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Strategic Alliance for Vietnam Domestic Real Estate Companies Using a Hybrid Approach Combining GM (1,1) with Super SBM DEA

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Abstract: The high economic development in Vietnam contributes much momentum to boost the estate industry in this country. However, competition in this market is also increased. To survive better in this industry, the estate companies in the Vietnam estate industry can apply strategic alliance which, however, depends heavily on forming the right partnership. For this purpose, a hybrid approach combining Grey Theory with Data Envelopment Analysis (DEA) has been proposed in this research to assess and predict the performance of some Vietnamese estate companies, in addition to helping to form the right partnership. For empirical study, 16 companies in the Vietnam estate industry have been selected as Decision Making Units (DMUs). After collecting these DMUs' historical data in the time period 2012-2017, the grey model GM (1,1) was first used to forecast the performance of these DMUs in 2018-2020. Then, the slacks-based measure (SBM) super efficiency (super SBM) model was used to assess their performance. To initiate partnerships, Becamex Infrastructure Development Joint Stock Company (IJC) has been selected as a target company and it can develop 15 different strategic alliance scenarios. The experimental results show that only some of the scenarios are beneficial. Thus, prudence is a necessity when using strategic alliance.

Keywords: DEA; grey system theory; real estate; strategic alliance

1. Introduction

Vietnam has achieved high economic development in recent years. The GDP growth of Vietnam hit 7.08% in 2018, which is the highest since 2008. The high economic development has also helped sustain the growth of Vietnam asset market. The solid supply and demand across residential, office, and industrial sectors have paved a solid foundation for the Vietnam estate market, making 2018 being a good year for the real estate market in Vietnam. The prosperous outlook in the Vietnam estate market is expected to continue for many years [1].

The Vietnam real estate outlook 2019 report gives more details about the Vietnam estate market. In terms of apartment, the supply in Q4 2017 increased by 8559 units, which is a 12% quarter-on-quarter increase [1]. In 2018, the apartment supply for the middle class increased while high-end and luxury apartment supply increased slightly. In addition, high-value transactions of merger and acquisition

(M&A) in the residential, commercial, and industrial segments also increased, showing that real estate in Vietnam is attractive to foreign investors. In the M&A market, real estate, consumer goods, banking, and finance are main subjects to acquires. Those properties in big cities or new urban areas with high population and resorts and hotels in the city center are popular products to investors [2]. The excess demands and less supplies make more successful deals in the estate market. Specifically, housing, industrial area estate, and resort have attracted Korean and Japanese. This trend is expected to continue in many coming years and the M&A activities are expected to grow [3]. In 2017, the rapid growth in the real estate sector has attracted many investors worldwide [4].

However, one challenge faced by estate companies in Vietnam is increasing competition. For the Vietnam estate companies, how to better survive in the estate industry is an emerging issue. There are different approaches for an estate company to improve its competitiveness, including scaling up its business operation by self-expansion and using the strategy of alliance. In the past, companies, especially those of small sizes, focused on using the approach of self-expansion to achieve economies-of-scale that could offer competitiveness. The use of strategic alliance has been mostly neglected, especially in an emerging estate market. However, compared with self-expansion, the strategy of alliance appears to provide more benefits, such as fast to scale up its operations, lower cost, and complimentary to weak company. The use of strategic alliance appears to be able to gain competitiveness with a relatively lower cost and less time due to a joint effort. For a company that has nearly approached its economies of scale, this strategy becomes more important because of fewer solutions available. However, one essential key to the success of a strategic alliance is the formation of a right partnership that indeed depends on a scientific and systematic approach. Literature shows that almost all of the past researches were dedicated to the assessment of the efficiency for estate companies, and the use of strategic alliance for estate companies to improve competitiveness has been rarely appeared. One possible reason is the lack of a concrete and systemic approach to assist estate companies to implement the strategy of alliance. As the competition in the Vietnam estate market becomes increasingly fierce, such an approach has become important for estate companies to gain competitive advantage and survive better in this industry.

Literature also shows that various approaches have been proposed to assess the operational efficiency of real estate companies, such as the translog cost function [5], traditional Data Envelopment Analysis (DEA) [6–8], super-slacks-based measure (SBM) DEA [8], and stochastic frontier models [9]. However, each of these tools alone cannot help the implementation of a strategic alliance on a reasonable basis as they are mainly used to assess the past performance of a company. For a strategic alliance, the partnership based on future performance is more meaningful. Thus, the combination with a forecast model is reasonable and necessary. Thus, in this research, a hybrid approach combining Data Envelopment Analysis (DEA) with grey forecast is used. In addition, a concrete and systematic approach is proposed to facilitate the implementation of the strategy of alliance.

For empirical study, 16 companies in the Vietnam estate industry were selected as Decision Making Units (DMUs). Having determined the input and output variables, the historical data of these DMUs in the time period 2013–2017 were collected. Then, the GM(1,1) was employed to predict their future performance (data) in the time period 2018–2019. Then, the super-SBM DEA was used to evaluate the past, current, and future performance for these DMUs. For strategic alliance, one of the DMUs, Becamex Infrastructure Development Joint Stock Company (IJC), was selected as the target company to illustrate the formation of right partnerships from 5 available scenarios for a strategic alliance. The results showed that the company Kinh Bac City Development Share Holding Corporation (KBC) is the best partner for the company IJC. In addition, it is found that not all partnerships are beneficial for the allied members, suggesting that prudence is still required when using the strategy of alliance.

The rest of this paper is organized as follows. Section 2 includes a literature review, including some definitions of strategic alliance, DEA, and grey systems theory, and definition of mean absolute percentage error (MAPE). Section 3 introduces the methodology. Section 4 includes an empirical study and an analysis of results. Section 5 gives a conclusion and suggests future research direction.

2. Background and Literature Review

2.1. Strategic Alliance

Some scholars have defined the meaning of strategic alliance. Das and Teng [9] defined strategic alliance as "brings together otherwise independent firms to share resources in product design, production, marketing, or distribution." This simply means that strategic alliance is sometimes just regarded as a "partnership" that offers businesses a chance to join efforts for a mutually beneficial opportunity and sustained competitive advantage. Zikmund et al. [10] considered key coalition as "lasting helpful assertion between the organizations, including the inflow and connecting of assets, and its agreeable object is completing their organization missions in key coalition." Though with different statements, these authors share the common view of benefits for allied members with partnership. The joint effort can offer a better achievement for all allied members.

In this research, the strategic alliance is defined as "collaboration among independent companies to achieve higher business objectives or business results." Common objectives of the strategic alliance include expanding market channels, increasing production capacity, or improving a company's operational efficiency, etc. These benefits have attracted the uses of strategic alliance in many different areas. However, a scientific and systematic approach is definitely necessary for the evaluation of the performance of enterprises and forming the right partnership.

2.2. Data Envelopment Analysis (DEA)

In 1957, Farrell [11] proposed a concept for efficiency evaluation using multiple inputs and one single output. Based on that, Charnes et al. [12] proposed a mathematical model with linear combination to convert accumulated statistics into practical inputs and outputs. Being a data-oriented model, this approach can be used to evaluate peer entities, which are especially termed as Decision Making Units (DMUs). A DMU can be a bank, manager, or a shipping company, etc., which converts multiple inputs to multiple outputs. The measurements resulted from the DEA approach are relative efficiency scores of these selected DMUs and their values are within the interval [0, 1].

The DEA has been recognized as a useful tool for performance measurement. It has been widely used by economists and politicians in both private and public sectors [13]. For example, Färe et al. [14] used an input-based Malmquist productivity index, which is a non-parametric (linear programming) method, to assess Swedish pharmacies in the time period 1980–1989. In Färe et al. [15], the authors used DEA to assess 17 OECD countries in 1979-1988. This study found that productivity growth in the U.S. was slightly above average while Japan had the highest performance due to better technical efficiency.

The common advantages for the DEA include:

- Multiple outputs and inputs, each being stated in different units, may be included simultaneously to produce a single measure.
- A priori weights are not required for outputs or inputs.
- Specific output increases, input reductions, or both needed to achieve efficiency are provided.
- DEA focuses on the achievable best performance.

2.3. Grey Systems Theory

Grey System Theory was proposed by Deng in 1982 [16]. This theory aims to extract realistic governing laws of the system based on available data, which is a process known as "generation of grey sequence." This theory is logical and reliable and has been widely used in various application domains [17–19]. The relational analysis of this theory has been used in decision-making process in various industries. For example, Wu et al. [20] used this theory to develop clustering algorithms. This theory can be used to acquire bioinformatics information, sales statistics, and marketing performance measure. In short, this theory is very useful and demonstrates many benefits for industries and few drawbacks regarding data input and output.

Grey model, which is one of the tools of Grey System Theory, can be used for forecasting. However, there are different types of grey models. In this research, the type of GM(1,1) is used. The GM(1,1) is further detailed in Section 3.2.

2.4. Relevant Studies

Some past studies were devoted to investigating the operational efficiency of Real Estate Investment Trusts (REITs). Bers and Springer [5] used the translog cost function to estimate economies of scale for some REITs in the time period 1992–1994. They found that economies of scale exist for REITs can be affected by characteristics such as type of management and degree of leverage. Using the DEA approach, Anderson et al. [6] estimated economies of scale and inefficiency for REITs based on their historical data in 1992–1996. They found poor input utilization and failure to operate at a constant returns-to-scale as two factors of technical inefficiency for the REITs, which suggests that company expansion can improve the technical inefficiency of these REITs. Using the stochastic frontier models and panel data, Miller and Springer [21] estimated the operational efficiencies of REITs. This model was able to identify frontier cost improvements, returns to scale, and cost inefficiencies over time. However, this model normally focuses on single input and not capable of dealing with multiple outputs at a time. Although these researches have addressed operational efficiency of REITs, there is still a lack of systematic analysis for the listed real estate companies.

Using the style analysis approach, Chau et al. [22] analyzed the returns of 12 listed property companies and one property company in Hong Kong. They found that indirect and direct real estate are becoming closer substitutes for each other. Moreover, the investment style, which is mainly characterized by the implied portfolio instead of management skills, can affect the results for property company considerably. Hui et al. [23] investigated the performance of some Hong Kong property companies in terms of economic value added (EVA). Those companies diversified into other sectors were found to have a better result than that only focus on the real estate sector. From an EVA perspective, they concluded that the property companies in Singapore and Hong Kong have not performed well. However, this does not necessarily mean that they are poorly managed. The empirical results show that the performance of a company is influenced dramatically by profits generated from the sale of non-property assets. Using the DEA approach, Wang and Wang [7] analyzed 20 Listed Real Estate Companies (LRECs) in China in the time period 2000-2007. They found that control policies can affect the real estate industry greatly. However, that study cannot identify those companies with extreme efficiency. In addition, that study only covers some but not all well-known LRECs in China, which might lead to incomplete and somehow biased analysis because the reputation and scale of a company do not necessarily mean a higher level of operational efficiency. Chau et al. [24] investigated the linkage between direct and indirect real estate in terms of corporate governance structures. Compared with the companies in Hong Kong, they found that the China-listed property companies had a weaker linkage between direct and indirect real estate. Using the three types of DEA models, CCR-DEA, BCC-DEA, and Super-Efficiency DEA, Zhen et al. [8] measured the performance and efficiency of the 94 LRECs in China stock markets based on their 2009 Annual Financial Statements. In that study, Registered Capital, Asset Value, Employee Number, and Operation Cost are used as input factors, while Revenue and Profit were used as output factors. In addition, an integrated assessment system was applied and generated a performance ranking for these LRECs. In that study, information such as Overall Efficiency (OE), Pure Technical Efficiency (PTE), and Scale Efficiency (SE) of the LRECs were derived. They found 69% of the inefficient LRECs are classified as increasing returns to scale and could further increase operating efficiency by scale expansion. Finally, they found that the inefficient LRECs have an employee slack prevalent at 18.96%. Bello et al. [25] conducted a study measuring the contribution of real estate to GDP in Nigeria. A total of 44 of the 108 industries in the industrial town of Ota in Nigeria were randomly sampled. Then, data between 2008 and 2012 were collected and analyzed using descriptive statistics. This result provides guidance for industrial investors to measure past achievements and provide a basis for planning and control decisions. The results showed that at an aggregate level, industrial properties in Ota, Nigeria contributed 19% performance to the manufacturing success of industrial establishments.

3. Methodology

3.1. Research Procedure

This research uses a procedure with 9 steps. Each of the steps is detailed as follows.

Step 1: Data collection.

The data of DMUs were collected from the General Statistics Office of Vietnam, and some financial reports were collected from VietStock and CafeF, which are two famous stock markets in Vietnam. In this research, one DMU was selected and is defined as a target company that is a basic company that selects other companies as partners for a strategic alliance.

Step 2: Selection of input/output variables.

Inputs and outputs are main impact factors used by DEA model to measure the relative efficiency of a DMU to other DMUs.

Step 3: Forecasting.

Grey Prediction is to forecast the results of enterprises based on historical data. In this research, the GM(1,1) was used for forecasting.

Step 4: Forecast accuracy analysis.

The error in prediction is unavoidable. Therefore, the MAPE (Mean outright percent blunder) was used to gauge the exactness esteems in measurements. The smaller the MAPE indicates the higher prediction accuracy. In case of high forecasting error, it needs to reselect the information sources. Mean absolute percentage error (MAPE):

Mean absolute percentage error (MAPE) is a measurement that can be used to measure the accuracy between the actual and forecasting data. The smaller the MAPE, the higher the forecasting accuracy is. Equation (1) shows the formula for calculating the MAPE

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

where the Actual_t are Forecast_t observations at the time period t and n is the total number of observations. Lewis [26] defined the four classes of reliability for MAPE to help understand the level of reliability of the forecasted data (see Table 1).

Table 1. Accuracy classes of MAPE.

Class	MAPE
• High accuracy forecasting:	<10%
• Good forecasting:	10–20%
• >Reasonable forecasting:	20–50%
• Inaccurate forecasting:	>50%

Step 5: Selection of DEA model.

In this step, the Super-SBM-I-V was used to measure the efficiency of different DMUs.

Step 6: Pearson correlation analysis.

DEA was used for incompetency estimation for DMUs by developing a comparative effectiveness score through the change of the multiple foundation data into a ratio of a single virtual output to a single virtual input. Subsequently, correlation testing for collected input and output is quite important. In this research, the Pearson Correlation Coefficient Test was used to check the suitability of selected input and output variables.

Step 7: Analysis before strategic alliance.

This step aimed to select one target company and understand its performance before applying strategic alliance with allied members. This helped to understand the performance of the target company after applying the strategic alliance in the next step.

Step 8: Analysis after strategic alliance.

This step aimed to analyze the performances of various alliances available for the target company selected in the previous step. From the results available from different strategies of alliance, we can identify the best one for a selected target company. The performance of each strategic alliance can be estimated by using the supper-SBM-I-V model.

Step 9: Summary.

This step aimed to summarize a suggestion, based on the previous step. Basically, the strategic alliance should result in positive results that can benefit all allied members.

3.2. *The Grey Forecasting Model GM(1,1)*

The grey model GM(1,1) associates with time series and includes some differential equations that have structure varying with time. It has been widely used for forecasting. One advantage of the GM(1,1) is computational efficiency, another advantage is that only a few series of data are required. Basically, at least 4 consecutive data with equal time intervals are required for the GM(1,1) to obtain a reasonably accurate prediction. Figure 1 shows the procedure of Grey prediction.

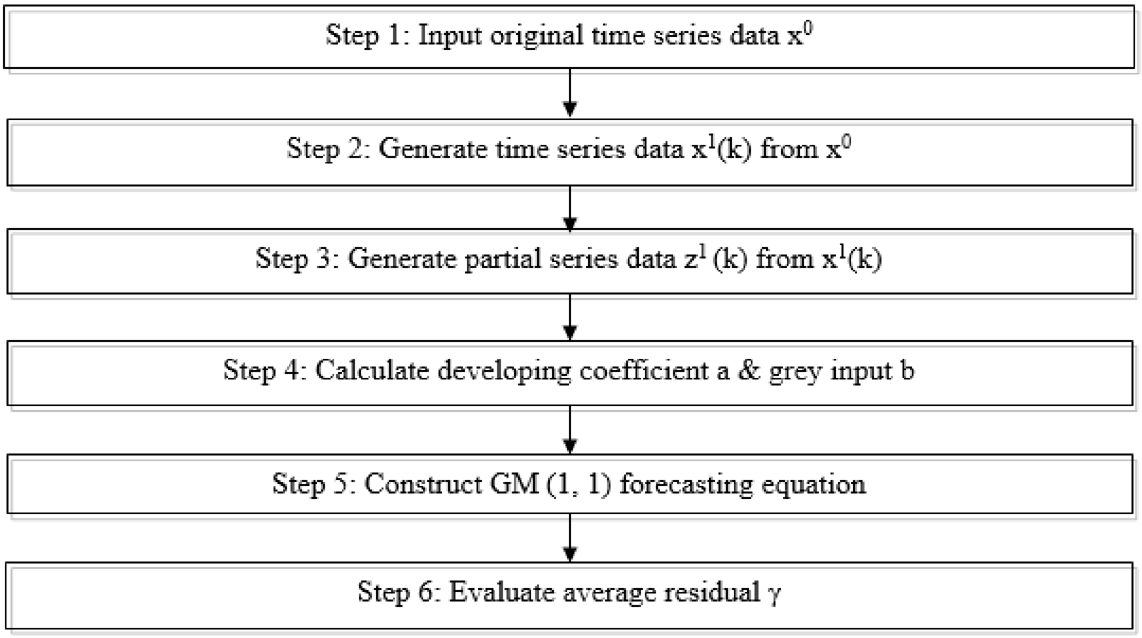

Figure 1. The procedure of grey prediction using GM(1,1).

The procedure of grey prediction using GM(1,1) is detailed as follows. Given the variable primitive series $X^{(0)}$ as Equation (2), the construction of the GM(1,1) model is detailed as follows.

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

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

The Accumulating Generation Operator (AGO) is one of the most important characteristics of grey theory, which can be used to eliminate uncertainty of these primitive data and smooth randomness. The AGO is defined in Equation (3).

$$X^{(1)} = \left((X^1(1),\ X^1(2), \ldots,\ X^1(n)\right), n \geq 4 \tag{3}$$

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

The $Z^{(1)}$ is defined in Equation (4).

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

where $Z^{(1)}$ (k) is the mean value of adjacent data defined in Equation (5)

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

Based on the $X^{(1)}$, a GM(1,1) model that corresponds to the first order different equation $X^{(1)}(k)$ can be constructed by the Equation (6).

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

where parameters a and b are called developing coefficient and grey input, respectively.

In practice, parameter a and grey input b are not calculated directly from Equation (6). Instead, the solution of the above equation is obtained using the least square method, i.e., Equation (7).

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

where $\hat{X}^{(1)}(k+1)$ 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 as defined in Equations (8), (9), and (10).

$$[a, b]^T = \left(B^T B\right)^{-1} B^{\mathrm{T}} Y \tag{8}$$

and

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

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

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

We obtained $\hat{X}^{(1)}(k)$ as follows. Let $\hat{X}^{(0)}$ be the fitted and predicted series.

$$\hat{X}^{(0)} X^{(0)}(1), \hat{X}^{(0)}(2),\ \ldots, \hat{X}^{(0)}(n)$$

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

Applying the inverse accumulated generation operation (IAGO), i.e., Equation (11).

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

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

In this study, the non-radial Slack-based measure of super-efficiency (super SBM) of DEA is used. This model was introduced by Tone in 2001 [27].

In the super SBM model, given 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. Let λ be a non-negative vector in R^n. The vectors $S^- \in R^m$ and $S^+ \in R^s$ indicate the input excess and output shortfall, respectively. This model provides a constant return to scale. It is defined in Equation (12) that subjects to Equation (13) [27].

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

$$\text{s.t } x_0 = X\lambda + S^-,\ y_0 = Y\lambda - S^+,\ \lambda \geq 0,\ S^- \geq 0,\ S^+ \geq 0 \tag{13}$$

The variables S^+ and S^- measure the distance of inputs $X\lambda$ and outputs $Y\lambda$ of a virtual unit from those of the unit evaluated. The numerator and the denominator in the objective function measure the average distance of inputs and outputs, respectively, from the efficiency threshold.

Let an optimal solution for SBM be $(p^*, \lambda^n, s^{-*}, s^{+*})$. *A* DMU (X_0, Y_0) is SBM-efficient, if $p^* = 1$. This condition is equivalent to $s^{-*} = 0$ and s^{+*}, $s^{+*} = 0$ no input excesses and no output shortfalls in any optimal solution. The SBM model is non-radial and deals with input/output slacks directly. The SBM returns and efficiency measure is between 0 and 1.

The best performers have the full efficient status denoted by unity. The super SBM model is based on the SBM model. Tone (2001) [27] 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 defined in Equation (14) and subject to Equation (15).

$$\min \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \overline{X}_i / x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \overline{y}_r / y_{r0}} \tag{14}$$

$$\text{s.t } \overline{x} \geq \sum\nolimits_{j=1,\neq 0}^{n} \lambda_j x_j,\ \overline{y} \leq \sum\nolimits_{j=1,\neq 0}^{n} \lambda_j x_j,\quad \overline{y} \geq x_o \text{ and } \overline{y} \leq y_o,\ \overline{yy} \geq y_o,\quad \lambda \geq 0 \tag{15}$$

The input-oriented super SBM model is derived from Equation (14) with the denominator set to 1. The super SBM model returns a value of the objective function that is greater or equal to 1. The higher the value, the more efficient the unit is.

3.4. Company Selection

In this research, 20 household recorded land organizations with the most noteworthy market capitalization were initially targeted as DMUs due to their significance in the real estate industry in Vietnam.

However, four of these companies, including C.E.O Group Joint Stock Company, LDG Investment Joint Stock Company, NoVa Land Investment Group Corporation, and Vincom Retail Joint Stock Company, were excluded due to the unavailability of their historical data. As a result, only 16 of 20 companies were included and listed in Table 2.

Table 2. List of 16 real estate companies and their capitals, unit: VND (millions).

DMU	Company Code	Company Name	Company Capital
DMU1	VIC	Vingroup Joint Stock Company (VIC)	309,139,372
DMU2	KDH	Khang Dien House Trading and Investment JSC	14,058,921
DMU3	DXG	Dat Xanh Real Estate Service &Construction Corporation	11,027,112
DMU4	PDR	Phat Dat Real Estate Development Joint Stock Company	9,057,230
DMU5	KBC	Kinh Bac City Development Share Holding Corporation	6,271,299
DMU6	DIG	Development Investment Construction JSC	6,121,607
DMU7	NLG	Nam Long Investment Corporation	5,801,654
DMU8	FLC	FLC Group JSC	4,266,859
DMU9	HDG	Ha Do Group Joint Stock Company	3,721,610
DMU10	QCG	Quoc Cuong Gia Lai Joint Stock Company	3,714,243
DMU11	SCR	Sai Gon Thuong Tin Real Estate JSC	3,219,100
DMU12	SJS	Song Da Urban & Industrial Zone Investment & Development JSC	2,961,354
DMU13	ITA	Tan Tao Investment and Industry Corporation	2,814,965
DMU14	NBB	NBB Investment Corporation	1,802,495
DMU15	IJC	Becamex Infrastructure Development JSC	1,439,522
DMU16	TDH	Thu Duc Housing Development Corporation	1,249,014

3.5. Input and Output Variables Selection

The input and output variables selected for evaluating DMUs are important. These selected variables should be able to reveal the performance of DMUs. In this research, some past researches in the real estate area were referred in order to find suitable variables as inputs and outputs. Table 3 shows the summary of input and output variables used in some past research for the assessment of DMUs.

Table 3. Summary of input and output variables used in previous studies.

Research Title	Input Variable	Output Variable
Efficiency assessment of listed real estate companies: an empirical study of China [8]	Registered capital Employees Asset Value Operating Cost	Profit Revenue
Analysis on the Efficiency of Real Estate Industry Based on DEA in Ningbo City [28]	Gross investments Complete land development area Employed numbers in realty industry	Gross opening revenue Sales amount Floor space completed
Empirical Analysis on Efficiency of Listed RealEstate Companies in China by DEA [29]	Main business cost Total assets Number of employees	Main business income Gross profit Return on equity
How efficient are real estate and construction companies in Iran's close economy? [30]	Registered capital Employees number Asset Value Operating Cost	Profit Revenue
The Empirical Study on Productivity of Chinese RealEstate Enterprises Based on DEA-based Malmquist model [31]	Total assets Employee salaries	Operation income Operation profit
Data Envelopment Analysis of Efficiency of Real Estate Investment Trusts in Singapore [32]	Operating Expenses Management Fees Interest Expenses	Total assets Total Revenue Net Asset Value
Measuring Efficiency of Real Estate Investment Trust Using Data Envelopment Analysis Approach [33]	Operating Expenses Administrative Expenses Management Fees Interest Expenses	Total Assets Total Revenue Net Asset Value

In this research, charter capital, asset value, selling expense, and general and administrative expenses are selected as input variables, while revenue from sales of goods and services and profit before Tax (PBT) are selected as output variables. These variables are further detailed as follows:

1. **Charter capital (I)**: is capital stated in company's charter as a reflection of its business scale to investors. Capital includes both tangible assets, such as factories or manufacturing facilities, and financial value of the firm's intangible assets.
2. **Asset Value (I)**: this is the total asset value the enterprise owns, which is an internal resource that can be used to create benefits in the future.

3. **Selling Expense (I)**: this refers to costs occurred when selling products, both directly and indirectly. Direct expenses include costs for delivery or sales commissions. Indirect expenses can be put as expenditure spent to earn sales. Some typical categories of indirect expense are budget for marketing and salaries of sales and marketing staff.
4. **General and Administrative Expense (I)**: this refers to costs a firm needs for daily operation and business administration. These expenses are incurred regardless of no production or sales occur. This means companies with centralized management have a tendency to have higher G&A expense.
5. **Revenue from Sales of Goods and Services (O)**: this is an output variable about the revenue firms generated from selling their products and services. The term is also referred as Operating revenue because the revenue is generated from the company's daily business operation.
6. **Profit before tax (PBT) (O)**: this is an output variable that refers to a company's profit before subjected to corporate income tax, with all expenses generated from revenue deducted, including interest expenses and operating expenses.

Table 4 shows the data of these input and output variables collected from the Vietstock Website [34].

Table 4. Collected Data of all Decision Making Units (DMUs) in 2013.

DMU	CCL (I)	AVE (I)	SCT (I)	CCT (I)	NRE(O)	PBX(O)
VIC	403,526,174	3,294,462,975	19,568,368	63,757,490	799,027,776	423,481,999
KDH	20,900,000	75,705,547	132,807	2,031,281	4,891,009	7,654,589
DXG	22,956,391	55,139,786	2,717,122	3,532,437	14,895,267	5,238,524
PDR	56,608,696	245,998,527	269,553	932,158	1,722,536	168,041
KBC	130,434,783	544,884,317	460,273	2,418,780	46,644,410	3,730,346
DIG	62,172,000	201,394,134	3,131,720	2,913,371	32,740,163	2,452,605
NLG	41,527,609	144,509,413	1,537,796	4,820,793	26,162,892	2,418,576
FLC	33,556,522	91,341,804	155,656	1,481,354	75,826,651	5,958,681
HDG	24,211,913	101,208,633	377,524	2,833,980	42,986,216	7,918,480
QCG	55,250,826	276,554,357	170,439	630,917	42,298,127	543,344
SCR	65,282,130	242,906,824	3,424,890	4,798,089	47,542,040	3,141,350
SJS	43,478,261	243,792,884	133,901	5,738,400	27,454,035	3,247,829
ITA	269,151,261	467,839,774	161,260	2,393,544	488,855	2,390,331
NBB	15,591,565	134,089,386	197,061	1,115,023	8,814,771	1,907,379
IJC	119,215,000	209,037,230	1,851,551	867,555	26,745,771	8,070,895
TDH	16,587,130	98,247,682	244,332	2,252,241	17,803,546	1,034,810

CCL: Chartered Capital; AVE: Asset Values; SCT: Selling Cost; CCT: G&A Cost (CCT); NRE: Net Revenue from Sale of Goods and Services; PBX: Profit before tax (PBX).

4. Empirical Results and Discussion

4.1. Data Processing

Table 5 shows the collected data of Chartered Capital for the company TDH (DMU16) in the time period 2013–2017 (Source: Vietstock [34]).

Table 5. Collected data for the TDH (DMU16) (2013-2017).

Years	Inputs (Dollars)				Output (Dollars)	
	CCL	AVE	SCT	CCT	NRE	PBX
2013	16,587,130.43	244,332.04	17,803,546.48	16,587,130.43	403,355.74	24,707,147.17
2014	16,587,130.43	403,355.74	24,707,147.17	18,245,521.74	475,736.48	38,364,16261
2015	18,245,521.74	475,736.48	38,364,162.61	30,864,521.74	311,391.70	46,099,806.00
2016	30,864,521.74	311,391.70	46,099,806.00	35,493,043.48	171,078.83	80,000,785.17
2017	35,493,043.48	171,078.83	80,000,785.17	47,616,582.50	190,976.37	109,889,67.88

CCL: Chartered Capital; AVE: Asset Values; SCT: Selling Cost; CCT: G&A Cost (CCT); NRE: Net Revenue from Sale of Goods and Services; PBX: Profit before tax (PBX).

Based on Table 5, the forecast data of CCL for the company TDH in the year of 2018 by using GM(1,1) are derived and illustrated as follows. The primitive series of data is as follows.

$$X^{(0)} = (16,587,130.43;\ 16,587,130.43;\ 18,245,521.74;\ 30,864,521.74;\ 35,493,043.48)$$

Using the AGO, we can derive the accumulated values as follows.

$$X^{(1)} = (16,587,130.43;\ 33,174,260.87;\ 51,419,782.61;\ 82,284,304.35;\ 117,777,347.83)$$

Each of the data is derives as follows.

$$\begin{aligned}
x^{(1)}(1) &= x^{(0)}(1) = 16,587,130.43\\
x^{(1)}(2) &= x^{(0)}(1) + x^{(0)}(2) = 33,174,260.87\\
x^{(1)}(3) &= x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) = 51,419,782.61\\
x^{(1)}(4) &= x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) = 82,284,304.35\\
x^{(1)}(5) &= x^{(0)}(1) + x^{(0)}(2) + x^{(0)}(3) + x^{(0)}(4) + x^{(0)}(5) = 117,777,347.83
\end{aligned}$$

The accompanying mean means can be then derived as follows.

$$\begin{aligned}
z^{(1)}(2) &= \tfrac{1}{2}(16,587,130.43 + 33,174,260.87) = 24,880,695.65\\
z^{(1)}(3) &= \tfrac{1}{2}(33,174,260.87 + 51.419.782,61) = 42,297,021.74\\
z^{(1)}(4) &= \tfrac{1}{2}(51,419,782.61 + 82,284,304.35) = 66,852,043.48\\
z^{(1)}(5) &= \tfrac{1}{2}(82,284,304.35 + 117,777,347.83) = 100,030,826.1
\end{aligned}$$

Substitute the crude arrangement esteems to Gray differential conditions, we can derive the following equations.

$$\begin{cases}
16,587,130.43 + a \times 24,880,695.65 = b\\
18,245,521.74 + a \times 42,297,021.74 = b\\
30,864,521.74 + a \times 66,852,043.48 = b\\
35,493,043,48 + a \times 100,030,826.1 = b
\end{cases}$$

Linear equation is rewritten in matrix form as follows:

$$\text{Let } B = \begin{bmatrix} -24,880,695.65 & 1\\ -42,297,021.74 & 1\\ -66,852,043.48 & 1\\ -100,030,826.1 & 1 \end{bmatrix},\ \hat{\theta} = \begin{bmatrix} a\\ b \end{bmatrix},\ y_N = \begin{bmatrix} 16,587,130.43\\ 18,245,521.74\\ 30,864,521.74\\ 35,493,043.48 \end{bmatrix}$$

Least square method is then applied to find a and b

$$\begin{bmatrix} a\\ b \end{bmatrix} = \hat{\theta} = \left(B^T B\right)^{-1} B^T y_N = \begin{bmatrix} -0.2751572273\\ 9,196,688.815 \end{bmatrix}$$

Apply a and b determined an incentive to the differential condition to create the brightening condition

$$\frac{dx^{(1)}}{dt} - 0.2751572273 \times x^{(1)} = 9,196,688.815$$

Prediction model is as the formula.

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

By substituting different values of k into the equation, we can derive the forecast data in 2018 as shown in Table 6.

Table 6. Forecast data of Chartered Capital for the company TDH (DMU16) in 2018.

k	$X^{(1)}(k)$	$X^{(0)}(k)$
$k = 0$	$X^{(1)}(1) = 16{,}587{,}130.43$	$X^{(0)}(1) = 16{,}587{,}130.43$
$k = 1$	$X^{(1)}(2) = 32{,}427{,}348.66$	$X^{(0)}(2) = 15{,}840{,}218.23$
$k = 2$	$X^{(1)}(3) = 53{,}284{,}760.95$	$X^{(0)}(3) = 20{,}857{,}412.29$
$k = 3$	$X^{(1)}(4) = 80{,}748{,}501.73$	$X^{(0)}(4) = 27{,}463{,}740.79$
$k = 4$	$X^{(1)}(5) = 116{,}911{,}044.2$	$X^{(0)}(5) = 36{,}162{,}542.48$
$k = 5$	$X^{(1)}(6) = 164{,}527{,}626.7$	$X^{(0)}(6) = 47{,}616{,}582.50$
$k = 6$	$X^{(1)}(7) = 227{,}226{,}175.4$	$X^{(0)}(7) = 62{,}698{,}548.64$
$k = 7$	$X^{(1)}(8) = 309{,}783{,}717.2$	$X^{(0)}(8) = 82{,}557{,}541.84$
$k = 8$	$X^{(1)}(9) = 418{,}490{,}343.8$	$X^{(0)}(9) = 108{,}706{,}626.60$
$k = 9$	$X^{(1)}(10) = 561{,}628{,}455.7$	$X^{(0)}(10) = 143{,}138{,}111.90$

All DMUs information sources and yields information in the period 2018–2021 can be determined by utilizing the above computational process. A case of conjecture layout can be seen beneath and all the forecasted results are shown in the Appendix A as references.

Table 7 shows the forecast data for all the input/output variables in the year of 2018, and the forecast data of the years from 2019 to 2021 are listed in Tables A1–A3 in Appendix A, respectively. However, due to space limitations, we only illustrate the computational process by using the data of the year 2018.

Table 7. Forecast data of all DMUs in the year 2018.

DMU	CCL	AVE	SCT	CCT	NRE	PBX
VIC	1,474,095,898	12,216,332,305	679,902,621	424,693,844	5,606,473,892	475,400,205
KDH	204,730,026	558,696,474	8,530,484	8,775,796	246,748,685	54,320,364
DXG	165,496,730	679,405,925	20,738,538	15,065,403	207,625,113	90,950,734
PDR	114,541,663	516,825,786	12,984,850	3,402,658	97,241,994	21,199,682
KBC	268,435,456	728,070,687	1,280,313	8,310,980	73,517,896	49,070,717
DIG	113,083,687	285,961,865	4,332,670	4,815,896	93,138,434	3,182,375
NLG	73,744,428	428,188,262	13,809,442	9,395,346	213,355,320	67,675,565
FLC	360,163,163	1,561,724,707	40,973,848	33,886,698	738,929,856	41,577,660
HDG	35,657,602	574,945,291	42,589,676	7,213,783	115,026,759	16,853,316
QCG	153,392,236	557,130,010	2,224,605	1,054,092	62,242,133	679,256,078
SCR	110,295,329	508,366,296	5,923,124	5,274,845	61,908,774	17,662,423
SJS	33,554,432	286,628,589	408,756	641,605	5,813,269	8,743,201
ITA	460,276,084	582,138,764	145,727	10,490,711	27,750,072	1,015,027
NBB	46,408,179	267,192,580	3,896,457	942,197	2,028,463,095	3,543,489
IJC	70,274,445	402,517,218	1,440,754	3,409,057	61,067,224	6,882,559
TDH	47,616,582	133,736,401	190,976	5,474,358	109,889,674	10,951,788

In this paper, Mean Absolute Percent Error (MAPE) defined in Equation (1) is used to assess the accuracy of forecasting data. Table 8 shows the MAPE results of the DMUs.

Some of the 16 DMUs are found with an average MAPE greater than 20%, due to remarkable changes in their business data in recent years. The change in the estate market in 2013–2017 is found big. Real estate prices have been rising robustly in recent years, propelled by Vietnam's recovery from the housing bust of 2009–2013 and by a booming economy. For example, in Q4 of 2017, the primary market apartment prices in Ho Chi Minh City (HCMH) went up by 3.6%, according to Jones Lang LaSalle. Secondary market apartment prices witness an increase of 0.5% yearly during the same period. The average asking price of HCMC villas and townhouses rose by 13.6% in Q4 of 2017. In the secondary market, asking prices of villas and townhouses went up by 4.5% annually, rose by 44% in Q4 of 2017. Villas and townhouse sales in HCMC increased by 25% both from the previous quarter and from the same quarter last year, according to Savills World Research. In Hanoi, apartment prices fell during the year to Q4 of 2017. Primary market apartment prices fell by 2.5% during the year to Q4 of 2017, according to Jones Lang LaSalle. Secondary market apartment prices fell by 6.6%. The continuous growth of supply in Hanoi, as well as a shift in buyer interest to mid-end and affordable segments, in part, might have contributed to the softening of property prices in the capital [31]. With the exception of these companies, the average MAPE of all DMUs is around 11% that is acceptable for this research.

Table 8. MAPE Results of all DMUs based on forecast data in 2018.

DMU	MAPE	DMU	MAPE
VIC-DMU_1	15.54551795%	HDG-DMU_9	5.32514230%
KDH-DMU_2	5.23548620%	QCG-DMU_{10}	8.58742360%
DXG-DMU_3	4.52314580%	SCR-DMU_{11}	17.62913539%
PDR-DMU_4	10.23514850%	SJS-DMU_{12}	6.53268450%
KBC-DMU_5	14.39795736%	ITA-DMU_{13}	12.53264850%
DIG-DMU_6	16.14010755%	NBB-DMU_{14}	23.85321490%
NLG-DMU_7	4.84132807%	IJC-DMU_{15}	13.08780903%
FLC-DMU_8	5.45238650%	TDH-DMU_{16}	8.98386654%
Average MAPE			10.81%

4.2. Pearson Correlation Analysis for Input and Output Data

One prerequisite of the input and output data for the DEA is the existence of isotonicity relationship among them, which means more input will lead to more output, or at least the same level of output, under the same operation condition. To check the isotonic relationship, Pearson correlation coefficients are used in this research. Table 9 shows the degree of correlation between two variables.

Table 9. Degree of correlation.

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

A correlation coefficient > 0.8 means a very high correlation between two variables, a correlation coefficient between 0.6–0.8 means a high correlation, a correlation coefficient between 0.4–0.6 means a medium correlation, a correlation coefficient between 0.2–0.4 means a low correlation, and a correlation coefficient < 0.2 means a very low correlation.

Table 10 shows the results of Pearson correlation coefficients obtained from the year 2013 to 2017.

Table 10. Pearson correlation coefficients of inputs and outputs in 2013–2017.

2013	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.869498	0.767186	0.788677	0.782500	0.800426
AVE	0.869498	1	0.949463	0.979598	0.979612	0.984545
SCT	0.767186	0.949463	1	0.974625	0.967969	0.971524
CCT	0.788677	0.979598	0.974625	1	0.990688	0.994918
NRE	0.782500	0.979612	0.967969	0.990688	1	0.995741
PBX	0.800426	0.984545	0.971524	0.994918	0.995741	1
2014	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.924079	0.853429	0.868897	0.870041	0.884891
AVE	0.924079	1	0.976556	0.986826	0.986585	0.988442
SCT	0.853429	0.976556	1	0.991387	0.987828	0.986870
CCT	0.868897	0.986826	0.991387	1	0.996155	0.994145
NRE	0.870041	0.986585	0.987828	0.996155	1	0.998198
PBX	0.884891	0.988442	0.986870	0.994145	0.998198	1

Table 10. *Cont.*

2015	CCL	AVE	SCT	CCT	NRE	PBX
CCL	1	0.920459	0.880184	0.888046	0.900461	0.876880
AVE	0.920459	1	0.992724	0.994487	0.988687	0.920138
SCT	0.880184	0.992724	1	0.998788	0.988242	0.909243
CCT	0.888046	0.994487	0.998788	1	0.992137	0.916374
NRE	0.900461	0.988687	0.988242	0.992137	1	0.950452
PBX	0.876880	0.920138	0.909243	0.916374	0.950452	1
2016	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.953140	0.926734	0.936870	0.932625	0.921518
AVE	0.953140	1	0.995311	0.997073	0.995379	0.975832
SCT	0.926734	0.995311	1	0.998332	0.996959	0.972704
CCT	0.936870	0.997073	0.998332	1	0.998276	0.979724
NRE	0.932625	0.995379	0.996959	0.998276	1	0.983196
PBX	0.921518	0.975832	0.972704	0.979724	0.983196	1
2017	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.951487	0.930213	0.943429	0.938942	0.921947
AVE	0.951487	1	0.996305	0.998051	0.996432	0.987373
SCT	0.930213	0.996305	1	0.998962	0.995927	0.990621
CCT	0.943429	0.998051	0.998962	1	0.997101	0.989299
NRE	0.938942	0.996432	0.995927	0.997101	1	0.985922
PBX	0.921947	0.987373	0.990621	0.989299	0.985922	1

CCL: Chartered Capital; AVE: Asset Values; SCT: Selling Cost; CCT: G&A Cost (CCT); NRE: Net Revenue from Sale of Goods and Services; PBX: Profit before tax (PBX).

Table 11 shows the results of Pearson correlation coefficients obtained from the year 2018 to 2020. These Pearson correlation coefficients show solid isotonic relationships between the input and output variable in each year, which indicates the suitability of these input and output variables used in this research.

Table 11. Pearson correlation coefficients of inputs and outputs (forecasted for 2018–2020).

2018	CCL	AVE	SCT	CCT	NRE	PBX
CCL	1	0.957571	0.938719	0.952097	0.912398	0.539317
AVE	0.957571	1	0.996779	0.998625	0.939695	0.570040
SCT	0.938719	0.996779	1	0.997980	0.937216	0.581444
CCT	0.952097	0.998625	0.997980	1	0.937673	0.586298
NRE	0.912398	0.939695	0.937216	0.937673	1	0.535784
PBX	0.539317	0.570040	0.581444	0.586298	0.535784	1
2019	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.935459	0.890194	0.893046	0.900461	0.776880
AVE	0.935459	1	0.992724	0.994487	0.988687	0.920138
SCT	0.890194	0.992724	1	0.998788	0.988242	0.909243
CCT	0.893046	0.994487	0.998788	1	0.992137	0.916374
NRE	0.900461	0.988687	0.988242	0.992137	1	0.950452
PBX	0.776880	0.920138	0.909243	0.916374	0.950452	1
2020	**CCL**	**AVE**	**SCT**	**CCT**	**NRE**	**PBX**
CCL	1	0.964303	0.953042	0.961869	0.958396	0.918758
AVE	0.964303	1	0.995904	0.996952	0.99702	0.960976
SCT	0.953042	0.995904	1	0.999142	0.997897	0.962402
CCT	0.961869	0.996952	0.999142	1	0.997929	0.962763
NRE	0.958396	0.99702	0.997897	0.997929	1	0.962343
PBX	0.918758	0.960976	0.962402	0.962763	0.962343	1

CCL: Chartered Capital; AVE: Asset Values; SCT: Selling Cost; CCT: G&A Cost (CCT); NRE: Net Revenue from Sale of Goods and Services; PBX: Profit before tax (PBX).

4.3. Performance Analysis before Strategic Alliance

In this section, the Becamex Infrastructure Development Joint Stock Company (IJC) is selected as the target company that is supposed to form a partnership with other companies in the Vietnam estate industry. The IJC is an estate company established in 2007 in Vietnam. This company owns capital about VND 2,741,945,250,000 and focuses on investing assets of transport infrastructure, real estate, and service business, etc.

The software Super-SBM-I-V was used to obtain the efficiency scores DMUs before applying strategic alliance. Table 12 shows the ranking and efficiency scores of the 16 DMUs in the year 2017 (before applying strategic alliance).

Table 12. Efficiency scores and rankings of the DMUs in 2017 (before strategic alliance).

Rank	DMU	Score
1	ITA	9.09871
2	TDH	5.10371
3	FLC	1.74273
4	HDG	1.08342
5	VIC	1
6	NLG	0.68725
7	SJS	0.64887
8	DXG	0.5746
9	NBB	0.49455
10	KBC	0.47647
11	KDH	0.46101
12	IJC	0.3558
13	DIG	0.28936
14	SCR	0.28069
15	PDR	0.23181
16	QCG	0.22951

Table 12 shows that in the year 2017 the company ITA performed the best with the efficiency score (9.0987132), while the IJC performed poorly due to being ranked to 12. For further investigation, we run the software again to understand the rankings of these DMUs in the time period 2013–2016. Table 12 shows the rank (R) and score (S) of each DMU (D).

Table 13 shows that about half of the DMUs perform efficiently as their efficiency scores are greater than 1, implying they are efficient in the time period 2013–2016.

Table 13. The efficiency scores and rankings of 16 DMUs from in the time period 2013–2016.

2013			2014			2015			2016		
R	**D**	**S**	**R**	**D**	**S**	**R**	**D**	**S**	**R**	**D**	**S**
1	SJS	3.897194	1	SJS	11.91993	1	FLC	7.560845	1	TDH	3.075262
2	FLC	3.873288	2	FLC	2.608183	2	TDH	2.335036	2	KDH	1.79659
3	DXG	1.477137	3	HDG	1.610788	3	SJS	1.544867	3	FLC	1.440101
4	KDH	1.314863	4	TDH	1.492063	4	HDG	1.266548	4	ITA	1.371136
5	HDG	1.155461	5	NBB	1.292304	5	ITA	1.254306	5	DXG	1.117553
6	TDH	1.101043	6	DXG	1.095865	6	DXG	1.039797	6	HDG	1.11456
7	NBB	1.060361	7	NLG	1.019468	7	VIC	1	7	NBB	1.072395
8	NLG	1.035391	8	VIC	1	8	NBB	0.661859	8	SJS	1.040171
9	VIC	1	9	QCG	0.620953	9	NLG	0.639502	9	VIC	1
10	QCG	0.550841	10	KDH	0.50424	10	PDR	0.470154	10	NLG	0.86412
11	SCR	0.517089	11	PDR	0.470955	11	SCR	0.438809	11	KBC	0.504416
12	PDR	0.389877	12	SCR	0.450992	12	QCG		12	**IJC**	0.498959
13	ITA	0.368997	13	**IJC**	0.354286	13	KDH		13	SCR	0.476573
14	DIG	0.346073	14	DIG	0.333957	14	DIG		14	QCG	0.43801
15	KBC	0.256459	15	ITA	0.328855	15	KBC		15	PDR	0.373463
16	**IJC**	0.222918	16	KBC	0.22265	16	**IJC**		16	DIG	0.316049

R: Rank; D: DMU; S: Score.

As the company (IJC) once again shows a poor ranking number, which implies that this company requires a change on its current status, thus in this research the IJC was selected as the "target company" to investigate opportunities (partnerships) to change its current status and improve its efficiency.

4.4. Performance Analysis after Strategic Alliance

As a target company, the IJC is used to combine with other DMUs to form a different partnership for strategic alliance. A total of 31 scenarios (16 of them are individual DMUs and 15 of them are combinations of the IJC with other DMUs) are initiated for comparison. Table 14 shows the efficiency scores and rankings derived for these scenarios, after applying a strategic alliance based on the data in 2017.

These scenarios of strategic alliance can be separated into two groups: Good alliance partnership and Bad alliance partnership. For the IJC, the Good alliance partnership includes the alliances with the following companies: KBC, DXG, FLC, KDH, KLC, and NLG. Especially, the alliance with the KBC company is the best partner for IJC as this alliance can improve the ranking of the IJC from 21 to 6. The bad partnerships include the alliances with SJC, NBB, TDH, QCG, PDR, HDG, SCR, DIG, and ITA as these alliances recess the efficiency for the IJC.

Table 14. Rankings and efficiency scores of different strategic alliance scenarios in 2017.

Rank	Scenarios	Efficiency Score	Good/Bad Partnership
1	TDH	3.52126	
2	QCG	1.40939	
3	SJS	1.40914	
4	NBB	1.3511	
5	KBC	1.31719	
6	IJC+KBC	1.27373	Good
7	IJC+DXG	1.24602	Good
8	NLG	1.23663	
9	DXG	1.14646	
10	KDH	1.11736	
11	IJC+FLC	1.11669	Good
12	FLC	1.10792	
13	HDG	1.0967	
14	IJC+KDH	1.05857	Good
15	IJC+NLG	1.04012	Good
16	VIC	1.0169	
17	PDR	1.01379	
18	IJC+VIC	1	
19	IJC+SJS	0.82591	Bad
20	IJC+NBB	0.75139	Bad
21	IJC	0.73292	
22	IJC+TDH	0.71426	Bad
23	IJC+QCG	0.6767	Bad
24	IJC+PDR	0.64689	Bad
25	IJC+HDG	0.63891	Bad
26	IJC+SCR	0.59173	Bad
27	SCR	0.53582	
28	DIG	0.50622	
29	IJC+DIG	0.48855	Bad
30	ITA	0.43922	
31	IJC+ITA	0.22569	Bad

For further investigation, we have run the software to understand the performance of different scenarios of strategic alliance in the future time period from 2018 to 2020. Table 15 shows the efficiency scores and rankings of different scenarios in the year 2018.

Table 15. Rankings and efficiency scores of different strategic alliance scenarios in 2018.

Rank	DMU	Score	Good/Bad Partnership
1	TDH	5.15713	
2	SJS	2.85533	
3	QCG	1.67704	
4	NBB	1.49272	
5	NLG	1.39442	
6	KBC	1.38943	
7	IJC+KDH	1.17683	Good
8	IJC+DXG	1.16689	Good
9	DXG	1.16570	
10	IJC+KBC	1.16150	Good
11	KDH	1.15979	
12	HDG	1.09686	
13	IJC+NLG	1.07951	Good
14	FLC	1.06364	
15	IJC+FLC	1.05356	Good
16	VIC	1.01456	
17	IJC+VIC	1.00000	
18	IJC+NBB	0.72334	Bad
19	IJC+QCG	0.71929	Bad
20	PDR	0.63765	
21	IJC+SJS	0.60985	Bad
22	IJC+HDG	0.55993	Bad
23	IJC	0.53841	
24	IJC+DIG	0.52728	Bad
25	IJC+PDR	0.52473	Bad
26	SCR	0.51107	
27	DIG	0.49190	
28	IJC+SCR	0.48282	Bad
29	ITA	0.45579	
30	IJC+TDH	0.43950	Bad
31	IJC+ITA	0.17892	Bad

Table 15 shows that for the IJC company the alliances with companies KDH, DXG, KBC, NLG, and FLC can lead to good partnerships. Especially, this result ensures again that, for the IJC company, the alliance with the KBC can achieve the best result. Table 16 shows the results of these scenarios in the year 2019.

Table 16. Rankings and efficiency scores of different strategic alliance scenarios in 2019.

Rank	DMU	Score	Good/Bad Partnership
1	QCG	4.68694	
2	TDH	3.59209	
3	SJS	3.46978	
4	IJC+KBC	2.0401	Good
5	NBB	1.76355	
6	KBC	1.46055	
7	NLG	1.45748	
8	IJC+TDH	1.42397	Good
9	IJC+KDH	1.39748	Good
10	IJC+DXG	1.31721	Good
11	HDG	1.30145	
12	IJC+NLG	1.18962	Good
13	KDH	1.16543	
14	IJC+FLC	1.15179	Good
15	IJC	1.09658	
16	DXG	1.06288	
17	FLC	1.04639	
18	VIC	1.01643	
19	IJC+VIC	1	
20	IJC+NBB	0.59132	Bad
21	PDR	0.53511	
22	DIG	0.51186	
23	SCR	0.50218	
24	IJC+DIG	0.46797	Bad
25	IJC+SJS	0.44683	Bad
26	IJC+QCG	0.4376	Bad
27	IJC+HDG	0.4185	Bad
28	IJC+PDR	0.41782	Bad
29	IJC+SCR	0.41696	Bad
30	ITA	0.34119	
31	IJC+ITA	0.15449	Bad

Table 16 once again shows that for the IJC company good partners include companies KBC, TDH, KDH, DXG, NLG, and FLC due to improved efficiency from these partnerships. The company KBC once again is the best partner for the IJC company. In fact, this alliance can benefit both allied companies. The partnerships IJC+TDH, IJC+KDH, and IJC+DXG are found beneficial for the IJC company as these strategic alliances can improve its efficiency and ranking. Table 17 shows the efficiency scores of different scenarios in the year 2020.

Table 17. Rankings and efficiency scores of different strategic alliance scenarios in 2020.

Rank	DMU	Score	Good/Bad Partnership
1	QCG	8.58483	
2	SJS	4.46662	
3	TDH	4.19987	
4	NBB	1.91718	
5	IJC+KBC	1.88931	Good
6	IJC+TDH	1.60734	Good
7	IJC+KDH	1.49419	Good
8	KBC	1.46558	
9	NLG	1.43658	
10	HDG	1.28432	
11	IJC+NLG	1.22838	Good
12	KDH	1.16761	
13	IJC+FLC	1.09947	Good
14	FLC	1.02717	
15	VIC	1.01324	
16	IJC+VIC	1	
17	IJC+DXG	0.61796	Bad
18	IJC	0.56375	
19	DXG	0.5222	
20	DIG	0.5055	
21	SCR	0.46364	
22	IJC+NBB	0.45784	Bad
23	PDR	0.45599	
24	IJC+SJS	0.38918	Bad
25	IJC+DIG	0.36944	Bad
26	IJC+HDG	0.34118	Bad
27	IJC+PDR	0.33486	Bad
28	IJC+SCR	0.33003	Bad
29	IJC+QCG	0.30437	Bad
30	ITA	0.26786	
31	IJC+ITA	0.13583	Bad

Table 17 shows that KBC, TDH, KDH, NLG, and FLC are good partners for the IJC company in 2020 due to improved efficiency. Again, the company KBC is the best partner for the IJC company and both companies can benefit from this alliance.

4.5. Discussion

(1) From Tables 14–16, we know that for the IJC the company KBC is not the best partner in the year 2018, but the KBC becomes the best partner in the years of 2019 and 2020. This indicates that the KBC is a good long-term partner for the IJC. In 2020, the strategic alliance of IJC+KBC can benefit both companies as the efficiency score of this alliance is 1.88931 that is better than the individual efficiency scores 0.56375 and 1.46558 for the IJC and KBC, respectively.

(2) From Table 16, we know that for the IJC the company TDH is the 2nd best partner in the year 2020 as the efficiency of the IJC can be improved from 0.56375 to 1.60734. However, the individual efficiency of the TDH this year is 4.19987 that is much higher than that of the alliance with the IJC. Consequently, the TDH is expected to be reluctant to an alley with the IJC.

(3) Reference [8] is one rare research that has employed the super-SBM DEA model to assess the performance of real estate companies in China. One merit of the super-SBM DEA model is that it can better discern companies at the frontier. In this present research, we have employed this kind of model to assess the performance of estate companies in Vietnam. To our best knowledge, this is the first paper employing this kind of model to assess the real estate companies in Vietnam. In addition, in this present research, the super-SBM DEA has combined with the grey

model GM(1,1) as a hybrid approach to assess the forecast performance for the estate companies. In Reference [8], it only includes the super-SBM DEA model. This present research is one step forward to better utilize this model for an advanced purpose.

(4) The approaches proposed in past researches, such as the translog cost function [5], traditional DEA [6–8], super-SBM DEA [8], and stochastic frontier models [9], have been only focused on evaluating companies in terms of past performance. They have not been promoted to support the implementation of a strategic alliance based on more reasonable data.

(5) This hybrid approach is a systemic methodology as it can implement the strategic alliance step by step. Not only for the real estate industry but this approach can also be applied to other industries to extend its applications and impacts.

(6) This research focused on a new emerging real estate market in Vietnam. No such assessment has been performed in this market. Therefore, this research has its specific application domain.

(7) In this research, we focus on using the strategic alliance to improve efficiency for companies or the competitiveness for companies. Essentially, this strategy can be regarded as a fast way to scale up the operation of a company at a fast speed. In Reference [6], the authors found that economies of scale of a company may improve the company's technical efficiency. We consider the strategic alliance is one fast approach to achieve the economies of scale for a company and at a lower cost.

(8) The real estate industry in Vietnam is still at an early stage and has much potential to be further developed. In this research, we have identified and quantified the input factors that affect the efficiency of real estate companies in Vietnam. This essentially helps individual companies improve their input efficiency and enhance their chance of survival in the current competitive environment.

(9) In Reference [23], the authors found that those estate companies diversified into other sectors had a better result than that only focus on the real estate sector. Therefore, the strategic alliance with companies in a different industry, i.e., horizontal strategic alliance, can be a future research direction.

5. Conclusions

Along with high economic development, the real estate industry in Vietnam grew very fast in recent years. However, this also introduces fierce competition into this industry. Advanced management becomes increasingly essential for Vietnam estate companies to gain competitiveness and survive. To achieve this, a strategic alliance is one applicable approach. For a strategic alliance, a concrete and systematic approach is necessary.

In this research, we have proposed concrete and systematic procedure implementing strategic alliance. A hybrid approach combining GM(1,1) with super-SBM DEA model has been used to forecast and assess the past, current, and future performance. In addition, the bad and right partnerships have been identified, from which a target company can find the right partner for a strategic alliance. For empirical study, 16 estate companies have been selected from the estate industry in Vietnam as DMUs. Furthermore, 4 inputs and 2 outputs have been used as variables and the data of these DMUs in 2012–2017 were collected. The Pearson correlation test confirms the isotonic relationships of these variables. Then, the GM(1,1) forecasts the future performance of these DMUs in 2018–2020. The MAPE shows acceptable accuracy of the forecasting data. Then, the Super-SBM model assesses the performance of these DMUs and gives a "past-current-future" view from 2012 to 2020.

The IJC company is selected as the target company applying the strategic alliance. This initiates 15 possible partnerships for the IJC company. With the efficiency scores, it is concluded that the partnership IJC+KBS is the best as it improves both companies. In addition, the results also show that only some of the scenarios beneficial, implying that prudence is still required when applying the strategic alliance. A right partnership is a key to the success of a strategic alliance. The contributions of this research are summarized as follows:

(1) This research proposes a hybrid approach combining GM(1,1) and super-SBM DEA models for assessing business performances of DMUs.
(2) This research conducts an assessment of the real estate companies in Vietnam, giving a "past-present-future" insight view for these companies. In addition to understanding their past performances, these companies can predict their future performances. Such information facilitates companies to initiate a strategic alliance based on a reasonable basis. The formation of a good partnership enables companies to improve their performances and gain competitive advantage. A concrete procedure for forming the right partnership has been provided.
(3) Though there are some past studies devoting to the assessment of the real estate companies, there is still a lack of concrete and systemic approaches for them to implement the strategic alliance. This research provides a concrete and systemic approach.
(4) The approach proposed in this research can be applied to other areas to extend its impacts on different industries.

Though with some research results, still the following directions can be focused to advance the current research. First, only some of the estate companies in Vietnam have been included in this research due to the limitations of research resources and data availability. Thus, including more Vietnam estate companies to give a whole picture in the Vietnam estate industry can be focused. Second, only some specific input and output variables have been selected and used in this research. The use of other input and output variables may provide another view to better understand these companies. Third, comparing the domestic Vietnam estate companies with worldwide estate companies can understand the performance of these Vietnam estate companies on a global basis. Forth, the extension to horizontal strategic alliance can be a future research direction. Finally, the comparison to other approaches can be performed in future research.

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Appendix A

Table A1. Forecast data of all DMUs in the year 2019.

DMU	CCL	AVE	SCT	CCT	NRE	PBX
VIC	1,785,824,801	5,639,183,301	1,129,298,741	587,962,672	8,579,411,754	637,655,287
KDH	300,756,116	707,152,175	11,519,287	12,359,034	365,125,860	85,286,043
DXG	262,960,690	1,150,432,970	31,396,613	21,465,711	312,707,011	147,185,175
PDR	131,452,426	605,671,574	29,024,667	4,661,415	142,744,858	29,713,789
KBC	134,217,728	776,806,396	1,326,227	10,450,574	78,592,870	59,760,132
DIG	122,428,371	307,160,975	4,819,607	5,541,173	30,314,834	6,807,286
NLG	79,651,398	538,886,181	19,154,046	10,708,227	321,491,963	125,502,025
FLC	33,882,539	2,368,850,377	87,043,762	52,414,692	1,180,935,014	43,178,333
HDG	37,909,160	880,757,727	99,801,293	9,305,505	134,315,106	20,178,916
QCG	180,224,327	658,730,869	3,334,217	1,263,982	77,612,946	2,818,614,571
SCR	22,813,636	640,505,060	9,006,319	5,462,101	117,698,441	24,479,244
SJS	67,108,864	300,820,435	565,002	364,508	3,314,351	8,402,933
ITA	501,492,719	595,717,069	165,455	18,357,738	30,671,722	621,512
NBB	56,316,608	314,621,745	12,713,448	964,243	7,088,719,583	4,146,543
IJC	60,321,042	431,513,818	1,375,115	4,721,478	66,004,093	6,261,162
TDH	62,698,549	141,866,411	153,169	6,300,028	162,468,309	16,755,738

Table A2. Forecast data of all DMUs in the year 2020.

DMU	CCL	AVE	SCT	CCT	NRE	PBX
VIC	2,163,475,404	20,021,070,825	1,875,732,799	814,000,000	13,128,805,639	855,288,367
KDH	441,822,057	895,055,225	15,555,269	17,405,342	540,294,242	133,903,909
DXG	417,822,906	1,948,019,542	47,532,152	30,585,094	470,972,288	238,189,126
PDR	150,859,870	709,790,543	64,878,013	6,385,828	209,540,071	41,647,286
KBC	134,217,728	828,804,384	1,373,788	13,140,988	84,018,172	72,778,097
DIG	132,545,254	329,931,631	5,361,271	6,375,676	182,330,272	14,561,181
NLG	86,031,520	678,202,420	26,567,147	12,204,566	484,436,397	232,739,221
FLC	522,691,039	3,593,112,208	184,913,473	81,073,109	1,887,334,092	44,840,630
HDG	40,302,889	1,349,231,286	233,866,490	12,003,748	156,837,833	24,160,744
QCG	211,750,012	778,860,142	4,997,294	1,515,665	96,779,609	11,696,013,275
SCR	136,752,747	806,990,421	13,694,426	5,656,005	223,763,486	33,927,021
SJS	33,554,432	315,714,962	780,973	207,084	1,889,630	8,075,908
ITA	546,400,205	609,612,087	187,854	32,124,280	33,900,977	380,558
NBB	68,340,547	370,470,028	41,481,724	986,805	24,772,422,757	4,852,229
IJC	51,777,401	462,599,279	1,312,468	6,539,155	71,340,075	5,695,868
TDH	82,557,542	150,490,654	122,847	7,250,229	240,204,112	25,635,517

Table A3. Forecast data of all DMUs in the year 2021.

DMU	CCL	AVE	SCT	CCT	NRE	PBX
VIC	2,620,988,253	25,630,703,936	3,115,538,346	1,126,931,021	20,090,600,898	1,147,200,071
KDH	649,053,236	1,132,887,495	21,005,328	24,512,103	799,499,296	210,236,706
DXG	663,886,227	3,298,566,916	71,960,163	43,578,708	709,337,777	385,460,423
PDR	173,132,600	831,808,255	145,019,981	8,748,158	307,591,055	58,373,453
KBC	268,435,456	884,283,021	1,423,054	16,524,028	89,817,985	88,631,855
DIG	143,498,146	354,390,335	5,963,810	7,335,857	255,107,780	31,147,214
NLG	92,922,694	853,535,570	36,849,305	13,910,000	729,967,306	431,606,938
FLC	629,677,154	5,450,093,202	392,825,307	125,400,890	3,016,279,416	46,566,922
HDG	42,847,767	2,066,885,146	548,024,314	15,484,379	183,137,300	28,928,291
QCG	248,790,319	920,896,755	7,489,899	1,817,463	120,679,516	48,533,321,274
SCR	152,273,920	1,016,750,031	20,822,858	5,856,792	425,410,032	47,021,172
SJS	33,554,432	331,346,962	1,079,498	117,648	1,077,345	7,761,610
ITA	595,329,051	623,831,204	213,285	56,214,408	37,470,221	233,020
NBB	82,931,671	436,231,900	135,347,500	1,009,895	86,570,349,136	5,678,013
IJC	44,443,849	495,924,079	1,252,674	9,056,602	77,107,434	5,181,613
TDH	108,706,627	159,639,176	98,527	8,343,744	355,133,969	39,221,175

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