMU14 worst efficient after even strategic alliance (the DMUs’ ranking reduced dramatically). It would not be our choice with these companies because of no any benefits for the target company.

**4.9. Partner selection**

In previous section 4.8, the study finds the good alliance partnership based on the position of the target company DMU<sub>14</sub>. In reality, we need to analyze the possibility of alliance partnership against the category of the Good Alliance Partnership (Table 16). We take the DMUs’ ranking before alliance and after alliance of the companies in the category of the Good

Alliance Partnership into consideration on their position to find out which companies are willing to

cooperate with the target company. We use Table 16 and find out the results as follows.

**Table 15:** The good and bad alliance partnership

Number order	Virtual Alliance	Target DMU14 ranking (1)	Virtual Alliance ranking (2)	Difference - (2)
1 <sup>st</sup> Group				
Good Alliance				
1	DMU14+DMU8	14	6	8
2	DMU14+DMU3	14	8	6
3	DMU14+DMU13	14	9	5
4	DMU14+DMU5	14	10	4
5	DMU14+DMU2	14	11	3
6	DMU14+DMU4	14	12	2
7	DMU14+DMU11	14	13	1
2 <sup>nd</sup> Group				
Bad Alliance				
1	DMU14+DMU15	14	17	-3
2	DMU14+DMU7	14	19	-5
3	DMU14+DMU6	14	22	-8
4	DMU14+DMU1	14	24	-10
5	DMU14+DMU12	14	25	-11
6	DMU14+DMU10	14	26	-12
7	DMU14+DMU9	14	29	-15

As clearly shown in Table 16, there are 06 companies including DMU3, DMU13, DMU5, DMU2, DMU4, and DMU11 would not willing to cooperate with the target company DMU14 because the ranking of these companies after alliance reduced in comparison with original ones. In other words, the performance of these companies is already good; if no special circumstances, they no need to make the alliance partnership with the DMU14.

applied and the process established in this study, we can still get results with the reference value.

**Table 16:** The impossible alliance partners

Impossible Alliance			
Number	DMUs	No Alliance Ranking	Virtual Alliance Ranking
1	DMU3	2	8
2	DMU13	1	9
3	DMU5	6	10
4	DMU2	4	11
5	DMU4	5	12
6	DMU11	3	13
Possible Alliance			
	DMU8	14	6

Source: Calculated by researcher

### 5. Conclusion

We still cannot deny some errors of the method used for this studies and the limitation of data which are collected from only 14 companies. The limited number of input – output variables cannot completely reflect the overall oil industry. Future research should also address how strategic alliances can be managed successfully to ensure that both partners’ requirements are satisfied through the partnership. This is especially important when the partners are based in countries with vastly different institutional environments. Exploring this issue requires a broad based comparative study across several countries and institutional environments.

By applying the effective applications of GM (1,1), and DEA model, this study is presented to help the target company, to find suitable partner for strategic alliance activity. The target firm is employed to test whether the strategic alliance benefits exist if it has alliances with other companies in the same industry and give the firms suggestions and the direction of improvement.

By reviewing the Table 16 and checking the performance before and after the formation of an alliance, those figures clearly highlight the combination between DMU8 and the target DMU14. Before alliance, the efficiency of DMU8 does not reach the DEA frontier; however, the ranking of DMU8 is improved after alliance with DMU14. It means the alliance can exhibit the good scenario for productivity improvement not only for the DMU14 but also for the DMU8. In the other words, by implementing alliance, both of DMU14 and DMU8 might have the chance to manage their resource more effectively. Hence, DMU8 would have strong desire to form alliance. This research strongly recommends DMU8 to cooperate with the target company DMU14 because DMU8 is the best efficiency improvement for the target company.

The researchers would like to contribute to implement the integrated research methodologies to provide meaningful and helpful results to the development of the industry. The methodology of combining Grey theory, neural network and super-SBM-O-V model to aggregate and analyze data in an empirical study is quite new. The proposed method in this research may help to provide an overall and concise evaluation of Indian electricity industry through carefully describing the performance of these testing companies in the current market with specific efficient and ranking scores. Besides, the data are also deeply treated by applying Grey theory to forecasting business performance, which help readers to gain a prospective view of Indian electricity industry in the near future and help the author to find right partner for the target company for that period of time.

In actual alliances or union, the enterprises may have different considerations, such as the industry expansion, technology acquisition, market development, etc. As long as we can properly adjust the input and output factors through the method

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