Available online at http://ijdea.srbiau.ac.ir

Int. J. Data Envelopment Analysis (ISSN 2345-458X)

Vol.7, No.2, Year 2019 Article ID IJDEA-00422, 20 pages
Research Article

International Journal of Data Envelopment Analysis
Science and Research Branch (IAU)

A two-Stage Study of Grey System Theory and DEA in Ttrategic Alliance: An Application in Vietnamese Steel Industry

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Received 29 September2018, Accepted 27 March2019

Abstract

Throughout the years, Vietnam has experienced the higher economic growth. It leads more development in many various fields including steel industry. However, it necessary to have more strategic alliances among those steel companies for an incredible and sustainable growth. To have successful cooperation, it requires many special skills, efforts and considerations. This paper applies DEA model and Grey Theory to calculate the effectiveness and proposes a method to find out the most suitable strategic partners. Seventeen biggest companies in the Vietnam steel industry are chosen to research. The input factors (Net assets, operating cost, Cost of good sold) and the output factors (Net sales and net profits) are collected from realistic published financial reports of the Vietnam issued stock market in seven consecutive financial years (2011-2017). The Hoa Sen Group is considered as the target decision making unit (DMU). According to the empirical results, Pomina Steel corporation (DMU4) is the most feasible beneficial alliance partner for Hoa Sen Group. In addition, the proposed process in this paper is applied to not only the steel industry, but also to other manufacturing fields.

Keywords: Strategic alliance; Grey forecasting model; Data envelopment analysis (DEA); Vietnam steel industry.

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1. Introduction

Steel industry plays an important role in developing economic, especially in construction residential appliances, rail sectors. By 2025, the global steel market is estimated to reach USD 1.01 trillion with CAGR: 2.6% [1] According to the report of Vietnam Steel Association, the production volume of crude steel in Vietnam reached 10.3 million tons in 2017, with CAGR of 16.5% in 2013-2017. In the period 2018-2022, the Vietnam steel market is expected to become one of the most rapid developing markets with the CAGR of crude steel production volume is planned to over 20%.There is a fact, however, that most of the domestic steel manufacturers are operating with 50-60% capacity. Moreover, the products quality is not a competitive advantage due to using the outdated equipment. Most recently, there is a decline in production and sale of steel between 5/2018 (14.9%) compared to 6/2018 (only 1.25%).

Most Vietnamese steel manufacturers are small and medium enterprises. The steel industry encounters many challenges such as how to diversify products and to adjust developing strategies that can bring more competitive advantages, especially how to compete with imported products. In specific, some major issues are related to upgrading modern technology selection; innovating products; maintaining a stable and capable workforce and floating capital. If firms are doing individually, it is very challenged to overcome such issues. Especially, when the information is limited and incomplete, the choosing a good partner to build strategic alliance is quite difficult. This paper, hence, propose a research model by combining Data Envelopment Analysis (DEA) model and Grey Theory to recommend the alliance partners for steel companies to overcome those challenges. When information errors are unavoidable, these two techniques are suitable to forecast the business operation and evaluate the performance in firms' efficiency ranking. In addition, this paper has an advantage of using information of 7 consecutive years data for Grey forecasting model, it causes more accurate than most previous studies that predicted on only 5 years data. However, a disadvantage is that the study cannot take all current steel companies into account due to lack of public data. Therefore, the study was compelled to conduct on the top 17 steel enterprises that played a major role and could entirely represent the whole steel industry. Established in August 2001, Hoa Sen Group is one of the leaders in steel sheet production and trading in Vietnam and Southeast Asia. Its market share in the domestic steel sheet market and the steel pipe market are 30 per cent and 20 percent in respectively. The group also provide products to more than 70 countries and territories around the world. However, the group encounter with many difficulties in the performance, such as in 2016, Hoa Sen group saw a decrease in market share of galvanized steel by 7.8 percent compare to 2012 and in the most recent financial report for the first quarter of 2018 , its net profit was only VND115 billion that is only one-fifth of last year's figure. Moreover, the results of using DEA model to calculate the efficiency of performance show that the efficiency score of Hoa Sen Group is less than 1 most periods from 2011-2017 and it implies that they did not have a good business performance. Therefore, Hoa Sen Group is chosen to be the target company in this research.

The constricted competition among steel manufacturers require the incessant development of science and technology as well as its competence to satisfy the customers' needs. There are many significant issues related to the future strategies and performance of Hoa Sen

Group and the steel industry. For instance, how will it improve its competitive advantages? How will it strengthen the future performance? How will it optimize value for both customers and the company itself?

The purpose of this study is to suggest suitable potential strategic alliances by using the Grey theory and DEA model with many thoughtful considerations. The model predicts future performance efficiency basing on critical input and output variables and setting of Hoa Sen Group as a target DMU. Alliances can be concerned as a good strategic for future development, however, there are not many enterprises with successful alliances since they are failed to satisfy the conditions of alliances. This research aims to contribute to a literature review about models related to strategic alliances and the results can be as references for many fields.

The following section 2 would present the research methodology. The result and analysis is section 3 and the final section 4 is conclusion and further study.

2. Literature Review:

Strategic Alliance

To adapt to a dramatic growth of global business activities, firms need to have devising appropriate forms of management and organization to increase their competitive advantage. One of the most requisite concerns of any firms is strategic alliance that has been much attracted in literature of strategic management.

Strategic alliance is distinguished as a horizontal cooperative association without equity ties or creating of a new entity as in joint ventures [2]. Chan et al. [3] defined strategic alliance is a collaborative agreement between different firms to share properties from distribution to production. A strategic alliance, hence, could be defined as an "inter-firm collaboration over a give economic space and time for the attainment of mutually defined goals" [4]; [5]; [6].

The different type of alliance is implemented with different structures or objectives of each firm. The types of alliances range from simple agreements without exchanging equity to more formal arrangements involving equity ownership and shared managerial control over joint activities [7]. The example of alliance activities can be code-sharing , supplier–buyer partnerships, joint research projects, outsourcing agreements, technical collaboration, shared manufacturing arrangements, common distribution agreements, cross-selling arrangements, and etc. [5]; [7]

[8] listed three main motivations to form strategic alliances, including the high transaction costs resulting from small-number bargaining; secondly, a pursuit for organizational learning perspectives to gain some critical knowledge from the other; and thirdly, enhancing a firm's market power.

On the other hand, it is not necessary that partner firms have only complementary motives of strategic alliances. [9] defined "asymmetric alliances" under the network approach, that small firms from developing country are willing to invest more and gain less from alliance with larger and more reputable firms in advanced countries.

To sum up, the definition of strategic alliance is noted with a number of vital characteristics:

• An alliance works as inter-firm agreements that operate across the frontiers and limitation of an enterprise.

• For all firms, it is required to have collaborations in which some input of resources must be supplemented.

• It covers both time and destination, i.e. from real time to the unsure moment that objectives are achieved, from inside to outside of a country.

• It is not necessary to have the same perspective or objectives for all partners. The part of alliance's function is achieving its own certain goals.

Needs for strategic alliance

Allelign [15] affirmed strategic alliances as an efficient pattern to approach the resources needed for innovation in dynamic environment. Alliances form is considered to help firms to conserve resources and share risks when firms are in susceptible strategic positions [10]. For example, firms serve alliances as signals of enhanced legitimacy [11] and as opportunities for attempting new competencies or having market power in highly competitive industries, or pioneering technical strategies [12].

Strategic alliances are investigated in various industry, such as telecommunication, automobile, etc. [7]. There are a wide range of well-known success alliances that have clearly benefited the partner firms, including Renault-Nissan; Toshiba -Timer Warner; Merck and AB Astra; British Petroleum, Eli Lilly, IBM, Starbucks, Siebel Systems, General Electric, Corning Glass, Federal Express, Cisco Systems, and Millennium Pharmaceuticals [5]; [13]; [7]

[16] also showed that about 60 percent of alliances can be failed by unsatisfactory cooperation or conditions of their partner. One of the main reasons is that firms fail to identify a "suitable partner". It emphasizes the importance of selecting suitable partners in a success alliance. Hence, the development of the efficiency strategic alliance formation models is typical issues in literature of strategy and management.

Strategic alliance formation

There are two main approaches in strategy literature, namely "competitor analysis" and "the resource-based view" of the firm. Das & Teng [5] defined the combination of the approaches as ''partner analysis'' that to examines the overall match between the partner firms. It covers partners' market commonality, resource characteristics, and resource alignments.

In addition, many studies developed the stages in alliance process from initiation and negotiation to alliance evaluation and even termination [14]. For example, Das and Teng [17] suggest that the process may be divided into seven stages – including "choosing an alliance strategy, selecting partners, negotiation, setting up the alliance, operation, evaluation, and modification". Meanwhile, Brouthers et al. [18] propose a five-stage process model- "selecting the mode of operation, locating partners, negotiation, managing the alliance, and evaluating alliance performance".

Regardless the number of stages in the process, it is clear to realize that "selecting/ locating partners" is an important and indispensable stage in strategic alliance models. The purpose of this study is to propose a model combining the Grey system and DEA for identifying proper candidates for alliances

Grey System and DEA model

Grey System Theory was introduced in 1982 by Deng. In the last twenty years, the grey system theory has been widely developed and successfully applied to various systems such as social, technological, economic, and so on. The main process of grey generating is to find the realistic governing laws of the system using available data. Hence, it is used to reduce randomness and promote the regular pattern of disorderly and unsystematic [19].

Charnes et al. [20] introduced Data Envelopment Analysis (DEA) to measure the performance of multiple "decision making unit" (DMUs), such as manufacturing units, educational institutions, bank branches, etc. This is a

"data oriented" approach converting multiple input into multiple output.
Various DEA models are recently applied in private and public sectors of different countries. [7]. For example, Martín and Roman [21] used DEA to evaluate the technical and operation efficiency in Spanish airport. Wang et al., [19] developed an effective model by combining Grey model and DEA to help the hi-tech industries in Taiwan to evaluate the performance efficiency and find the proper candidates for alliances.
As a result, the proposed method of integrating model of Grey and DEA in alliance decision making is a new effective approach. It help managers to have a deeper understanding of alliance in business strategy. The model uses critical input and output variables to predict future business and measures performance efficiency of firms. Steel manufacturers, thus, can locate potential partners for alliance strategies.

3. Research methodology:

3.1. Grey forecasting model:

When there is a limited historical data in the competitive environment, Grey model becomes a suitable technique for decision makers to forecast. Due to its computational efficiency, the most frequently used grey forecasting model is GM (1,1) [6]. In this study, GM (1,1) was applied to get estimating results. This model is a time series predicting model, including a group of various differential equations based on the generated sequence. The model has some following characteristics: the potency of the series must be at least four; the data must be taken at equal intervals and in consecutive order without bypassing any data; simple calculating process; being able to predict short-term and long-term prediction with high accurate results [19]; [6]. The specific implementation steps of the GM (1,1) model are described as following
Denote the variable primitive series:

$$X^{((0))} = \left(x^{((0))}(1), x^{((0))}(2), \cdots, x^{((0))}(n)\right),\quad n \geq 4 \tag{1}$$

Where $X^{((0))}$: a non-negative sequence ; n: the number of data observed
$X^{((1))}$: is the 1-Accumulating Generation Operator (1-AGO) sequence of $X^{((0))}$ that aims eliminating the uncertainty of the primitive dataand smoothing the randomness. Its formation that

$$X^{((1))} = \left(x^{((1))}(1), x^{((1))}(2), \cdots, x^{((1))}(n)\right),\quad n \geq 4 \tag{2}$$

Where

$$x^{(1)}(k) = \sum_{i=1}^{k} x^{(0)}(i),\quad k = 1,2, \cdots n. \tag{3}$$

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

$$Z^{((1))} = \left(z^{((1))}(2), z^{((1))}(3), \cdots, z^{((1))}(n)\right), \tag{4}$$

Where

$$z^{((1))}(k) = 1/2\left(x^{((1))}(k) + x^{((1))}(k-1)\right),\quad k = 2,3,\ldots,n \tag{5}$$

The following differential equation :

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

Where: parameters a and b are called the developing coefficient and grey input, respectively. However, these parameters a and b are undetermined from Eq.(6). Instead, the least square method below can be used :

$$\hat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a},\quad k=1,2,3... \tag{7}$$

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:

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

And

$$B = \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \cdots & \cdots \\ -Z^{(1)}(n) & 1 \end{bmatrix} \tag{9}$$

$$Y_N = \begin{bmatrix} X^{(0)}(2) \\ \cdots \\ X^{(0)}(n) \end{bmatrix} \tag{10}$$

(B is data matrix, Y_N is data series, $[a,b]^T$ is parameter series)

$\hat{X}^{(1)}$is acquired from Eq. (7). Let $\hat{X}^{(0)}$be the GM (1,1) fitted and predicted series :
$\hat{X}^{(0)} = \left(\hat{X}^{(0)}(1), \hat{X}^{(0)}(2), \dots, \hat{X}^{(0)}(n), \dots\right)$

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

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

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

(k=1,2,3...) (11)

All the process of Grey prediction was showed

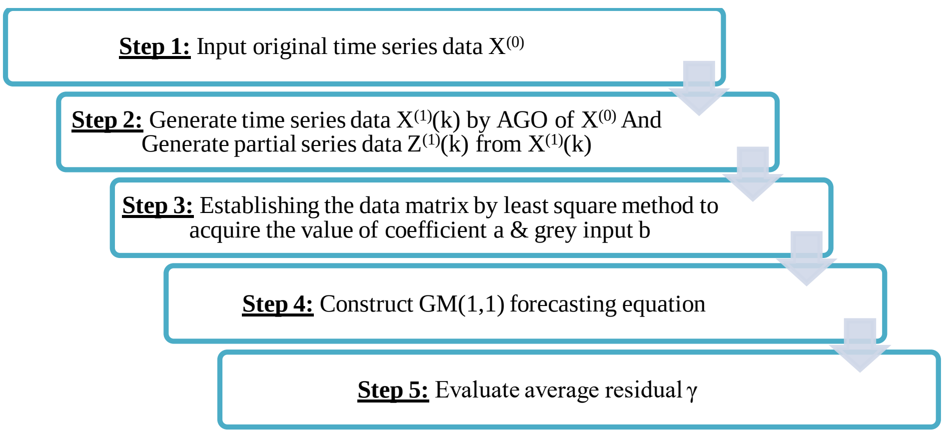

Figure 1:The Process of Grey Prediction

3.2. DEA model

By the nature of things, output may be negative that many DEA models including Slacks-based measure of efficiency (SBM) cannot handle. Until a new scheme was introduced in DEA-Solver pro 4.1 Manuel [6], it supposes that $y_{r0} \leq 0$ and defines $\bar{y}_r^+$ and $\bar{y}_{-r}^+$ by

$$\bar{y}_r^+ = \max_{j=1,\ldots n} \{y_{rj} | y_{rj} > 0\}, \quad (12)$$

$$\bar{y}_{-r}^+ = \min_{j=1,\ldots n} \{y_{rj} | y_{rj} > 0\}, \quad (13)$$

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

$$s_r^+ / \frac{y_{-r}^+(\bar{y}_r^+ - y_{-r}^+)}{\bar{y}_r^+ - y_{r0}} \text{ if } \bar{y}_r^+ > y_{-r}^+ \quad (14)$$

$$s_r^+ / \frac{(y_{-r}^+)^2}{B(\bar{y}_r^+ - y_{r0})} \text{ if } \bar{y}_r^+ = y_{-r}^+ \quad (15)$$

Where B is a large positive number, in DEA-solver B=100.
Moreover, the denominator is positive and strictly less than y_{-r}^+. In addition, it is inverse to the distance $\bar{y}_r^+ - y_{r0}$. This scheme, hence, concerns the magnitude of the nonpositive output positively. The score obtained is units' invariant; i.e., it is independent of the units of measurement used [22].

3.3. Development of research

GM (1,1) and DEA models are combined in a group of methodical prediction and evaluation models. The data information of Vietnamese Steel Industry and all related documentations are selected and used in this research. After confirming subjects, the development of this study is presented in Figure 2.

Step1: *Data collection*

Top 17 candidates in the Vietnamese steel industry is collected as our DMUs. The information and data was obtained from General statistics office of Vietnam, Vietnam Steel Association and the reliable and well-known financial information company including VietStock and CafeF. From all of those sources, we collect all the financial reports of our DMUs published in Vietnam stock market during seven consecutive years, 2011-2017.

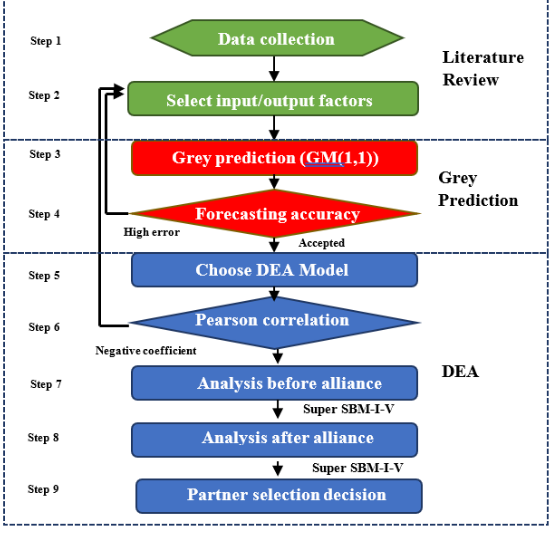

Figure 2: Research development

Step 2: *Inputs/ Outputs selection*

The efficiency of evaluation model (DEA) depends on choosing the inputs and outputs factors. In this paper, five inputs/outputs used are defined below:
Input factors:

- Fixed assets: Fixed assets are composed of land, property equipment, etc.
- Cost of goods sold Capital: Capital is the amount of cash and other assets owned by a business. These business assets include accounts receivable, equipment, and land/buildings of the business
- Operating Costs: the expenses which are related to the operation of a business, or to the operation of a device, component, and piece of equipment or facility. They are the cost of resources used by an organization just to maintain its existence.

Output factors:

- Net sales: The amount of sales generated by a company after the deduction of returns, allowance for damaged or missing goods and any discounts allowed
- Net profits: is calculated by subtracting a firm's total expenses from total revenue. It is what the firm has earned (or lost) in a given period of time (usually one year).

Step 3: *Grey prediction model*
Based on grey model GM(1,1) , it is used to forecast the values of 2018. Nevertheless, The estimation always exist error. The Mean Absolute Percent Error (MAPE), hence, is employed to measure the accuracy values in statistics. The smaller value of MAPE refers to more reasonable forecasting values.

Step 4: *Forecasting accuracy*
The prediction error is unavoidable when uncompleted information is used to predict future results. Hence, the MAPE is implemented to quantify the forecasting accuracy. If the value of MAPE is too high (more than 20%), the data of inputs and outputs must be recollected.

Step 5: *Choosing the DEA model*
In this study, the Super -SBM-I-V is applied to show how proficiency can be accommodated each effective unit in comparison to different DMUs.

Step 6: *Pearson correlation*
The DEAis used incompetency valuation for decision making units by developing a competitive efficiency score through the transferring of the multiple foundation data into a ratio of a single virtual output to a single virtual input. The Pearson correlation Coefficient, therefore, is very important to test if the selected inputs and outputs have a positively association.

Step 7: *Analysis before alliance*
This step aims to figure out a target firm rank for measuring the proficiency of virtual alliance in the predicted value of 2018. In this stage, the super-SBM is applied in the realistic data of 2017 to rank the efficiency of each DMU
To evaluate efficiency of DMU(x_0, y_0), the SBM models are established as per [23].

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

Step 8: *Analysis after alliance*
All the alliancing between the target DMU and the other DMUs is analysed via the super-SBM model basing summing the forecasting value factors. Then, the difference in efficiency ranking between "before" and "after" alliance are compared and analysed.

Step 9: *Summary*
When a firm has a non-proficient operation before strategic alliance, but its performance is more efficiency after that, then the strategic alliance is recommended. Inversely, in case that the company is worse after strategic alliance, we would not suggest strategic alliance due to its potential risks.

4. EMPERICAL ANALYSIS AND RESULTS:

4.1. Collecting the DMUs

As mentioned above, the using information of 7 consecutive years' data for Grey prediction model is an advantage of this study since it provides more accurate value than basing on only 5 years' data. However, a disadvantage is that the study cannot take all current steel companies into account due to lack of public data. Therefore, the study was compelled to conduct on the leading 17 steel enterprises that demonstrated a steady performance with the full published financial data for consecutive financial years (2011-2017).

According to Vietnam Steel Association reports, in 2016, the group including Hoa Phat Group (HPG), Hoa Sen Group (HSG), Dai Thien Loc Corporation (DTL), Pomina Steel corporation (POM), Nam Kim Steel JSC (NKG) is the top steel producer with the largest market share of most steel products. Total market shares of these 5 top companies are more than 50% in galvanized steel sheets (HSG with 31.6%, followed by NKG with 14.9%) ; more than 55% in steel pipes (HPG with 19.7%; followed by HSG with 18.1%); more than 40% in constrional steel market (HPG with 20.27%; followed by POM with 11.63%). The enterprises played a key role and could fully represent the whole Vietnam Steel Industry. The detailed list as follows in Table 1.

4.2. Input/output variables selection

To sufficiently score the efficiency of a DEA model and grey forecasting model, it is necessary to select prudently input and output factors. These elements are considered according to the literature review of DEA, steel industry reports, and appropriate relationships among elements. In this study we choose three input variables namely fixed assets, operating cost, and cost of good sold (COGS) that are important to the sources of steel manufacturers.

Table 1: List of steel companies (DMUs)

No.	DMUs	Stock Code	Company Name
1	DMU1	HPG	Hoa Phat Group Joint Stock Company
2	DMU2	HSG	Hoa Sen Group
3	DMU3	DTL	Dai Thien Loc Corporation
4	DMU4	POM	Pomina Steel Corporation
5	DMU5	NKG	Nam Kim Steel Joint Stock Company
6	DMU6	TIS	Thai Nguyen Iron And Steel Joint Stock Corporation
7	DMU7	VIS	Vietnam - Itaty Steel Jsc
8	DMU8	SMC	SMC Trading- Investment Joint Stock Company
9	DMU9	TLH	Tienlen Steel Corporation Joint Stock Company
10	DMU10	VGS	Vietnam Germany Steel Pipe Joint Stock Company
11	DMU11	HMC	VNSTEEL - Hochiminh City Metal Corporation
12	DMU12	VCA	VNSTEEL - Vicasa Joint Stock Company
13	DMU13	DNY	Dana-Y Steel Joint Stock Company
14	DMU14	TDS	Thu Duc Steel Joint Stock Company
15	DMU15	KMT	Central Vietnam Metal Corporation
16	DMU16	TNB	VNSTEEL - Nha Be Steel Joint Stock Company
17	DMU17	SSM	Steel Structure Manufacture Joint Stock Company

In addition, two participations including Net sales, Net profits as two output factors. These indicators are good signals to analysis the company's financial effectiveness. The example of detailed data are shown in the Table 2 below is the data from 2017 selected at prestige Vietnamese stock market websites.

4.3. Variables calculations – Forecast inputs/outputs by GM(1,1)

The values for the year of 2018 and 2019 is forecasted by GM (1,1) model on the realistic inputs/outputs factors from 2011 to 2017. After running Grey forecasting model, the results of all DMUs in 2018 and 2019 is shown in Table3 and Table4.

Table 2: Input and output factors of 17 steel companies in 2017

		Input Factors (in Mil. VND)			Output Factors (in Mil. VND)	
	DMUs	Fixed Assets	Operating Cost	COGS	Net Sales	Net Profits
1	DMU1	13,197,797	1,559,503	35,536,121	46,161,692	9,252,124
2	DMU2	7,179,737	3,124,927	23,716,142	28,269,056	1,529,362
3	DMU3	645,868	141,925	2,803,075	3,166,157	224,076
4	DMU4	2,255,530	352,956	10,265,817	11,369,575	749,638
5	DMU5	3,859,555	721,868	11,250,913	12,619,284	781,490
6	DMU6	1,894,227	524,699	9,166,558	9,725,418	122,691
7	DMU7	415,821	162,888	5,895,922	6,105,119	55,267
8	DMU8	673,911	428,441	11,952,938	12,653,940	334,007
9	DMU9	320,157	193,300	4,372,612	4,971,552	436,100
10	DMU10	130,246	166,497	5,747,587	5,980,106	83,417
11	DMU11	37,575	115,224	2,570,830	2,768,734	100,495
12	DMU12	84,213	47,713	1,768,354	1,894,197	81,039
13	DMU13	741,100	105,868	2,179,211	2,365,987	88,149
14	DMU14	57,587	68,985	1,870,642	2,027,197	90,646
15	DMU15	52,810	101,140	2,144,696	2,243,506	15,004
16	DMU16	148,282	59,054	1,644,877	1,716,784	1,403
17	DMU17	22,063	18,509	252,666	258,906	10,536

Table 3: Forecasted inputs/outputs data for the year of 2018

		Input Factors (in Mil. VND)			Output Factors (in Mil. VND)	
	DMUs	Fixed Assets	Operating Cost	COGS	Net Sales	Net Profits
1	DMU1	15,853,599	1,557,362	39,518,921	53,468,585	13,800,066
2	DMU2	7,976,322	3,926,218	25,858,785	32,103,813	472,147
3	DMU3	787,198	142,269	3,136,433	3,554,502	209,856
4	DMU4	2,041,270	368,918	8,958,167	9,951,460	300,141
5	DMU5	4,130,315	772,076	13,506,241	15,432,716	1,197,401
6	DMU6	2,300,471	463,106	8,966,604	9,507,208	163,891
7	DMU7	387,301	162,680	3,317,604	3,523,071	74,899
8	DMU8	721,219	487,187	11,415,590	12,214,560	681,500
9	DMU9	358,583	239,722	4,592,857	5,374,860	824,891
10	DMU10	160,127	187,970	6,535,508	6,857,960	14,367
11	DMU11	185,506	96,540	1,762,853	1,897,089	128,086
12	DMU12	73,269	40,374	1,668,475	1,779,156	68,457
13	DMU13	943,097	110,458	2,192,482	2,368,610	17,209
14	DMU14	51,593	60,299	1,610,349	1,852,049	74,275
15	DMU15	58,196	56,798	2,222,172	2,349,395	5,418
16	DMU16	147,683	55,516	1,989,997	1,800,926	10,566
17	DMU17	25,296	19,940	201,380	231,794	20,612

Table 4: Forecasted inputs/outputs data for the year of 2019

		Input Factors (in Mil. VND)			Output Factors (in Mil. VND)	
	DMUs	Fixed Assets	Operating Cost	COGS	Net Sales	Net Profits
1	DMU1	18,543,964	1,586,870	47,505,806	65,677,207	19,554,839

2	DMU2	9,816,477	5,031,074	31,037,668	39,055,058	459,476
3	DMU3	786,105	141,319	3,547,167	4,054,504	213,356
4	DMU4	1,835,181	356,368	8,682,435	9,774,267	307,286
5	DMU5	5,961,195	951,115	17,446,440	20,282,101	1,549,420
6	DMU6	2,476,179	405,771	9,426,012	9,935,691	170,383
7	DMU7	330,232	155,225	3,292,794	3,492,914	87,003
8	DMU8	848,140	542,226	11,883,735	12,822,176	1,017,030
9	DMU9	378,370	293,959	4,979,699	5,979,615	1,185,160
10	DMU10	149,757	209,254	8,044,829	8,453,688	14,083
11	DMU11	192,242	85,835	1,555,701	1,686,495	170,871
12	DMU12	68,103	38,392	1,639,069	1,758,373	90,298
13	DMU13	1,001,020	113,081	2,311,965	2,508,191	18,080
14	DMU14	46,707	59,122	1,567,519	1,830,926	96,278
15	DMU15	59,641	57,524	2,465,297	2,614,842	5,911
16	DMU16	145,355	56,152	2,373,653	1,995,084	11,397
17	DMU17	26,117	20,405	201,364	233,116	24,384

4.4. Accurate checking

Predictions are always not accurate especially when the uncompleted information are used to forecast. Thus, the MAPE must be implemented to check the accuracy of prediction in percentage and shown as follows (Table 5)

The prediction is good and qualified if the value of MAPE is less than 10%, it means that. As results, The table 5 indicated the forecasting value of DMUs are accurate since most of MAPE of DMUs smaller than 10% and the average of all 17 steel companies is 9.65% which confirm Grey model GM (1,1) suitable in this study. This paper has an advantage of using information of 7 consecutive years data for Grey forecasting model, it causes more accurate than most previous studies that predicted on only 5 years data.

Table 5 : Average MAPE of DMUs (in %)

DMUs	Fixed Assets	Operating Cost	COGS	Net Sales	Net Profits	Average MAPE of DMUs
DMU1	10.63	12.25	7.68	5.76	11.46	9.55
DMU2	11.52	2.04	10.93	7.26	3.83	7.12
DMU3	16.86	1.64	5.56	7.85	6.83	7.75
DMU4	2.44	18.14	8.86	9.64	5.24	8.87
DMU5	12.61	12.91	9.12	8.39	18.84	12.37
DMU6	10.37	12.13	5.00	4.46	19.12	10.22
DMU7	9.21	7.44	6.07	6.75	14.47	8.79
DMU8	9.44	3.45	10.29	8.84	21.35	10.68
DMU9	5.92	6.03	9.58	4.14	26.72	10.48
DMU10	18.42	5.14	4.97	4.86	11.83	9.05
DMU11	14.77	10.30	15.27	16.87	9.18	13.28
DMU12	5.37	13.30	2.02	2.04	20.47	8.64
DMU13	11.95	3.33	8.32	9.18	27.99	12.15
DMU14	1.56	9.00	11.89	6.29	18.16	9.38
DMU15	10.73	1.46	10.06	9.55	18.12	9.98
DMU16	4.17	6.36	2.78	4.37	16.17	6.77
DMU17	6.84	5.28	9.17	8.95	14.50	8.95
Average MAPE of all 17 DMUs						9.65

4.5. DEA model choosing

There are many recent models proposed to manage negative information that the standard of typical DEA models cannot deal with. However, most these models assess the quantity of DMUs as efficiency but do not consider the necessities of one unit over the others [6]. To deal with this issue, hence, the Super-SBM is utilized in this study.

4.6. Pearson Correlation

There are two major basic DEA data expectation that are homogeneity and isotonicity. A highly positive connection between the data of inputs and outputs, hence, is required. In this paper, therefore, the Pearson Correlation is employed to see if our data are isotonicity to put into the DEA model. The results in Table 6 -12 show strong positive associations between input and output variables (higher than 0.6) and comply with prerequisite condition of the DEA model.

Table 6: Correlation of input and output data in 2011

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.918**	.808**	.839**	.864**
COGS	.918**	1	.857**	.883**	.820**
Operating costs	.808**	.857**	1	.998**	.783**
Net Sales	.839**	.883**	.998**	1	.817**
Net Profits	.864**	.820**	.783**	.817**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 7: Correlation of input and output data in 2012

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.862**	.885**	.901**	.879**
COGS	.862**	1	.845**	.881**	.898**
Operating costs	.885**	.845**	1	.996**	.799**
Net Sales	.901**	.881**	.996**	1	.841**
Net Profits	.879**	.898**	.799**	.841**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 8: Correlation of input and output data in 2013

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.897**	.817**	.837**	.784**
COGS	.897**	1	.809**	.825**	.655**
Operating costs	.817**	.809**	1	.996**	.812**
Net Sales	.837**	.825**	.996**	1	.855**
Net Profits	.784**	.655**	.812**	.855**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 9: Correlation of input and output data in 2014

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.894**	.803**	.826**	.761**
COGS	.894**	1	.917**	.928**	.748**
Operating costs	.803**	.917**	1	.995**	.788**
Net Sales	.826**	.928**	.995**	1	.840**
Net Profits	.761**	.748**	.788**	.840**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 10: Correlation of input and output data in 2015

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.899**	.938**	.958**	.908**

COGS	.899**	1	.916**	.929**	.704**
Operating costs	.938**	.916**	1	.996**	.810**
Net Sales	.958**	.929**	.996**	1	.848**
Net Profits	.908**	.704**	.810**	.848**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 11 : Correlation of input and output data in 2016

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.664**	.938**	.959**	.939**
COGS	.664**	1	.787**	.789**	.417
Operating costs	.938**	.787**	1	.996**	.825**
Net Sales	.959**	.789**	.996**	1	.857**
Net Profits	.939**	.417	.825**	.857**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

Table 12 : Correlation of input and output data in 2017

	Input factors			Output factors	
Pearson Correlation	Fixed Assets	COGS	Operating costs	Net Sales	Net Profits
Fixed Assets	1	.773**	.963**	.976**	.876**
COGS	.773**	1	.813**	.796**	.408
Operating costs	.963**	.813**	1	.997**	.812**
Net Sales	.976**	.796**	.997**	1	.847**
Net Profits	.876**	.408	.812**	.847**	1
**. Correlation is significant at the 0.01 level (2-tailed).					

4.7. Analysis before alliance

The super-SBM-I-V is used with the realistic data of 2017 to measure and rank the efficiency of all DMUs before alliance. The empirical results in Table 13 indicated that DMU2 is chosen as a target firm for alliance strategy by reason of couple of reasons. Firstly, DMU2 is one of major steel firms. Secondly, the efficiency score of DMU2 is less than 1 most periods from 2011-2017 and it implies that they did not have a good business performance. Hence, the target firm DMU2 should develop an alliance model to get its advantages and to boost the efficiency of the company's performance.

4.8. Analysis after alliance

The target firm DMU2 is combined with the rest of DMUs to form 33 virtual DMUs (17 original firms and 16 alliances). Then, the DEA-solver software with Super-SBM-I-V model is used to calculate the efficiency score and rank for 33 DMUs in 2018 (Table 14)

Table 13: Performance ranking of DMUs 2017

Rank	DMU	Score
1	DMU17	5.3161547
2	DMU8	1.8032528

3	DMU10	1.4169518
4	DMU9	1.3271411
5	DMU15	1.1414304
6	DMU14	1.0664919
7	DMU12	1.0226289
8	DMU4	1.0003606
9	DMU1	1
10	DMU11	0.7912577
11	DMU2	0.7266436
12	DMU3	0.7204858
13	DMU16	0.6923648
14	DMU5	0.6558052
15	DMU7	0.6551876
16	DMU6	0.6221683
17	DMU13	0.5995008

Table 14: Performance ranking of virtual alliance 2018

Rank	DMU	Score	Group
1	DMU17	4.3533335	
2	DMU1	2.1514410	
3	DMU10	1.5347879	
4	DMU9	1.5148720	
5	DMU8	1.4887350	
6	DMU14	1.1399023	
7	DMU15	1.1189268	
8	DMU12	1.1182940	
9	DMU2+DMU8	1.0476164	2
10	DMU2+DMU1	1.0000000	2
11	DMU2+DMU10	0.9178947	2
12	DMU2+DMU9	0.8648130	2
13	DMU2+DMU4	0.8559267	1
14	DMU2+DMU5	0.8380329	1
15	DMU2+DMU6	0.8173981	1
16	DMU2+DMU7	0.8092849	1
17	DMU2+DMU15	0.8057510	2
18	DMU2+DMU14	0.7934810	2
19	DMU2+DMU12	0.7887731	2
20	DMU2+DMU3	0.7817928	1
21	DMU2+DMU11	0.7815359	1
22	DMU2+DMU16	0.7793887	1
23	DMU4	0.7655028	
24	DMU2+DMU17	0.7481532	2
25	DMU2	0.7436515	
26	DMU5	0.7368258	
27	DMU2+DMU13	0.7358085	3
28	DMU3	0.6906191	
29	DMU16	0.6806590	
30	DMU11	0.6799042	
31	DMU6	0.6379068	
32	DMU7	0.6214343	
33	DMU13	0.5468907	

Table 15: Performance ranking of virtual alliance 2019

Rank	DMU	Score	Rank
1	DMU17	4.1567258	

2	DMU1	2.3937626	
3	DMU10	2.0033206	
4	DMU9	1.6129761	
5	DMU8	1.2279166	
6	DMU14	1.1709721	
7	DMU12	1.131529	
8	DMU15	1.1086237	
9	DMU2+DMU8	1.0220619	2
10	DMU2+DMU1	1	2
11	DMU2+DMU10	0.9503628	2
12	DMU2+DMU9	0.8549256	2
13	DMU2+DMU4	0.8307006	1
14	DMU2+DMU15	0.7808978	2
15	DMU2+DMU7	0.7799318	1
16	DMU2+DMU6	0.7702881	1
17	DMU2+DMU5	0.7652768	1
18	DMU2+DMU14	0.7582286	2
19	DMU2+DMU3	0.7559967	1
20	DMU2+DMU12	0.7527605	2
21	DMU2+DMU16	0.7475017	1
22	DMU2+DMU11	0.7372424	1
23	DMU4	0.716943	
24	DMU2+DMU17	0.7162358	2
25	DMU3	0.7161276	
26	DMU2	0.7148104	
27	DMU2+DMU13	0.7063962	3
28	DMU5	0.7036665	
29	DMU11	0.6887403	
30	DMU16	0.664471	
31	DMU7	0.6088264	
32	DMU6	0.6061264	
33	DMU13	0.5350855	

4.9. Partner selection

In the examination, the **Error! Reference source not found.** shows the target firm DMU2 was ranked as 25th in comparison to others in 2018 with 16 alliance strategy options in total. However, the table indicates that there are 15 potential good partners (DMU4,DMU5,DMU6,DMU7,DMU3,DMU11,DMU16,DMU8,DMU1,DMU10,DMU9,DMU15,DMU14,DMU12,DMU17) that brings the higher ranking for the target DMU2 after alliance. However, these 15 potential alliance partnerships are divided into two groups:

Group 1: These alliance partnerships are the first prioritized because both firms acquire the better outcome and more efficiency after strategic alliance. By comparing to the performance score in 2017 (Table 13) and confirming with the performance ranking of virtual alliance in 2019 (Table 15), this group includes total 7 companies in Table 16, that are arranged in order of priority.

Table 16: The first prioritized in alliance strategy

DMU	Score	Group	Target DMU2 & Partner DMU ranking before alliance (1)	Target DMU2 & Partner DMU ranking after alliance (2)	Change in Ranking (1)-(2)
DMU2+DMU4	0.8559267	1	25& 23	13	12&10
DMU2+DMU5	0.8380329	1	25& 26	14	11& 12
DMU2+DMU6	0.8173981	1	25& 31	15	10& 16
DMU2+DMU7	0.8092849	1	25& 32	16	9& 16
DMU2+DMU3	0.7817928	1	25& 28	20	5& 8
DMU2+DMU11	0.7815359	1	25& 30	21	4& 9
DMU2+DMU16	0.7793887	1	25& 29	22	3& 7

The table shows that DMU4 is the most prioritized partner since the target DMU2 gets better from 25th ranking to 13th ranking and the partner DMU4 also increases the position from 23rd to 13th after strategic alliance.

Group 2:

The target DMU increases performance after strategic alliance while its partners get worst, i.e. their ranking is lower. This group, hence, is the second priority since these firms have current good performance and they have no incentive to cooperate with the target firm DMU2. Total 8 DMUs are in this group are shown in Table 17.

According to the Table 17, the target DMU2 will have most efficiency and get the highest ranking (9th position) if the firm could build a strategic alliance with the partner DMU8. However, this would be very hard to persuade since the DMU8 would get worst from 5th ranking to 9th ranking after the partnership.

On the other hand, the firm DMU13 would be not chosen to corporate because it does not help the target enterprise to get its advantages even becoming worst after strategic alliance.

Table 17 : The second prioritized in alliance strategy

DMU	Score	Group	Target DMU2 & Partner DMU ranking **BEFORE** alliance (1)	Target DMU2 & Partner DMU ranking **AFTER** alliance (2)	Change in Ranking (1)-(2)
DMU2+DMU8	1.0476164	2	25 &5	9	16&-4
DMU2+DMU1	1.0000000	2	25 & 2	10	15& -8
DMU2+DMU10	0.9178947	2	25 & 3	11	14& -8
DMU2+DMU9	0.8648130	2	25 & 4	12	13& -8
DMU2+DMU15	0.8057510	2	25 & 7	17	8& -10
DMU2+DMU14	0.7934810	2	25 & 6	18	7& -12
DMU2+DMU12	0.7887731	2	25 & 8	19	6& -11
DMU2+DMU17	0.7481532	2	25 & 1	24	1& -23

5. Conclusion

Nowadays, numerous challenges and more competition dramatically arise in any industries including steel industry. In Vietnam, the steel companies still encounter with the questions such as How to acquire competitive advantages? How to reduce risk and overcome issues? How to apply new technology to reduce production costs? A strategic alliance is taking into account and concerns by most enterprises currently. However, there are many challenges in setting a partnership among Vietnamese firms, including lack of information, "uncertain success in business future" due to input/output factors fluctuate in various periods. This paper, therefore, we propose a new decision making model which combines the GM (1,1) and DEA model to suggest the good alliance partners for target firm by using several input and output variables.

An advantage of this study is that we use the realistic data in 7 consecutive years instead of 3-5 years as previous studies [24],[7] in order to increase the accurateness of prediction. By using public data of 17 steel companies in Vietnam from 2011 to 2017, the research apply the GM(1,1) and DEA model to predict and assess firms' performance with input elements (Fixed assets, Operating cost, COGS) and output elements (Net Sales, Net Profits). The accurate forecast value is examined by average MAPE, 9.65% implying that GM (1,1) is high reliable.

This study shows that the DEA is a sensitive method for factors selection. Small difference in inputs/outputs selection could impact on the results. Hence, the robust checking is essential in this study. The super-SBM model is used to assess performance efficiency all real 17 steel companies separately and 33 virtual firms. The empirical results show that 15 potential candidates are advisable for the target company DMU2 (i.e. Hoa Sen Group) to form strategic alliances, in which DMU4, DMU5, DMU6, DMU7, DMU3, DMU11, DMU16 are the first priority group. Especially, the DMU4 (i.e. Pomina Steel Corporation) is highly recommended because both companies are able to achieve the outstanding performance after strategic alliances. If such an association is concerned, it requires much effort from both the target firm and its partner. For example, they should have a collaborative innovation agreement and renewal products or conduct extensive a performance evaluation before and after the alliance in many aspects.

For further study, although GM(1,1) and DEA model are flexible and efficient tool to estimate and assess the firm's performance , the sensitive analysis for different inputs/outputs or data of different years can be taken into account in the future studies. Qualitative data could be concerned in developing the methodology. The proposed model can be applied for other industries in future research.

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