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Usage of Two-Stage Integrating Data Envelopment Analysis to Propose the Best Strategic Alliance

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Abstract

Strategic alliance is also considered to be a highly intelligent approach. Strategic alliances are also seen as a smart way of green supply. E-business is growing rapidly and efficiently because the direction of search is the main balance in the world. Economic development and environmental protection. However, appropriate methods of evaluating and analyzing a couple's performance are also important for senior managers to make effective decisions. Applies to business strategies, including future alliance strategies. This will improve business performance and reduce carbon dioxide (CO_2) emissions among the hot trend of development of green logistics providers. Over past to future forecasting, this paper tries to propose a new approach of data envelopment analysis (DEA) based on grey forecasting and neural network, helping the target company – CSX Group make a well-considered decision to select the best strategic alliance candidates. The results indicate that Hiz Cor. and Conz Freight are the very best candidates for CSX to have strategic alliances. This combination is suggested not only good for the target company but also beneficial for the partners as well. This is a new studying method in both academic research studies and practical applications by combining Grey theory, neural network and DEA model which probably gives a better "past-present-future" insights into evaluation performance of an industry.

Keywords: Strategic alliance; Green logistics; Decisions making; DEA; Grey forecasting; Neural network.

1. Introduction

The current trend in business, companies often create strategic alliances – a form of exchanging or using others' resources to make primary advantages in making their cooperative strategies (Das and Teng, 2000). Recent studies have shown that strategic alliance is becoming an important issue in the economic world with the fast pace of internationalization (Blomqvist *et al.*, 2008; Nguyen *et al.*, 2015). One or more advantages of strategic alliance is that it can help increase the chance of competitiveness in markets with maintaining and create economic values, multidimensional inter-firm network, and inter-organizational coordination.

However, to make good decision requires a lot of information, and strict formation is considered to identify an appropriate alliance structure, which may include the performance and relational risk (Das and Teng, 2001). Some resources and capabilities can be acquired by having good inter-organizational relationships, when working or cooperating with partners or alliances can develop additional resources and capabilities to make more competitive advantages (Zaheer *et al.*, 2000).

In the wave of internationalization, many companies use strategic alliance like an approach to establish facilities, management etc. on other countries to reduce cost. Thus, the socio-political factors are also the concerns affecting strategic alliance as well as international business.

In this research, we will provide a very typical and empirical case of strategic alliance, which is the green logistics industry. Green logistics describes all attempts to measure and minimize the ecological impact of logistics activities (McKinnon *et al.*, 2012). All activities are involved in the work of transporting products, services and information the original and consumption point forward and backward. This research study intends to increase the core sources for sustainable companies with a balance of balance of economic and environmental efficiency – green logistics. The term green logistics can be understood and applied from the mid of 1980s i.e., utilizing the current advanced technology and equipment in reducing or minimizing any possible damage to the environment during operations, but also create values and maximizing the strength of the logistics systems (Thiell *et al.*, 2011). The energy and pollution reduction associated with better transportation planning, and the use of less packaging materials, could be considered as a part of the Green Logistics agenda; as Rogers and Tibben-Lembke (2001) pointed out, "if no goods or materials are being sent 'backward,' the activity probably is not a reverse logistics activity."

On the other aspect, electronic commerce (e-commerce) and the Internet are widely used worldwide, and the trend is still steadily increasing in the future. Through the Internet and mobile applications, e-commerce is surely becoming a new phenomenon which has a huge impact on the way people shopping, transacting, distributing products and so on. For example, people can easily use their smart-phones to order food or any essential things within short minutes (Giuffrida *et al.*, 2016; Spicer and Johnson, 2004).This business will open an entirely new market for actors in the logistics field. Thus, managing the logistics and distribution systems efficiently and effectively in all respects will become a crucial part for the success of the companies involved. This indicates that the manufacturing companies, and its partners – especially logistics or green logistics providers must figure out the best solutions of logistics in order to create competitiveness in the current marketplace. Thus, strategic alliance is considered to be a highly intelligent approach to handle the above issues of green logistics, which is best for environment and e-commerce (Cantor *et al.*, 2012).

A form of strategic alliance is an arrangement between two organizations which may share some resources and benefits in the hope of getting mutual beneficial results (Taylor, 2005). Strategic alliances can allow two firms, individuals or other entities to work towards and particular objectives. Thus, they can trust and provide or exchange any resources such as products, distribution channels, manufacturing capability, project funding, capital equipment, knowledge, expertise, or intellectual property. Moreover, this strategy may provide more flexibility than for example joint ventures since all involved parties do not have to merge any assets or funds to conduct alliance (Nguyen *et al.*, 2015). The alliance is a co-operation or collaboration which aims for a synergy where each partner hopes that the benefits from the alliance will be greater than those from individual efforts (Kelly *et al.*, 2002). The alliance often involves technology transfer (access to knowledge and expertise), economic specialization, shared expenses and shared risk (Mowery *et al.*, 1996).

Moreover, nowadays, the demand to use natural resources efficiently becomes crucial for the future sustainable growth especially during economic downturn period. Moreover, the development of logistics providers requires them to have better methodologies in operating but reducing the bad impact to environment, especially the amount of carbon dioxide (CO2) (Zeng *et al.*, 2010). Research studies also found out that logistics firms run their activities for example freight transporting, warehousing, packaging, and materials handling at the possible minimum cost (Nguyen and Tran, 2017;2019), but the fact that, they have to obtain out sources to prevent the environmental problems occurring during operations (Seuring and Müller, 2008). In short, those firms have to try their best to make greener operations of logistics, which may make them tend to be in term of corporate social responsibility (CSR) then more sustainable development in order to protect environment also.

As mentioned earlier, it is crucial to get into the past performance of a firm, then to analyze the current situation, and finally it is the target to forecast the future performance. Thus, our objectives are to analyze and evaluate the past and current performance of the American green logistics companies by collecting all the data relating to their operations recently, after that we would like to propose and help potential investors in this field choose or select the best alliance in which they can both improve business performance and reduce the bad impact to climate change. Over the 4-year time frame from 2015 to 2018 (latest year), and next 4 years (2019-2022) of forecasting, we try to propose a new approach of data envelopment analysis (DEA) model based on grey forecasting and neural network in selecting the best candidate for strategic alliance; specifically, helping the target company–CSX Corporation to make a well-considered decision in finding the right partners. At the same time, the study also provides the prediction about firms' business in the future – GM(1,1) and neural network, which is relevant for them when setting strategies for production capacity planning and for investment decision making whether should expand their business in international market or not.

Forecasting based on input-output factors always contains errors, and this seems not a good science in academic field, but while forming a strategic alliance forecasting is a must, which requires good efforts to have good forecasting. The reason is that strategic alliance contains risks, so good predicting will give executives many good analyses. In forecasting demands, some models have been used for example; regression or moving average, but they maintain the biggest drawbacks i.e. huge errors. Thus, neural networks or some advanced models such as grey system for forecasting (GM(1,1), Verhults; DGM(1,1)) can offer some best results of the aspects of wide range of applicability, and superior accuracy (Curry *et al.*, 2002).

The neural networks have to get a huge redundancy and a big effort of computing, but these networks are able to release high accuracy and applicability (Crone *et al.*, 2011). Moreover, neural networks can make calculation and forecasting for nonlinear constraints, which no formal models are required. In this aspect, networks can prove their advancement compared to other linear traditional forecasting methods. The main manner of neural networks is to continually learn from its environment and adapts to new patterns of data, which are large and time-costing.

One of the important points that neural networks forecasting does not require a formal model, for example; regression model needs to fit data onto line, or the exponential smoothing model is sensitive to the choice of the smoothing parameter. That means networks just adapt data, learn from data of the inputs and release results of forecasting based on its understanding. Provided that a sizable network is used, the neural network is insensitive to the parameters selected (Hansen and Nelson, 2003). However, this is mentioned as a drawback of the neural network also, which is a relatively large network must be constructed. A large scale data has to be described and analyze for the networks, which is mentioned more clearly in the later part.

This study is to provide useful information for decision makers of the green logistics companies in selecting their ideal partners in the future, which then these decisions will be very helpful and applicable. And this paper is organized as following, one part for short reviews of green logistics and information to this field; section 2 for describing methodology including data collection, and especially grey GM (1,1) model, neural network, and DEA; the next section for analyzing results discussions, and conclusions resulting from this study.

2. Methodology

2.1. Data Collection

The data were collected through the period of 2012 to 2014. The variables were carefully considered to aim at top representatives for the industry. Those are mentioned as inputs and outputs. After researching in the field, we considered 75 green logistics providers in the world. They are having and owing the very best networks of logistics and services providers.

Table 2.1 shows us the companies and groups selected based on the factors of contributions and reputations to the logistics industry. Moreover, those decision making units (DMUs) are providing consistent and relevant data that help this research improving the quality and reliability. Those statements are proved by running correlations. Table 2.1 also shows the 16 qualified DMUs with their stock codes and also DMU-code which are suitable to this research.

In this study, DMU_{12} is set as the target company. To make it easier to follow and consistent, DMU12 from the Table 2.1 is marked as the target DMU for analysis with an asterisk. This is CSX Group

Table-2.1. Companies selected for this study

Denoting	Full name	Stock Code
DMU_1	Ridol	R
DMU_2	Winner XV	WXV
DMU_3	Hiz Coroperation	HIZ
DMU_4	CN Worldwide	CNW
DMU_5	Fix Ed	FiX
DMU_6	UNZ Services	UNS
DMU_7	Freight Hight	CNW
DMU_8	JN Group	JNG
DMU_9	Conz Group	CON
DMU_{10}	Donimano Shipping Services	DPS
DMU_{11}	Sala Inc	SALA
*DMU_{12}	CSX Group*	CSX
DMU_{13}	North South Cor.	NSC
DMU_{14}	V-knight	KNX
DMU_{15}	Pacific	UNP
DMU_{16}	Swift VNI	SWFT

*** Note:** Target company

The input and output data of USA stock exchange cooperation companies in this study were gathered during the period of 2015-2018. The input data variables include: Total assets, total operating expense, and total current liabilities, while output data contain net income, total revenue, and earnings-per-share (EPS). By the process DEA analysis, each of these GSCPs is used as a decision making unit (DMU). Total data were completely displayed in Tables 2.2 and 2.3. This study was primarily focused on analyze and suggest suitable and potential partners as its previous objectives. As one part of DEA, input and output factors were closely and seriously carried out into the analysis. To successfully gain this step, many literatures of "Logistics and Supply Chain Management Consulting" related to accounting and logistics costs' impact on logistics providers' effectiveness have been carefully reviewed. As the results of this process, the set of input factors which include total assets, total operating expense, and total current liabilities are determined and net income, total revenue, and earnings-per-share (EPS) are employed as the output factors. In sum up, it is very important to use these factors to perform the company's' potential finance, to evaluate their capacity of cost management and their economic role in the industry.

Table-2.2. Samples of data collected

DMUs	(I_1) Amount of Capital		(I_2) Amount of Spending		(I_3) Loans		(O_1) Sale		(O_2) Profit		(O_3) EPS	
	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016	2015	2016
DMU_1	3252.37	3623.84	4018.86	5202.86	1321.52	1233.82	4116.44	4150.53	120.17	159.78	2.50	3.11
DMU_2	1221.55	1122.42	1530.44	1599.18	198.25	190.22	1725.02	2112.05	70.74	123.86	1.5	1.3
DMU_3	842.68	629.41	1833.74	2751.53	157.32	239.9	1763.86	2657.07	43.46	58.18	1.16	1.57
DMU_4	445,57	2384,04	8897,44	9643.62	771.61	876.63	9274.31	10336.4	387.03	431.61	2.33	2.62
DMU_5	25025	27508	32859	37049	5005	5497	34857	39427	1307	1575	4.58	6.41
DMU_6	33720	34824	44027	47148	6025	6637	49668	53228	3461	3927	3.33	3.84
DMU_7	3066,73	3100.02	4873.83	5082.02	651.89	723.47	4952	5289.95	3.98	88.44	0.07	1.58
DMU_8	2084,66	2267.33	3445.86	4082.61	509.95	438.51	3793.49	4526.84	199.62	257.01	1.56	2.11
DMU_9	572,48	416.67	508.79	537.46	127.02	141.17	528.62	568.25	3.93	15.26	0.18	0.67
DMU_{10}	1362,88	1513.07	1343.26	1669.73	170.05	204.81	1481	1903.8	75.65	139.47	0.9	1.63
DMU_{11}	575,16	474.89	890.56	1002.08	105.77	124.35	902.66	1030.22	1.96	11.37	0.08	0.47
DMU_{12}	28264	29467	7688	8448	2660	2681	10759	11918	1686	1977	1.35	1.7
DMU_{13}	28322	28661	6970	8089	2205	1824	9639	11295	1619	2039	4	5.45
DMU_{14}	799,99	737.58	635.49	766.18	40.47	50.02	730.71	866.2	59.07	60.25	0.7	0.74
DMU_{15}	43211	45219	12128	13961	3075	3440	17088	19680	2903	3415	2.76	3.36
DMU_{16}	2690,89	2640.18	2313.62	3456.93	326.18	316.81	2929.72	3778.96	343.09	102.75	2.57	0.74

Table-2.3. Samples of data collected (Part 2)

DMUs	(I_1) Amount of Capital		(I_2) Amount of Spending		(I_3) Loans		(O_1) Sale		(O_2) Profit		(O_3) EPS	
	2017	2018	2017	2018	2017	2018	2017	2018	2017	2018	2017	2018
DMU_1	8442.98	9227.78	6026.4	6133.37	1396.66	1355.14	6380.97	6543.28	333.98	361.79	3.91	4.63
DMU_2	1458.9	1478.1	1988.94	2013.46	300.19	291.73	2160.39	2153.18	227.03	210.78	1.4	1.18
DMU_3	1043.85	1171.94	3135.75	445.32	401.38	662.25	3248.11	3497.9	191.95	193.11	1.83	1.87
DMU_4	2928.22	2926.82	10807.8	12193.4	1356.22	1393.98	11483.1	12876.1	717.8	539.9	3.67	2.65
DMU_5	30027	33691	39618	41860	5874	5436	42804	44411	2156	1685	4.92	6.76
DMU_6	38987	36336	52908	48528	8514	7255	54251	55562	931	4496	0.83	4.61
DMU_7	3276.41	3403.93	5475.41	5388.4	831.69	869.95	5704.25	5597.36	228.55	223.15	1.85	1.73
DMU_8	2588.64	2943.4	4648.78	5131.86	626.76	836.3	5178.98	5708.57	434.35	466.38	2.59	2.87
DMU_9	644.71	765.16	676.19	688.98	226.28	208.89	722.95	737.65	149.54	151.26	1.12	1.17
DMU_{10}	1836.51	2056.09	1973.33	2123.21	349.14	356.12	2258.58	2461.65	293.45	330.11	1.97	2.39
DMU_{11}	643.69	740.8	1163.94	1188.68	265.3	264.86	1222.68	1263.09	156.05	167.63	1.29	1.73
DMU_{12}	30847	31906	8423	8677	2769	2548	11887	12150	1987	1988	1.79	1.83
DMU_{13}	30466	32607	8046	8118	2205	2429	11164	11369	1873	2034	5.37	6.04
DMU_{14}	906.51	931.12	951.77	979.33	177.82	187.06	1060.04	1093.24	188.12	193.28	0.8	0.86
DMU_{15}	47277	49855	14311	14642	3243	3915	21050	22087	4067	4512	4.14	4.71
DMU_{16}	2915.98	2933.01	3776.47	3895.69	507.45	508.37	4100.09	4242.19	264.09	279.42	1	1.09

2.2. Non-radial Super Efficiency Model (Super-SBM)

When the high correlation of those factors are well-determined, the data are continuously implemented by DEA model. DEA first developed by Charnes *et al.* (1978) is a methodology for constructing a best practice frontier The software of DEA-Solver is utilized to compute the non-negative sequences separately with super-SBM (Non-radial super efficiency model). Then the efficiency is achieved by ranking DMU's performance in the super SBM model which is considered as an appropriate version of DEA. This model illustrates the efficiency allocated for each units compared with other DMUs.

By applying the super SBM-O-V, the performance evaluation of each decision-making unit is then achieved in order ranking. The analysis result must derive from the realistic data from 2013 to 2017 based on the audited financial statement. In addition, this step can be recognized as the preparation for the strategic alliance which assists the author to test the efficiency of Target Company chosen in the first step. In case, the target DMU cannot satisfy the research condition, the researcher directly makes decision on which DMU is the most appropriate one in comparison with other competitors.

The result of virtual alliance ranking may enhance the productivity of both companies entering this strategic alliance. However, if the virtual ranking lessens the previous position of enterprise, they are not willing to cooperate with the target company. The next section indicates a supplemented equation which assists the researcher to define the feasible partnership.

Efficient DMUs ranking has an important effect on the development of various super-efficiency methods. Particularly, Tone in 2002 supposed that super- SBM model computed the distance between the target DMU and the nearest frontier whereas excluding the target sector in the model. The frequency of application of Grey forecasting and DEA model become widely proposed in experimental researcher in fields of banking Tone in 2002 electrical industry and online game as well. The combination of virtual alliances is run by DEA model to get the predicted data. Successively, observing the ranking positions could help researcher classify which are more efficient.

Strategic alliance is defined when business parties reach a settlement to facilitate them to obtain the expected goals. Applying a strategic alliance in explicit or implicit resources can ameliorate companies in acquiring their objectives. Its definition is also identified as the interdependence of at least two business organizations sharing the similar characteristics: they are legal independent entities; they have responsibilities to assign mutual rewards, managerial roles, internal and external resources in cooperation scope; they retain involvement in more than one strategic aspects.

In the present study, a DEA model "Slack-based measure of super-efficiency" (super SBM) was used. This model was developed on "Slacks-based measure of efficiency" (SBM) introduced by Tone (2001).

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

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

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

Subject to (s.t) $x_0 = X\lambda + s^-, y_0 = Y\lambda - s^+, \lambda \geq 0, s^- \geq 0, s^+ \geq 0$ (2)

The variables S+ and S- measure the distance of inputs Xλ and outptut Yλ of a virtual unit from those of the unit evaluated. The numerator and the denominator of the objective function of model (1) measures the average distance of inputs and outputs, respectively, from the efficiency threshold.

Let an optimal solution for SBM be$p^*, \lambda^*, s^{-*}, s^{+*}$. *A* DMU$(x_0, y_0)$ is SBM-efficient, if $p^* = 1$. This condition is equivalent to$s^{-*} = 0$and$s^{+*} = 0$, no input excesses and no output shortfalls in any optimal solution. SBM is non-radial and deals with input/output slacks directly. The SBM returns and efficiency measure 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 (2002) discriminated these efficient DMUs and ranked the efficient DMUs by super-SBM model. Assuming that the DMU (x_0, y_0) is SBM-efficient, $p^* = 1$, super-SBM model is as follows:

$$min \quad \delta = \frac{\frac{1}{m}\sum_{i=1}^{m} \bar{x}_i/x_{i0}}{\frac{1}{s}\sum_{r=1}^{s} \bar{y}_r/y_{r0}} \tag{3}$$

s.t $\quad \bar{x} \geq \sum_{j=1,\neq 0}^{n} \lambda_j, x_j, \bar{y} \leq \sum_{j=1,\neq 0}^{n} \lambda_j, x_j, \bar{y} \geq x_0 \; and \, \overline{y} \leq y_0, \overline{y}\bar{y} \geq xy_0, \lambda \geq 0$ (4)

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

As in many DEA models, it is crucial to consider how to deal with negative outputs in the evaluation of efficiency in SBM models too. However, negative data should have their duly role in measuring efficiency, hence a new scheme was introduced in DEA-Solver pro 4.1 Manuel and the scheme was changed as follows:

Let us suppose$y_{r0\leq}0$ it is defined by $\overline{y_r^+}$ and $\overline{y_r^+}$

$$\overline{y_r^+} = \max_{j=1,\ldots n}\{y_{rj}|y_{rj} > 0\}, \tag{5}$$

$$\overline{y_r^+} = \min_{j=1,\ldots n}\{y_{rj}|y_{rj} > 0\} \tag{6}$$

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

(1) $\overline{y_r^+} = y_{-r}^+ = 1$, the term is replaced by$s_r^+ / \frac{y_{-r}^+(\bar{y}_r^+ - y_{-r}^+)}{\bar{y}_r^+ - y_{r0}}$ (7)

(2)$s_r^+ / \frac{(y_{-r}^+)^2}{B(\bar{y}_r^+ - y_{r0})}$ (8)

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

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

2.3. Grey Forecasting Model

The GM (1,1), which is pronounced as ''Grey Model First Order One Variable", can only be used in positive data sequences (Deng, 1989). This model is a time series forecasting model. The differential equations of the GM(1,1) model have time-varying coefficients.

Let $X^{(0)} = (x^{(0)}(1), x^{(0)}(2), \ldots x^{(0)}(n))$be a sequence of raw data. Denote its accumulation generated sequence by $X^{(1)} = \left(x^{(1)}(1), x^{(1)}(2), \ldots, x^{(1)}(n)\right)$. Then

$$x^{(0)}(k) + ax^{(1)}(k) = b \tag{9}$$

is referred to as the original form of the GM(1,1) model, where the symbol GM(1,1) stands for first order grey model in one variable (Liu and Lin, 2010).

$$x^{(0)}(k) + az^{(1)}(k) = b \tag{10}$$

as the basic form of this model if $Z^{(1)} = \left(z^{(1)}(2), z^{(1)}(3), \ldots, z^{(1)}(n)\right)$;

That is $z^{(1)}(k) = \frac{1}{2}\left(x^{(1)}(k) + x^{(1)}(k-1)\right)$; with $k = 2,3, \ldots n$.

Theorem 1: Let $X^{(0)}, X^{(1)}$, and $Z^{(1)}$ be the same as above except that $X^{(0)}$ is non-negative. If$\hat{a} = (a, b)^T$ is a sequence of parameters, and

$$Y = \begin{bmatrix} X^{(0)} & (2) \\ X^{(0)} & (3) \\ \vdots & \\ X^{(0)} & (n) \end{bmatrix}, \quad B = \begin{bmatrix} -Z^{(1)} & (2) & 1 \\ -Z^{(1)} & (3) & 1 \\ \vdots & \vdots & \\ -Z^{(1)} & (n) & 1 \end{bmatrix} \tag{11}$$

then the equation (10) satisfies $\hat{a} = (B^TB)^{-1}B^TY$, so from theorem 1 notations, if

$[a, b]^T = (B^TB)^{-1}B^TY$, then $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$, (whitenization equation in equ.10)

We have made the extension of equation (10) and (11) to the theorem 2 as following:

Theorem 2: Let $B, Y, \hat{a}$ be the same as in theorem 1. If $\hat{a} = [a, b]^T = (B^TB)^{-1}B^TY$, then

(1) The solution of $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ given by

$$X^{(1)}(t) = \left(X^{(1)}(1) - \frac{b}{a}\right)e^{-at} + \frac{b}{a} \tag{12}$$

(2) The time response sequence of $\frac{dx^{(1)}}{dt} + ax^{(1)} = b$ given as following

$$\widehat{X}^{(1)}(k+1) = \left(X^{(0)}(1) - \frac{b}{a}\right)e^{-ak} + \frac{b}{a}, k = 1,2, \ldots, n \tag{13}$$

(3) The restored values of $x^{(0)}(k)'s$ are given: * marked as equation no. (14)

$$\hat{x}^{(0)}(k+1) = \alpha^{(1)}\hat{x}^{(1)}(k+1) = \hat{x}^{(1)}(k+1) - \hat{x}^{(1)}(k) = (1 - e^a)\left(x^{(0)}(1) - \frac{b}{a}\right)e^{-ak}, k = 1,2, \ldots, n$$

The grey system theory has been developed rapidly and caught the attention of many researchers. According to statistical figure, from 1982 to 2017, more than 50 thousand papers on grey system were retrieved from Chinese academic periodical database in China National Knowledge Infrastructure (CNKI). Some typical studies on forecasting with the utilization of Grey model are briefly summarized in the following paragraphs.

Kazemi *et al.* (2011), developed a prediction model of energy demand of industry sector in Iran. Based on a Markov chain grey model, the researcher estimates the annual energy demand of industry in Iran up to the year of 2020.

Alex *et al.* (2006), applied GM (1,1) to improve the investment performance of classical Markowitz efficiency frontier's investment portfolio. The study samples component securities of the Taiwan 50 Index from 1998 to 2005. The results show the Grey Markowitz efficiency frontier investment portfolio model could improve the investment performance effectively.

Based on GM (1,1), Li Juan (2011) proposed an improved grey model then utilized this model to predict Jingdezhen's tourism revenues from 2003 to 2010. The result shows that the improved model can improve prediction precision and obtain a much better prediction result.

Feng and Huang (2011), applied GM (1,1) in the study on city waste production forecast. Comparative analysis the waste production forecasting results of the traditional model and the optimization model in Shanghai between the years 2004 to 2009, it got verified the feasibility and effectiveness of the optimal of the background value in GM (1,1) model. The future waste production in Shanghai is also predicted by optimized GM (1,1) model.

Xiao and Mao (2005), discussed the ill-conditioned problem and modeling precision in grey prediction control GM (1,1) model. The researchers proposed a new and effective method basing on multiple transformations to original series and center parallel moving transformation to AGO series. Firstly, the parameter relationships and properties of the new model are discussed. Secondly, Based on the condition number and the modeling precision, a multi-objective optimization model is set up. By solving the model and choosing coefficients M and p, the condition number of coefficient matrix can be controlled; meanwhile, the prediction accuracy of the original grey model is improved. Finally, the researchers applied for case study to test the efficiency and accuracy of the proposed method.

Moreover, a lot of research studies have proved the good sides of grey system theory e.g., Chia-Nan and Ty (2013); Nguyen and Tran (2015), Nguyen and Tran (2016), Tran (2016), Tran (2017); Trinh and Tran (2017), but many of them have not shown out the combination between grey and neural networks, which is applied in this studies. We try to build this to work better for a better forecast, especially in Earning per share (EPS).

2.4. The Insights of the Models

The input layer has input units containing original information, which can be fed into the network. At the same time, in the hidden layer, each hidden unit is affected and identified by the input unit of the input layer through the communication connection and the system. The characteristics of the output unit depend on the performance of the hidden unit and the weight between the hidden unit and the output unit.

GM (1,1) and DEA model are conducted in the research as the foundation of a set of forecasting and selecting alliance partner models. A neural network includes neurons represented by nodes whose functions are to precede information in response to external inputs (Ham and Kostanic, 2001; Kurosaki *et al.*, 2000) The research development in this paper is implemented in construction industry and also selects all related documentations as references. Then after confirming the subject and proceeding industrial analysis (Jain *et al.*, 1996; Liao and Wang, 2004).

The researcher investigated construction enterprises which mainly aim at infrastructure to find all potential candidates to be DMUs list. As the DEA model is well defined as a benchmarking method and DMUs set should be a consistent group having the similar substantial proportion in related activities (1). Therefore, the researcher selects 15 companies based on mutual characteristic: more than 70% total revenue spent on construction work.

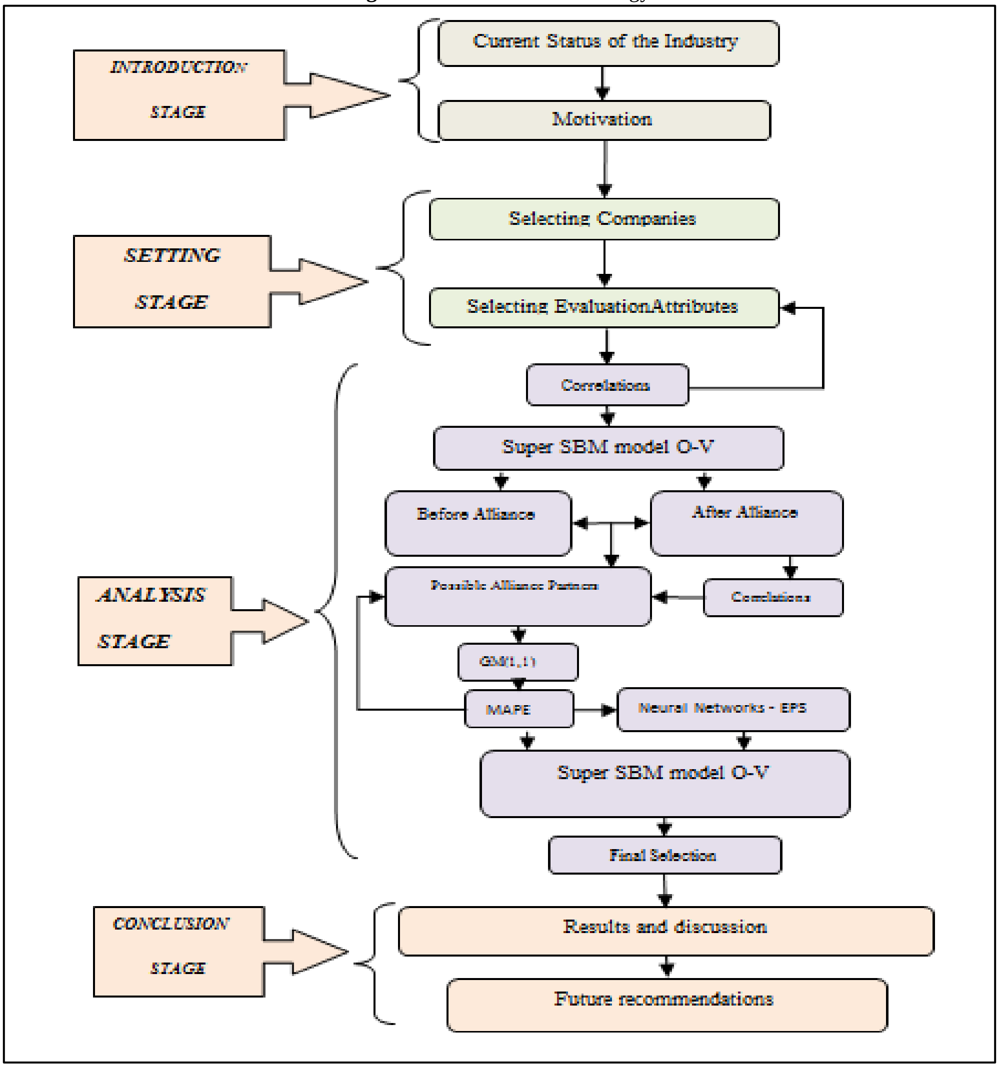
These layers of an artificial network are trained to learn the input factors and to characterize the output. The training process is depending on the architectures of the network. Thus, we also distinguish single-layer and multi-layer architectures. The single-layer organization, in which all units are connected to one another, constitutes the most general case and is of more potential computational power than hierarchically structured multi-layer organizations (Kishore *et al.*, 2010). In multi-layer networks, units are often numbered by layer, instead of following a global numbering.

2.5. Research Process

The setting up process for DEA requires stick consideration, especially input and output factors. As reviews are mentioned previously, elements of the operation for the green logistics providers are selected *total assets*, *total operating expenses* and *total current liabilities* as input factors and *net income*, *total revenue*, and *based EPS* as output factors. This work has to be analyzed carefully so that conclusion may not be misled. We use Figure 2.1 to summarize those import indices.

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

Figure-2.1. Research Methodology



The original DEA used past data to evaluate the past performances, and then the future performances could be similar with the past ones. This paper uses GM by past data to forecast the future data, after that the process of training neural networks is applied basing on the forecasted results from GM, and then uses the future data for inputting DEA to evaluate the future efficiency and rankings. In this way, the trend of each DMU can be considered much better than original DEA. Moreover, the primary objective of this model is to overcome the ranking inefficiency and to eliminate the subjective evaluation of DEA. According to the method, the judging matrix is formed by using the outputs of GM(1,1) as inputs for neural networks and these outputs of these utilized in DEA models. This method consists of the steps mentioned in Figure 2.1.

The setting stage is mentioned early, which is about introduction, motivation, selecting companies and selecting attributes of these firms. After the setting stage, each element will be gone to the correlation process, at which we will figure out the suitable correlations for the next steps. In the performing evaluation by ranking, Super SBM-O-V is employed. There will be *before alliance* rankings and *after alliance rankings* with the target company - DMU12. By doing deep analyses and comparisons, we will come with the possible results for suitable alliance partners. Correlations are again applied to see the possible of each parameter for the next steps.

For the future, the selected virtual companies are going to be forecasted by GM(1,1), which were tested for the accuracy by Mean Absolute Percent Error (MAPE), then can be used for future training of neural networks. We have to use neural network in this case because neural network is non-linear method to forecast. Moreover, earning per share (EPS) is sensitive variable which is calculated from many sources to get the result of EPS. After getting these results from two models, the super SBM-O-V is applied again to see the virtual companies' rankings. The final selection only comes when we get the rakings and efficiency changes among virtual companies in the future.

3. Results and Analysis

3.1. Parrallel Correlation

Correlations among factors are vital to apply DEA to make sure that they have good relationship. That means if the input quantity increase; the output quantity could not decrease under the same condition. The Pearson correlation is applied in this study to check the degree of correlation between two factors. It is simple that high coefficient correlation shows the good relation between two variable and vice versa (Nguyen and Tran, 2015).

Tryon (1929), described the interpretation of the correlation coefficient is explained in more detail as follows. The correlation coefficient is always between -1 and +1. The closer the correlation is to +/-1, the closer to a perfect linear relationship. Its general meaning was shown in Table 3.1.

Table-3.1. Pearson Correlation Coefficient

Correlation Coefficient	Degree of Correlation
>0.8	Very high
0.6–0.8	High
0.4–0.6	Medium
0.2–0.4	Low
<0.2	Very low

In this empirical study, the bellowing results in Tables 3.2, 3.3, 3.4, and 3.5 indicate that the correlation well complies with the prerequisite condition of the DEA model because their correlation coefficient shows strong positive associations. Therefore, these positive correlations also demonstrate very clearly the fact that the researcher's choice of input and output variables at the beginning is appropriate. Obviously, none of variables removal is necessary.

Even in the O_3 –EPS, the correlation coefficient show high positive when its parameters are >0.6 consecutively, except in 2017. This can be explained that EPS is calculated by single U.S dollars to come out with this little small index.

Table-3.2. Correlation of Input and Output Data in 2015

	I_1	I_2	I_3	O_1	O_2	O_3
I1	1	0.986806	0.947839	0.628145	0.963655	0.809597
I2	0.986806	1	0.963566	0.60369	0.907687	0.775602
I3	0.947839	0.963566	1	0.479309	0.866809	0.700412
O1	0.628145	0.60369	0.479309	1	0.632011	0.689052
O2	0.963655	0.907687	0.866809	0.632011	1	0.818656
O3	0.809597	0.775602	0.700412	0.689052	0.818656	1

Table-3.3. Correlation of Input and Output Data in 2016

	I_1	I_2	I_3	O_1	O_2	O_3
I1	1	0.970854	0.915757	0.606409	0.929933	0.771401
I2	0.970854	1	0.900945	0.545336	0.814696	0.647058
I3	0.915757	0.900945	1	0.404073	0.832813	0.727334
O1	0.606409	0.545336	0.404073	1	0.630018	0.78421
O2	0.929933	0.814696	0.832813	0.630018	1	0.872855
O3	0.771401	0.647058	0.727334	0.78421	0.872855	1

Table-3.4. Correlation of Input and Output Data in 2017

	I_1	I_2	I_3	O_1	O_2	O_3
I1	1	0.970644	0.943475	0.558271	0.921148	0.735406
I2	0.970644	1	0.954927	0.488512	0.800492	0.592585
I3	0.943475	0.954927	1	0.479871	0.805719	0.657185
O1	0.558271	0.488512	0.479871	1	0.600634	0.648232
O2	0.921148	0.800492	0.805719	0.600634	1	0.873607
O3	0.735406	0.592585	0.657185	0.648232	0.873607	1

Table-3.5. Correlation of Input and Output Data in 2018

	I_1	I_2	I_3	O_1	O_2	O_3
I_1	1	0.981277	0.924568	0.777802	0.927761	0.567541
I_2	0.981277	1	0.92344	0.728605	0.839801	0.465275
I_3	0.924568	0.92344	1	0.71945	0.808715	0.567287
O_1	0.777802	0.728605	0.71945	1	0.788766	0.636545
O_2	0.927761	0.839801	0.808715	0.788766	1	0.673468
O_3	0.567541	0.465275	0.567287	0.636545	0.673468	1

3.2. Alliance Processes

This study executes the software of Super-SBM-O-V for the realistic data of 2018, which is the latest year of data series, to calculate the DMUs' efficiency and get their ranking before alliances. The empirical results are shown in the Table 3.6 in which we just used the data of the latest year to examine the DMUs scores and their rankings since. The actual results of the order and business performance of the DMUs serve as a basis for the authors to choose future alliance partner. The previous year data would be used for forecasting and results for future virtual alliances. The virtual alliances will be established by adding up all the input and output parameters of the target DMU with the left other DMUs in this research.

Table-3.6. Efficiency and Ranking before Strategic Alliances

Rank	DMUs	Scores	Rank	DMUs	Scores
1	DMU_6	2.9059	9	DMU2	0.4131
2	DMU_4	1.3055	10	DMU16	0.3925
3	DMU_{10}	1.0707	11	DMU3	0.3532
4	DMU_{15}	1	11	DMU11	0.2822
5	DMU_5	0.7187	11	DMU9	0.2357
6	DMU_{13}	0.5464	11	DMU14	0.1738
7	DMU_1	0.4908	15	DMU12	0.0319
8	DMU_8	0.4633	16	DMU7	0.0300

The result indicated that the almost the selected companies in the industry of green logistics have the good efficiency (>1) – at top is DMU_6 with efficiency score at 2.9059 in 2018. The target company (DMU_{12}) together with DMU_7 is at low efficiency levels: 0.0319 and 0.03, respectively to be interpreted their businesses were not good or efficient. Four DMUs have the same efficiency level is at 1 that means they are neutral.

3.3. Analysis After Alliance

According to the above calculated result before alliance, the target company got the score equal to 0.0319, interpreting that its business in 2018 was not good. Moreover, the target company only is in the 15th out of 16 companies. Guided by the business philosophy of developing constantly, this company should boldly improve its production efficiency by the formation of the alliance. To implement the empirical research, the study starts to form virtual alliance and then executes DEA calculation. By combining the DMU_{12} with the rest of DMUs, the research gets 31 virtual alliances totally.

These 31 virtual alliances will be used their financial parameters equal to input variables and output variables. The correlations of these variables are analyzed to see the positive associations between these virtual ones. Table 3.7 illustrates these correlations coefficient. As mentioned earlier, these correlations show the very positive associations among the virtual input and output variables – around 0.6 - 0.9 accordingly. Therefore, this also demonstrates very clearly that these virtual alliances can be further analyzed for the purpose of the research.

Table-3.7. Correlation of Input and Output Data of 31 Virtual Companies

	I_1	I_2	I_3	O_1	O_2	O_3
I_1	1	0.6788097	0.8799605	0.9357852	0.7539332	0.8202567
I_2	0.6788097	1	0.9388018	0.7299762	0.9916583	0.7144433
I_3	0.8799605	0.9388018	1	0.9014087	0.9723645	0.810677
O_1	0.9357852	0.7299762	0.9014087	1	0.8068835	0.7134668
O_2	0.7539332	0.9916583	0.9723645	0.8068835	1	0.744217
O_3	0.8202567	0.7144433	0.810677	0.7134668	0.744217	1

The next important step is that the software of DEA-Solver Pro 5.0 built by Saitech Company is utilized to calculate Super-SBM-O-V model for 31 DMUs. Table 3.8 shows the score and ranking results of virtual alliance in 2018.

Table-3.8. Efficiency and Ranking after Strategic Alliances

Rank	DMUs	Scores	Rank	DMUs	Scores
1	DMU4	2.784548134	16	DMU11	0.618543821
2	DMU10	1.259842908	16	DMU3	0.61322988
3	DMU12+DMU6	1.108112935	16	DMU9	0.573026169
4	DMU6	1.035731045	20	DMU12+DMU1	0.552986942
5	DMU12+DMU15	1.035721737	21	DMU12+DMU8	0.507301799
6	DMU5	1.012311252	22	DMU12+DMU4	0.471683434
7	DMU13	1.010851299	23	DMU12+DMU10	0.420563475
8	DMU1	1.006846138	24	DMU12+DMU11	0.348320687
9	DMU12+DMU5	1	25	DMU12+DMU7	0.341809997
10	DMU12+DMU13	1	26	DMU12+DMU9	0.250427417
11	DMU15	1	27	DMU12+DMU2	0.216845058
12	DMU8	1	28	DMU12+DMU16	0.186479792
13	DMU12+DMU3	1.0145	29	DMU12+DMU14	0.132905565
14	DMU2	0.654597674	30	DMU12	0.11004828
15	DMU16	0.623726715	31	DMU7	0.0499341
16	DMU14	1			

Depending on the results depicted above, the research can easily compare the efficient frontiers among DMUs and virtual alliances. The changing from original target DMU_{12} to virtual alliance will clearly indicate the differences, which are positive alliance and negative alliance. Positive results in difference demonstrate the alliance is better than original DMUs. The more the difference is, the more efficient the alliance gets. In contrast, the negative result means the alliance is worse.

The results of Table 3.9 are from tables 3.6 and 3.8. As in Table 3.6, the target company – DMU_{12} and another DMU_7 got the lower efficient level at only below 0.03, respectively; whereas, DMU_3 got the score equal to 1, interpreting "good". After alliance in Table 3.8, the efficient levels change significantly. DMU_{12}+DMU_3 got the score above the efficient frontier at 1.0145, which is not only good for the target company but also for its partner. DMU_{12}+DMU_7 did not change to over frontier, but its efficiency is better for both at 0.34. Thus, this research proposes five virtual companies for further analysis in the future to get the final selection.

Table-3.9. The Possible Alliance Partnership

Virtual Alliance
DMU_3
DMU_7
DMU_{12}
DMU_{12}+DMU_3
DMU_{12}+DMU_7

The other combinations are not good and impossible for further analysis. They are changing in the efficient scores even better for the target DMU, but those are not beneficial for the partners because partners get lower scores. For instance, DMU_9 in Table 3.7 got the score at 1, but after alliance it got only 0.34 with DMU_{12} (DMU_{12}+DMU_9 in table 3.8), or the same situation with DMU_{13} and virtual DMU_{12}+DMU_{13} in Table 3.7 and Table 3.8, respectively. Even the virtual company got higher frontier score but it lowers efficiency score of DMU_{12}. Thus, this study only takes the possible alliance into account for analysis, which will be fair for both the target and partner alliance.

3.4. Forecasting Process

The researchers use *GM (1,1) model* to predict the realistic input/output factors for the next four years 2019 to 2022. Following, the study takes the company DMU_{12} as example to understand how to compute in GM (1,1) model in period 2015-2018.

Net income of $DMU_{12}$is selected as example to explain for calculation procedure, other variables are calculated in the same way. The procedure is carried out step by step as following.

Calculation process is presented by following steps when selecting the total asset of FLC company as example and the similar is true of other factors. Initially, GM (1,1) model is drawn on forecasting the variance of original sequence:

Construct the original sequence:

X(0) = (232.23; 421.79; 769.57; 979.59)

Implement the accumulated generating operation (AGO):

X(1) = (232.23; 654.02; 1423.59; 2403.18)

x(1)(1) = x (0)(1) = 232.23

x(1)(2) = x(0)(1) + x(0)(2) = 654.02

x(1)(3) = x(0) (1) + x(0) (2) + x(0)(3) = 1423.59

x(1) (4) = x(0) (1) + x(0) (2) + x(0)(3) + x(0)(4) = 2403.18

Create differential equation of GM (1,1) to find X(1) sequence and obtain the subsequent mean by the mean equation:

Z(1) (2) = $\frac{1}{2}(x^{(1)}(1) + x^{(1)}(2)) = 443.125$

Z(1) (3) = $\frac{1}{2}(x^{(1)}(2) + x^{(1)}(3)) = 1038.805$

Z(1) (4) = $\frac{1}{2}(x^{(1)}(3) + x^{(1)}(4)) = 1913.385$

Solving equation to get the result of a and b, the original sequence values are replaced into the form of a matrix:

$$\begin{cases} 421.79 + a \times 443.125 = b \\ 769.57 + a \times 1038.805 = b \\ 979.59 + a \times 1913.385 = b \end{cases}$$

Convert linear equation into practice:

Let,

$$\beta = \begin{bmatrix} -443.125 & .. & 1 \\ -1038.805 & .. & 1 \\ -1913.385 & .. & 1 \end{bmatrix}, \theta = \begin{bmatrix} a \\ b \end{bmatrix}, \quad \text{YN} = \begin{bmatrix} 421.79 \\ 769.57 \\ 979.59 \end{bmatrix}$$

and then conducting the least square method to get a and b

$$\begin{bmatrix} a \\ b \end{bmatrix} = \theta = (\beta T\beta)\text{-}1\ \beta TYN = \begin{bmatrix} -0.369037562 \\ 305.9837433 \end{bmatrix}$$

The differential equation is achieved by using the two coefficients and value of b:

$$\frac{dx^{(1)}}{dt} - 0.369037562 \times x^{(1)} = 305.9837433$$

Establish the prediction model from equation:

X(1) (k+1) = (X(0) (1) $-\frac{b}{a}$) $e^{-ak}\frac{b}{a}x^{(1)}(k+1) = (232.23 - \frac{305.9837433}{-0.369037562})\,e^{0.369037562\times k} + \frac{305.9837433}{-0.369037562}$

Then substituting distinctive values of k into the aboved equation:

k=0 x(1) (1) =232.23

k=1 x(1) (2) = 705.9638608

k=2 x(1) (3) =1391.145008

k=3 x(1) (4) = 2382.15123

k=4 x(1) (5) =3815.485082

Obtain the predicted value of x by originating the predicted one of the original sequence following the accumulated generating operation:

x(0)(1) = x (1) (1) = 232.23

x(0) (2) = x(1) (2) − x(1)(1) = 473.7338608

x(0) (3) = x(1) (3) − x(1)(2) = 685.1811467

x(0) (4) = x(1) (4) − x(1)(3) = 991.0062223

x(0) (5) = x(1) (5) − x(1)(4) = 1433.333853

In the same with above computation process, the study could get the forecasting result of all DMUs from 2019 to 2022; the detail numbers are shown in the two following tables, respectively.

3.5. Forecasting Accuracy

In this paper, the *MAPE* (Mean Absolute Percent Error) is employed to measure the accuracy of a method for constructing fitted time series values in statistics. MAPE is often used to measure forecasting accuracy. In the book of Stevenson (2009), it stated out clearly that MAPE is the average absolute percent error which measures of accuracy in a fitted time series value in statistics, specifically trending.

$$MAPE = \frac{1}{n}\sum \frac{|Actual - Forecast|}{Actual} \times 100$$; n is forecasting number of steps.

The parameters of MAPE stating out the forecasting ability as follows:

MAPE < 10% "Excellent"

10% < MAPE < 20% "Good"

20% < MAPE < 50% "Reasonable"

MAPE > 50% "Poor

Moreover, some papers have proved that GM(1,1) reaches a good level of forecasting (*cf.* (Chia-Nan and Ty, 2013; Nguyen and Tran, 2015;2019; Trinh and Tran, 2017). We also try to make some comparisons for better insights of GM (1,1) applicable to this topic. We use the Moving Average (MA) of three to make forecasting. The Moving Average demonstrates good trend when its forecasts with lower level of error (see Table 3.10). The same series of numbers used in GM (1,1) which are 10636; 11795; 11763; and 12026. The detailed results of both methods are shown in the Table 3.10. One or more drawbacks of MA is that it requires a large sequence of data, so when we conduct the MA of three, we do not have the results for the two first series (which can be done completely by GM (1,1)). With this sample calculation, we also see the high performance from MA of three when the error at low level (i.e. 1.39% and 3.20%, compared with 0.41% and 0.83% of the Grey forecasting model).

Table-3.10. The sample forecasting results and errors

Series	**Original (1)**	**GM prediction (2)**	***Residual error (2-1)***	**MA Prediction (3)**	***Residual error (3-1)***	**Error** $\frac{\|(1-2)\|}{2}\times 100\%$	**Error** $\frac{\|(1-3)\|}{3}\times 100\%$
1	10,636	10,636	0,00	--	--	0,00%	--
2	11,795	11,745.44	49,55	--	--	0,42%	--
3	11,763	11,860.86	97,86	11.398,00	365,00	**0,83%**	**3,20%**
4	12,026	11,977.40	48,60	11.861,33	164,67	**0,41%**	**1,39%**
***f1**	--	12,095.09	--	11.894,50	--	--	--
f2	--	12,213.93	--	12.026,00	--	--	--
f3	--	12,333.94	--	--	--	--	--

*f: as future forecasting

The same process is repeated for the whole data we used for this study. Gradually developing and calculating the data with those models, we get the new forecasted data for the next procedure of evaluation the industry. We have to use the highly-evaluated data with higher accuracy in forecasting. Thus, we make a table to summarize all the Mean Absolute Percentage Errors (MAPE) to see the differences. Table 3.11 gives us an overall of all the MAPEs for the DMUs for this study. The indexes in the table clearly show that the GM (1,1) and Moving Average models gain high accuracy. Based on that, we would see that both GM (1,1) and Moving Average are good models to be considered. Notably, the MAPE of the virtual alliances at only 2.02% and 4.00% from GM (1,1); and these numbers are higher from MA of three, which means that GM(1,1) is more accurate. Moreover, based on their MAPE values, it can be concluded that the calculated values based on these two models follow closely to the actual values; while GM(1,1) is strongly suggested since its relevant indexes in the tables are better, Moving Average demonstrates the trend at higher percentage of accuracy (the average of all MAPEs from GM(1,1) is at 2.51%; at this category, it takes to 15.15% when it's done by MA). Highly precise forecasting result will help the policymakers and the further analysis more accurate and reliable. The results of MAPE are displayed as follows (Table 3.11):

Table-3.11. Average MAPE of DMUs

DMUs	Average MAPE of GM (1,1)	Average MAPE of MA
DMU_3	3.63%	15.53%
DMU_7	1.66%	13.21%
DMU_{12}	1.25%	9.32%
DMU_3+DMU_{12}	4.00%	23.15%
DMU_7+DMU_{12}	2.02%	14.56%
Average of all MAPEs	2.51%	15.15%

The calculations of MAPE are almost smaller than 10%, especially the average MAPE of 5 DMUs reaches 2.51% (below 10% as well), it strongly confirms that the GM (1,1) model provides a highly accurate prediction. In short, we just applied the results of forecasting from the proposed model GM(1,1) and those numbers are shown in tables 3.12 and 3.13.

Table-3.12. Forecasted Results of Good-efficiency Companies in 2019 and 2020

DMUs	INPUTS (USD Millions)						OUTPUTS (USD Millions)			
	(I)Total Assest to I1		(I)Total Operating Income to I2		(I)Total Liabilities to I3		(O)Net Income to O1		(O)Total Revenue to O2	
	2019	2020	2019	2020	2019	2020	2019	2020	2019	2020
DMU_3	1162.17	1297.88	770.72	491.27	745.03	1123.91	3751.19	4146.44	76.48	83.03
DMU_7	3362.145285	3459.07	5415.414835	5509.53	748.746552	760.581	5631.45841	5725.89	108.1504702	114.038
DMU_{12}	33127.0957	34470.1	8624.084045	8742.69	2413.69553	2352.15	12095.0885	12213.93	1870.347431	1875.38
DMU_3+DMU_{12}	34280.55438	35744.6	8526.516242	7738.24	3039.86947	3110.24	15818.9381	16278	1946.403192	1957
DMU_7+DMU_{12}	36489.03399	37928.2	14039.83498	14252.7	3159.41932	3106.65	17727.1165	17940.4	1978.45784	1988.92

Table-3.13. Forecasted Results of Good-efficiency Companies in 2021 and 2022

DMUs	INPUTS (USD Millions)						OUTPUTS (USD Millions)			
	(I)Total Assest to I1		(I)Total Operating Income to I2		(I)Total Liabilities to I3		(O)Net Income to O1		(O)Total Revenue to O2	
	2021	2022	2021	2022	2021	2022	2021	2022	2021	2022
DMU_3	1449.43	1618.68	313.15	199.61	1695.46	2557.67	4583.35	5066.29	90.13	97.84
DMU_7	3558.79	3661.38	5605.29	5702.71	772.603	784.814	5821.91	5919.54	120.246	126.792
DMU_{12}	35867.6	37321.7	8862.93	8984.83	2292.18	2233.73	12333.95	12455.14	1880.42	1885.48
DMU_3+DMU_{12}	37271.1	38862.9	7022.84	6373.57	3182.23	3255.9	16750.3	17236.4	1967.65	1978.35
DMU_7+DMU_{12}	39424	40978.9	14468.7	14688.1	3054.76	3003.74	18156.2	18374.7	1999.45	2010.02

Table-3.14. EPS Forecasted Results of Good-efficiency Companies in 2019 to 2022

DMUs	EPS			
	2019	**2020**	**2021**	**2022**
DMU_3	1.87	1.86	1.34	1.07
DMU_7	1.78969153	1.789556	1.78975	1.79098
DMU_{12}	1.82985654	1.8298701	1.82983	1.83025
DMU_3+DMU_{12}	3.66804684	3.6735545	3.67475	3.67559
DMU_7+DMU_{12}	3.49499994	3.5679273	3.56755	3.56583

Grey system theory was introduced in 1982 with the main mission is to process the realistic laws in application using accessible source of data which is known as the initiation of the grey series. Decision makers who have reference for a shortcoming data can utilize the Grey model as an effective forecasting method.

GM (1,1) owns the computational efficiency in frequently applying grey forecasting model. In this research, GM (1,1) was utilized to forecast collected data in the future. Besides, a group of differential equations involve in computation for a time series forecasting model which is modified for parameter variance. It is not manipulated as a first order differential equation. The structure of difference equations is adapted to change over the time than constructing general difference equations. GM (1,1) presents its validity when the employed data has at least four series. More importantly, successive order and equivalent interval are prior requirement before running the Grey forecasting model. This model description is exhibited as follows:

Designate the variable original sequence X(0): X(0) = (X(0) (1), X(0) (2),... X(0) (n)), n≥ 4 where X(0): a non-negative sequence and n: the number of data constructed. Conducting the Accumulating Generation Operator (AGO) which is considered as one of the most pivotal features of Grey forecasting theory, in order to eliminate the ambiguity of the original data and facilitate the randomness.3

Earnings per Share - EPS is restated that the portion of a company's profit allocated to each outstanding share of common stock. EPS serves as an indicator of a company's profitability. It is also considered to be the single most important variable in determining a share's price to see the current "health" of a company (Mahmud, 2013).

$$EarningsperShare\ (EPS) = \frac{NetIncome - DividendsonpreferredStock}{AverageoutstandingShares}$$

When calculating, it is more accurate to use a weighted average number of shares outstanding over the reporting term, because the number of shares outstanding can change over time. Thus, in this research, we do not use a linear forecasting method to estimate the value of EPS. Neural network in this case is most suitable to handle to task of predicting EPS, which can use five parameters as the inputs on the input layer to predict one output layer – EPS.

Finally, the *DEA Super SBM-O-V model* is applied again to see the future rankings and efficiency scores of the virtual alliance companies. Table 3.15 summarizes the results. We also note that these results are the calculations from the forecasting outputs (2019-2022) of GM(1,1) and neural network mentioned earlier.

Table-3.15. Efficiency Scores and Rankings of Virtual Alliance Companies

	2019		2020		2021		2022	
DMUs	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**	**Score**	**Rank**
DMU_3	1	5	1	4	1	4	1	4
DMU_7	1.242957	2	1	4	1	4	1	4
DMU_{12}	1.082231	3	1.098353	2	1.108996	2	1.117996	2
DMU_3+DMU_{12}	1.359609	1	1.473608	1	1.60797	1	1.74801	1
DMU_7+DMU_{12}	1.043059	4	1.038056	3	1.060915	3	1.090978	3

From Table 3.14, we can easily recognize the future rankings and efficient scores of virtual alliances. DMU_3, itself, just ranks at the bottom among the virtual; however, DMU_3+DMU_{12} is always the best through the future period (2019-2022). DMU_7+DMU_{12} also proves the improvement even not well ranking, this virtual alliance always gets the efficient score above the frontier at around 1.03 to 1.09 in the future. As forecasting results, DMU_{12} gain good level, but not better than the virtual alliance.

In short, the results suggest that the target company should make alliance with DMU_3 finally to have the better performance in the future. The second choice would be with DMU_7, this alliance not only good for the target company, but also better for the partner.

4. Discussions

This study uses GM(1,1), neural network and DEA models to focus on the relationship between strategic alliances and the performance of enterprises in green logistics. The most important purpose of this study is to help target companies find suitable partners for strategic alliances. In this study, DMU12 is one of the green logistics companies (ranked among 75 green supply chain partners as of June 2014), used to test whether the benefits of strategic alliances exist. If DMU12 establishes alliances with other companies in the same industry and provides them to the company, after a comprehensive analysis of the past, present, and future evaluations in Section 4, the research finds the following companies: DMU3 (Hiz Cor.) DMU7 (Conz Freight) is a good choice for DMU12 to establish a strategic alliance; DMU3 is strongly recommended. In addition, the study also pointed out that DMU12 may be an ideal alliance partner. It is DMU7. Strategic alliances are not only good for DMU12, but also good for partners.

It is undeniable that this research still has limitation corresponding to the limited number of observed companies for an empirical study. Although the research already indicates conditions to select the input/ output variables to avoid the subjective results, it is only about the financial factors which cannot completely present for whole construction industry. The performance evaluation of any enterprise is also evaluated by various non-financial factors such as human resources allocation, effective equipment and so on. Further research should consider to develop more aspects based on the results of this paper and address to ensure that strategic alliances could be managed well and content it with partners' demands. Specially, when researching into the multinational companies with different working environments requires a broaden based study and methods to discuss more.

This research contribution is to assist the target company to seek for appropriate partnership entering the strategic alliance planning by conducting GM (1,1) and DEA model in forecasting the performance in the following next years. The researcher also proposed the added idea to integrate the combination of Grey theory, super SBM-O-V model which employs the target enterprise to determine alliance advantages if it has potential partners. Furthermore, the mentioned method provides a precise evaluation for Vietnam construction industry through detailed description by analyzing the efficiency and ranking position in order. Based on this, the company can develop the improvement planning for itself as well as take the business merits from partners.

Although, they are rivals in the same industry competing in the similar market to gain that much profit to maintain the business, alliance strategy is needed when it can enhance the mutual performance and bring the benefits for enterprise. The problem of any company is to balance the financial situation. Therefore, it is properly speaking they can be their partners as long as maintaining the improvement in the long-term.

5. Implications

In this study, the authors provide a method for finding and selecting the right strategic partner for green logistics enterprises. The selected plan is to promote the internal strength of all participating enterprises while promoting the strength of the alliance in accordance with high volume products, high quality, international quality, timely delivery, and competitive price needs. Authorities can rely on these research results to make the correct and appropriate strategic decisions in helping industries to develop when integrating with the global economy.Next, the very effective integrated method is proposed to help organizations in forming and creating partner in the future. Sometimes, companies have to make alliances based on their relationship and working styles in business, but sometimes, when they want to apply the quantitative method to show out the references. Then, DEA, GM(1,1) and neural networks integration is an advanced step in their process. Moreover, this study also uses effective economic aspect in evaluating the general management of the target DMU.

The study supports the company's selection process related to sustainability. In particular, it helps target DMUs understand their past, present and future business conditions. The empirical evidence from this study also provided meaningful recommendations for them to better improve their profitability, technology, scale efficiency and long-term planning. Therefore, it is important to measure the economic viability of the DMU and the activities of the organization.

Although the article shows that GM(1,1) and neural networks are flexible and easy-to-use models to predict what will happen in the future, DEA is an effective tool to help us, but we cannot deny the limitations of this approach and requires further research. The limitation of this study is that the amount of inputs and outputs is considered to be related to financial results. Another limitation is the way data exists, our four-year data. Vertical data can improve results. The number of companies available for analysis is limited. There is a need to study how green logistics providers can improve financial performance and environmental performance.

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