Usage of two-stage Integrating Data Envelopment Analysis to Propose the Best Strategic Alliance: A Case of the Green Logistics Providers

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Abstract
In the wave of internationalization, many companies use strategic alliance like an approach to expand and strengthen their businesses. Strategic alliance is also considered to be a highly intelligent approach in green logistics for environment and e-commerce growing quickly and effectively because this is the critical concern worldwide to balance the economic development with the environmental protection. However, a suitable methodology to evaluate and analyze performance of partners is a critical and significant issue for top managers to have effective decisions making for business strategy including alliance strategy in the future. This will improve business performance and reduce carbon dioxide (CO2) 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 Corporation make a well-considered decision to select the best strategic alliance candidates. The results indicate that Hub Group Inc. and Con-way 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 and Tran, 2015; Nguyen, 2019). 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 equipments 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 smartphones 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 and Tran, 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). 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, 2017a; 2017b), but the fact that, they have to obtain 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 production capacity planning and for investment decision making whether should expand their business in the 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).

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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

First of all, the published *Inbound Logistics’ 75 Green Supply Chain Partners (GSCP)* in June, 2014 lists down 75 top companies in the industry. Then, to have a valuable evaluation of performance, we collected inputs and outputs variables from various companies that are leading the way in sustainability and green logistics initiatives (Nguyen, 2020a; 2020b; Wang *et al.*, 2014).

After doing the survey the Inbound Logistics market segments, the study finds out 16 enterprises in the list of the world’s largest sustainable transportation and logistics providers. Then, the analysis was only conducted on these companies which are stable in market and can provide the completely data for 4 consecutive years (2010-2013). Moreover, these 16 qualified companies play major roles in the industry and can represent for whole industry in stock market (Table 2.1).

In this study, DMU12 is set as the target company with the headquarter located in Jacksonville, FL, United States of America. In the globalization and competition environment, strategic alliance could be a great way for DMU12 to require resources and extend its business map.

![Table 2.1. List of Final Selected Companies in the Green Logistics Industry](image)

| Denoting | Full name                          | Stock Code | Official Website                  |
|----------|------------------------------------|------------|-----------------------------------|
| DMU1     | Ryder                              | R          | http://www.ryder.com/            |
| DMU2     | Werner Enterprises, Inc.           | WERN       | http://www.werner.com/           |
| DMU3     | Hub Group Inc                      | HUBG       | http://www.hubgroup.com/         |
| DMU4     | C.H. Robinson Worldwide, Inc.      | CHRW       | http://www.chrobinson.com/       |
| DMU5     | FedEx Corporation                  | FDX        | http://www.fedex.com/            |
| DMU6     | United Parcel Service, Inc.        | UPS        | http://www.ups.com/              |
| DMU7     | Con-way Freight                    | CNW        | http://www.con-way.com/          |
| DMU8     | J.B. Hunt Transport Services, Inc. | JBHT       | http://www.jbhunt.com/           |
| DMU9     | Celadon Group, Inc.                | CGI        | https://www.celadontrucking.com   |
| DMU10    | Old Dominion Freight Line          | ODFL       | http://www.odfl.com/Home/        |
| DMU11    | Safa Inc                           | SAFE       | http://www.safacorp.com/         |
| DMU12    | CSX Corporation                    | CSX        | http://www.cssx.com/             |
| DMU13    | Norfolk Southern Corp              | NSC        | http://www.nscorp.com/           |
| DMU14    | Knight Transportation              | KNX        | http://www.knighttrans.com/      |
| DMU15    | Union Pacific Corporation           | UNP        | http://www.up.com/               |
| DMU16    | Swift Transportation Co             | SWFT       | http://www.swifttrans.com/       |

*Note: Target company

The data was collected from 2010 to 2013 about annuals of these companies of U.S.A stock exchange cooperation with three inputs: Total assets, total operating expense, and total current liabilities and three outputs: net income, total revenue, and earnings-per-share (EPS). Each of these GSCPs is treated as a decision making unit (DMU) in the DEA analysis. The complete data was shown in Tables 2.2 and 2.3.

As mentioned earlier, this study examined the economic aspects to analyze and propose partners. As one part of DEA, some input and output factors have to be considered closely and seriously. To do this, we have reviewed many previous studies which also mentioned about accounting and logistics costs’ impact on logistics providers’ effectiveness which is very carefully considered by the “Logistics and Supply Chain Management Consulting”.

Finally, total assets, total operating expense, and total current liabilities are chosen to be the input factors of this study; and net income, total revenue, and earnings-per-share (EPS) are the output factors. In short, these factors are crucial factors performing the financial health of the companies, and through those factors showing how well companies managing their costs effectively, and they positively influence the economic sustainability performance of the industry.

![Table 2.2. Financial Results of Logistics Companies in 2010 and 2011](image)

| DMU | (1) Total Asset | (2) Total Operating Income | (3) Total Liabilities | (4) Net Income | (5) Total Revenue | (6) Basic EPS |
|-----|----------------|---------------------------|-----------------------|----------------|-------------------|--------------|
| DMU1 | 2010           | 2010                      | 2010                  | 2010           | 2010              | 2010         |
| DMU2 | 665.239        | 701.84                    | 814.80                | 700.80         | 113.52            | 117.82       |
| DMU3 | 1311.35        | 1302.42                   | 1366.44               | 1289.18        | 168.44            | 198.82       |
| DMU4 | 629.41         | 842.68                    | 1763.57               | 2057.07        | 307.42            | 270.9        |
| DMU5 | 1995.72        | 2158.04                   | 6551.44               | 9043.62        | 771.01            | 876.53       |
| DMU6 | 25902          | 27352                     | 35726                 | 39026          | 8882              | 5374         |
| DMU7 | 33597          | 34701                     | 43904                 | 47023          | 5902              | 6513         |
| DMU8 | 2843.73        | 3199.02                   | 4372.83               | 5083.62        | 6519              | 725.47       |
| DMU9 | 1568.66        | 2267.34                   | 3145.86               | 4026.41        | 509.95            | 438.5         |
| DMU10| 440.48         | 416.67                    | 588.70                | 537.46         | 127.02            | 141.17       |
| DMU11| 1239.89        | 1347.26                   | 1670.73               | 1700.65        | 204.81            | 181.34       |
| DMU12| 452.16         | 474.89                    | 890.16                | 1007.08        | 105.77            | 124.35       |
| DMU13| 28141          | 29344                     | 7565                  | 8325           | 2537              | 2528         |
| DMU14| 28399          | 28538                     | 6847                  | 7066           | 2082              | 1701         |
| DMU15| 735.61         | 651.49                    | 706.18                | 906.18         | 40.47             | 58.02        |
| DMU16| 41088          | 45096                     | 12065                 | 13838          | 2923              | 3317         |

The data was collected from 2010 to 2013 about annuals of these companies of U.S.A stock exchange cooperation with three inputs: Total assets, total operating expense, and total current liabilities and three outputs: net income, total revenue, and earnings-per-share (EPS). Each of these GSCPs is treated as a decision making unit (DMU) in the DEA analysis. The complete data was shown in Tables 2.2 and 2.3.
2.2. Non-radial Super Efficiency Model (Super-SBM)

DEA first developed by Charnes et al. (1978) is a methodology for constructing a best practice frontier, which tightly envelops observed data on producers’ inputs and outputs. Current research on DEA indicates that several potential models can be utilized to evaluate overall efficiencies of decision making units that are responsible to convert a set of inputs into a set of outputs. However, the efficient DMUs obtained in most DEA models like CCR and BCC cannot be compared and they do not accomplish the intended purpose in examining the green logistics providers because of these following reasons:

First, all conventional DEA techniques seem to lack objectivity by not representing the true input/output conditions for each DMU when they directly assign ‘input-oriented’ or ‘output-oriented’ models. In the two stage production process model used in this study, it’s a difficult task to define input/output-oriented models without being subjective. In other words, non-radial measures should be the point of focus when aiming to achieve more realistic results because it directly deals with the excess input and the output shortfalls of the considered DMUs.

Second, the most significant problem when applying DEA model is to handle negative output/input data in the slacks-based measure models. As in some case, some variables are negative ones. Therefore, when engaging in performance evaluations, advanced techniques are required to handle with the negative output/input data in the slacks-based measure of super efficiency models. Third, in this study the assets of the largest logistics companies are many times as large compared to smallest logistics companies. A small-sized DMU refers to the input/output allocation experiences of some super large-sized DMUs, which cannot be achieved in reality. Therefore, the results of the two stage models could be biased because of extreme values while forming an efficiency frontier to determine the efficiency score for each DMU. Fourth, engaging in DEA with a small number of DMUs compared to total criteria used for evaluation may lead to problems in determining which DMUs are the best performers. Hence, during examination the performance efficiency and ranking of 16 green logistics companies, advanced techniques are required to sort out the best performers because in most DEA models, while the number of DMUs may be small, there will be multiple DMUs exhibiting an ‘efficient’ status with a score of one.

Therefore, when measuring the performance of EMS companies, the researcher applies advanced DEA techniques, slacks based measures of super efficiency (super SBM), as proposed to evaluate performance by combining the profitability and the efficiency of marketability. When the number of DMUs is relatively small compared to evaluation criteria, the super SBM is very useful tool to help differentiate all the efficient DMUs. The authors strongly consider that the super-SBM models used in the study results in acceptable and further convincing inquiry in the performance and ranking of the list logistics providers of transmutation of many inputs to many outputs.

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 $X = (x_{ij}) \in \mathbb{R}^{m \times n}$ and $X = (x_{ij}) \in \mathbb{R}^{s \times n}$, respectively $x$ is a non-negative vector in $\mathbb{R}^n$. The vectors $s^- \in \mathbb{R}^m$ and $s^+ \in \mathbb{R}^n$ indicate the input excess and output shortfall respectively.

The model formulation provides a constant return to scale is as follows:

$$\min \rho = \frac{1-\sum_{i=1}^{m} s_i^-}{\sum_{i=1}^{m} s_i^-} / x_0 \quad \frac{1+\sum_{i=1}^{n} s_i^+}{\sum_{i=1}^{n} s_i^+} / y_0$$

Subject to (s1) $x_0 = x\lambda + s^-$, $y_0 = y\lambda - s^+$, $\lambda \geq 0, s^- \geq 0, s^+ \geq 0$

### Table 2.3. Financial Results of Logistics Companies in 2012 and 2013

| DMUs | INPUTS (USD Millions) | OUTPUTS (USD Millions: except EPS) |
|------|-----------------------|-----------------------------------|
|      | (IQ) Total Asset      | (IQ) Total Operating Income       | (OQ) Total Liabilities |
|      | (IQ) Total Net Income | (IQ) Total Revenue                | (OQ) Basic EPS         |
| 2012 | 8318.98               | 9103.78                           | 6502.44               |
| 2013 | 1069.44               | 1145.1                            | 1164.94               |
| 2014 | 919.85                | 1047.94                           | 3011.75               |
| 2015 | 321.32                | 277.38                            | 532.25                |
| 2016 | 321.32                | 277.38                            | 532.25                |
| 2017 | 321.32                | 277.38                            | 532.25                |
| 2018 | 321.32                | 277.38                            | 532.25                |
| 2019 | 321.32                | 277.38                            | 532.25                |
| 2020 | 321.32                | 277.38                            | 532.25                |

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The variables S+ and S- measure the distance of inputs X and outputs Y 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 $\bar{\lambda}^*, \bar{S}^-, \bar{S}^+$. 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 because its variables are negative ones. No input excesses and no output shortfalls in any optimal solution. Hence, no input excesses and no output shortfalls in any optimal solution. Therefore, when measuring the performance of EMS companies, the researcher applies advanced DEA techniques to sort out the best performers because in most DEA models, evaluation may lead to non-robustness in results because it directly deals with the excess input and the output shortfalls of the considered DMUs.

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

DEA first developed by Charnes et al. (1978) is a methodology for constructing a best practice frontier, which tightly envelops observed data on producers’ inputs and outputs. Current research on DEA indicates that several potential models can be utilized to evaluate overall efficiencies of decision making units that are responsible to convert a set of inputs into a set of outputs. However, the efficient DMUs obtained in most DEA models like CCR and BCC cannot be compared and they do not accomplish the intended purpose in examining the green logistics providers because of the following reasons:

First, all conventional DEA techniques seem to lack objectivity by not representing the true input/output conditions for each DMU when they directly assign ‘input-oriented’ or ‘output-oriented’ models. In the two stage production process model used in this study, it’s a difficult task to define input/output-oriented models without being subjective. In other words, non-radial measures should be the point of focus when aiming to achieve more realistic results because it directly deals with the excess input and the output shortfalls of the considered DMUs.

Second, the most significant problem when applying DEA model is to handle negative output/input data in the slacks-based measure models. As in some cases, some variables are negative ones. Therefore, when engaging in performance evaluations, advanced techniques are required to handle with the negative output/input data in the slacks-based measure of super efficiency models.

Third, in this study the assets of the largest logistics companies are many times as large compared to smallest logistics companies. A small-sized DMU refers to the input/output allocation experiences of some super large-sized DMUs, which cannot be achieved in reality. Therefore, the results of the two stage models could be biased because of extreme values while forming an efficiency frontier to determine the efficiency score for each DMU.

Forth, engaging in DEA with a small number of DMUs compared to total criteria used for evaluation may lead to problems in determining which DMUs are the best performers. Hence, during examination the performance efficiency and ranking of 16 green logistics companies, advanced techniques are required to sort out the best performers because in most DEA models, while the number of DMUs may be small, there will be multiple DMUs exhibiting an ‘efficient’ status with a score of one.

Therefore, when measuring the performance of EMS companies, the researcher applies advanced DEA techniques, slacks based measures of super efficiency (super SBM). When the number of DMUs is relatively small compared to evaluation criteria, the super SBM is very useful tool to help differentiate all the efficient DMUs. The authors strongly consider that the super-SBM models used in the study results in acceptable and further convincing inquiry in the performance and ranking of the list logistics providers of transmutation of many inputs to many outputs.

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The model formulation provides a constant return to scale is as follows:

$$\text{min} \quad \rho = \frac{1 - \frac{1}{\sum_{i=1}^n \frac{S^-_i}{x_{i0}}}}{1 - \frac{1}{\sum_{i=1}^n \frac{S^+_i}{y_{i0}}}}$$

Subject to (s.t)

$$x_0 = X\lambda + S^- , y_0 = Y\lambda - S^+ , \lambda \geq 0, S^- \geq 0, S^+ \geq 0$$

The variables $S+$ and $S-$ measure the distance of inputs $X$ and outputs $Y$ 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 $P^*, X^*, S^-, S^+$. 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 discriminated these efficient DMUs and ranked the efficient DMUs by super-SBM model. Assuming that the DMU \((x_o, y_o)\) is SBM-efficient, \(z^* = 1\), super-SBM model is as follows:

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Figure 2.1. Research Methodology
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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 rankings and efficiency changes among virtual companies in the future.
3. Results and Analysis

3.1. Pearson 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 et al., 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.

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 O3–EPS, the correlation coefficient show high positive when its parameters are >0.6 consecutively, except in 2012. This can be explained that EPS is calculated by single U.S dollars to come out with this little small index.

| 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 |

| Table-3.2. Correlation of Input and Output Data in 2010 |
|-------------------------------------------|
| I₁ | I₂ | I₃ | O₁ | O₂ | O₃ |
|---|---|---|---|---|---|
| I₁ | 1 | 0.660045 | 0.845366 | 0.720007 | 0.940859 | 0.669529 |
| I₂ | 0.660045 | 1 | 0.950599 | 0.995846 | 0.761663 | 0.674958 |
| I₃ | 0.845366 | 0.950599 | 1 | 0.968244 | 0.870619 | 0.738103 |
| O₁ | 0.720007 | 0.995846 | 0.968244 | 1 | 0.81737 | 0.687655 |
| O₂ | 0.940859 | 0.761663 | 0.870619 | 0.81737 | 1 | 0.625193 |
| O₃ | 0.669529 | 0.674958 | 0.738103 | 0.687655 | 0.625193 | 1 |

| Table-3.3. Correlation of Input and Output Data in 2011 |
|-------------------------------------------|
| I₁ | I₂ | I₃ | O₁ | O₂ | O₃ |
|---|---|---|---|---|---|
| I₁ | 1 | 0.673978 | 0.832195 | 0.736531 | 0.950115 | 0.6835 |
| I₂ | 0.673978 | 1 | 0.964516 | 0.995417 | 0.752787 | 0.696802 |
| I₃ | 0.832195 | 0.964516 | 1 | 0.980629 | 0.861359 | 0.72977 |
| O₁ | 0.736531 | 0.995417 | 0.980629 | 1 | 0.812121 | 0.704389 |
| O₂ | 0.950115 | 0.752787 | 0.861359 | 0.812121 | 1 | 0.59712 |
| O₃ | 0.6835 | 0.696802 | 0.72977 | 0.704389 | 0.59712 | 1 |

| Table-3.4. Correlation of Input and Output Data in 2012 |
|-------------------------------------------|
| I₁ | I₂ | I₃ | O₁ | O₂ | O₃ |
|---|---|---|---|---|---|
| I₁ | 1 | 0.681172 | 0.806306 | 0.754682 | 0.88486 | 0.464465 |
| I₂ | 0.681172 | 1 | 0.976743 | 0.993586 | 0.391877 | 0.199625 |
| I₃ | 0.806306 | 0.976743 | 1 | 0.988006 | 0.516785 | 0.244674 |
| O₁ | 0.754682 | 0.993586 | 0.988006 | 1 | 0.493116 | 0.260462 |
| O₂ | 0.88486 | 0.391877 | 0.516785 | 0.493116 | 1 | 0.611233 |
| O₃ | 0.464465 | 0.199625 | 0.244674 | 0.260462 | 0.611233 | 1 |

| Table-3.5. Correlation of Input and Output Data in 2013 |
|-------------------------------------------|
| I₁ | I₂ | I₃ | O₁ | O₂ | O₃ |
|---|---|---|---|---|---|
| I₁ | 1 | 0.666687 | 0.844616 | 0.732274 | 0.923602 | 0.737087 |
| I₂ | 0.666687 | 1 | 0.953436 | 0.992972 | 0.702279 | 0.680943 |
| I₃ | 0.844616 | 0.953436 | 1 | 0.979482 | 0.866679 | 0.74163 |
| O₁ | 0.732274 | 0.992972 | 0.979482 | 1 | 0.775395 | 0.695324 |
| O₂ | 0.923602 | 0.702279 | 0.866679 | 0.775395 | 1 | 0.604438 |
| O₃ | 0.737087 | 0.680943 | 0.74163 | 0.695324 | 0.604438 | 1 |
3.2. Alliance Processes

This study executes the software of Super-SBM-O-V for the realistic data of 2013, 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 partners. 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    | DMU₆     | 1.3662341 | 9    | DMU₂     | 1.0123737 |
| 2    | DMU₄     | 1.331328  | 10   | DMU₁₆    | 1.0032672 |
| 3    | DMU₁₀    | 1.2908874 | 11   | DMU₃     | 1         |
| 4    | DMU₁₅    | 1.2697276 | 11   | DMU₁₁    | 1         |
| 5    | DMU₄     | 1.1408922 | 11   | DMU₉     | 1         |
| 6    | DMU₁₃    | 1.1326946 | 11   | DMU₁₄    | 1         |
| 7    | DMU₁     | 1.084461  | 15   | DMU₁₂    | 0.5761994 |
| 8    | DMU₆     | 1.0550204 | 16   | DMU₇     | 0.4499341 |

The result indicated that the almost the selected companies in the industry of green logistics have the good efficiency (>1) – at top is DMU₆ with efficiency score at 1.366 in 2013. The target company (DMU₁₂) together with DMU₇ is at low efficiency levels: 0.576 and 0.45, respectively to be interpreted their businesses were not good or efficient. Four DMUs have the same efficiency level are DMU₃, DMU₁₁, DMU₉ and DMU₁₄ 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 0.576, interpreting that its business in 2013 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 DMU₁₂ 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

|     | I₁ | I₂   | I₃   | O₁   | O₂   | O₃   |
|-----|----|------|------|------|------|------|
| I₁  | 1  | 0.6788097 | 0.8799605 | 0.9357852 | 0.7539332 | 0.8202567 |
| I₂  | 0.6788097 | 1     | 0.9388018 | 0.7299762 | 0.9916583 | 0.714433 |
| I₃  | 0.8799605 | 0.9388018 | 1     | 0.9014087 | 0.9723645 | 0.810677 |
| O₁  | 0.9357852 | 0.7299762 | 0.9014087 | 1     | 0.8068835 | 0.7134668 |
| O₂  | 0.7539332 | 0.9916583 | 0.9723645 | 0.8068835 | 1     | 0.744217 |
| O₃  | 0.8202567 | 0.714433 | 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 2013.
he more the difference is, the more efficient the alliance gets. In contrast, the virtual company got higher frontier score but it lowers efficiency score of DMU. Even the virtual company got higher frontier score but it lowers efficiency score of DMU. For instance, DMU got the score equal to 1, interpreting “good”. After alliance in Table 3.8, the efficient levels change significantly. DMU got the score above the efficient frontier at 1.0145, which is not only good for the target company but also for its partner. The results of Table 3.9 are from tables 3.6 and 3.8. As in Table 3.6, the target company – DMU12 and another DMU1 got the lower efficient level at only 0.576 and 0.45, respectively; whereas, DMU1 got the score equal to 1, interpreting “good”. After alliance in Table 3.8, the efficient levels change significantly. DMU12+DMU1 got the score above the efficient frontier at 1.0145, which is not only good for the target company but also for its partner. DMU12+DMU7 did not change to over frontier, but its efficiency is better for both at 0.766. Thus, this research proposes five virtual companies for further analysis in the future to get the final selection.

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 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 possible alliance into account for analysis, which will be fair for both the target and partner alliance.

| Rank | DMUs | Scores | Rank | DMUs | Scores |
|------|------|--------|------|------|--------|
| 1    | DMU4 | 1.331328 | 16   | DMU11 | 1      |
| 2    | DMU10| 1.2908874| 16   | DMU3 | 1      |
| 3    | DMU12+DMU6 | 1.2053093 | 16   | DMU9 | 1      |
| 4    | DMU6 | 1.1946775 | 20   | DMU12+DMU1 | 0.931126 |
| 5    | DMU12+DMU15 | 1.1489677 | 21   | DMU12+DMU8 | 0.890153 |
| 6    | DMU5 | 1.1107989 | 22   | DMU12+DMU4 | 0.883064 |
| 7    | DMU13 | 1.101708 | 23   | DMU12+DMU10 | 0.8617829 |
| 8    | DMU1 | 1.084461 | 24   | DMU12+DMU11 | 0.807101 |
| 9    | DMU12+DMU5 | 1.081483 | 25   | DMU12+DMU7 | 0.766059 |
| 10   | DMU12+DMU13 | 1.0669225 | 26   | DMU12+DMU9 | 0.7471963 |
| 11   | DMU15 | 1.0601287 | 27   | DMU12+DMU2 | 0.7459129 |
| 12   | DMU8 | 1.0550204 | 28   | DMU12+DMU16 | 0.7315953 |
| 13   | DMU12+DMU3 | 1.0124882 | 29   | DMU12+DMU14 | 0.7100164 |
| 14   | DMU2 | 1.0123737 | 30   | DMU12 | 0.5761994 |
| 15   | DMU16 | 1.0032672 | 31   | DMU7 | 0.4499341 |
| 16   | DMU14 | 1      |

Table 3.8: Efficiency and Ranking after Strategic Alliances

Table 3.9. The Possible Alliance Partnership

| Virtual Alliance |  |
|------------------|--|
| DMU3             |  |
| DMU7             |  |
| DMU12            |  |
| DMU12+DMU3       |  |
| DMU12+DMU7       |  |

3.4. Forecasting Alliance Partnership Performance

The researchers use GM (1,1) model to predict the realistic input/output factors for the next four years 2014 to 2017. Following, the study takes the company DMU12 as example to understand how to compute in GM (1,1) model in period 2010-2013.

Net income of DMU12 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.

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

1st: Create the primitive series:

| \(X^{(0)}\) | \(X^{(0)}\) | \(X^{(0)}\) | \(X^{(0)}\) |
|------------|------------|------------|------------|
| (10636; 11795; 11763; 12026) | (10636; 22431; 34194; 46220) | (10636; 22431; 34194; 46220) | (10636; 22431; 34194; 46220) |

2nd: Perform the accumulated generating operation (AGO):

\(x^{(1)} = x^{(0)} + x^{(0)} = 10636\)

\(x^{(2)} = x^{(1)} + x^{(0)} = 22431\)

\(x^{(3)} = x^{(2)} + x^{(0)} = 34194\)

\(x^{(4)} = x^{(3)} + x^{(0)} = 46220\)
3rd: Create the different equations of GM (1, 1)
To find \( x(i) \) series, and the following mean obtained by the mean equation is:
\[
z(i)(2) = \frac{1}{2}(10636 + 22431) = 16533.5
\]
\[
z(i)(3) = \frac{1}{2}(22431 + 34194) = 28312.5
\]
\[
z(i)(4) = \frac{1}{2}(34194 + 46220) = 40207
\]

4th: Solve equations:
To find \( a \) and \( b \), the primitive series values are substituted into the Grey differential equation to obtain:
\[
\begin{align*}
11795 + a \times 16533.5 &= b \\
11763 + a \times 28312.5 &= b \\
12026 + a \times 40207 &= b
\end{align*}
\]

Convert the linear equations into the form of a matrix:
\[
B = \begin{bmatrix}
-16533.5 & 1 \\
-28312.5 & 1 \\
-40207 & 1
\end{bmatrix}, \quad \hat{\theta} = \begin{bmatrix}
a \\
b
\end{bmatrix}, \quad Y_N = \begin{bmatrix}
11795 \\
11763 \\
12026
\end{bmatrix}
\]

Let
\[
\begin{align*}
a & = \hat{\theta} (B^T B)^{-1} B^T Y_N \\
b & = \hat{\theta} (B^T B)^{-1} Y_N
\end{align*}
\]

Use the two coefficients \( a \) and \( b \) to generate the whitening equation of the differential equation:
\[
\frac{dx(i)}{dt} - 0.0097779 x(i) = 11584.1191
\]

Find the prediction model from Equation:
\[
X(i)(k + 1) = \left( X(i)(1) - \frac{b}{a} \right) e^{-ak} + \frac{b}{a}
\]
\[
x(i)(k + 1) = \left( 10636 - \frac{11584.1191}{-0.0097779} e^{-0.0097779a} + \frac{11584.1191}{-0.0097779} \right) e^{-0.0097779a k} - 1184721
\]

Substitute different values of \( k \) into the equation:
\[
\begin{align*}
k=0 & \quad x(i)(1) = 10636 \\
k=1 & \quad x(i)(2) = 22381.4468 \\
k=2 & \quad x(i)(3) = 34242.303 \\
k=3 & \quad x(i)(4) = 46219.7028 \\
k=4 & \quad x(i)(5) = 58314.7913 \\
k=5 & \quad x(i)(6) = 70528.7248 \\
k=6 & \quad x(i)(7) = 82862.6711 \\
k=7 & \quad x(i)(8) = 95317.8095
\end{align*}
\]

Derive the predicted value of the original series according to the accumulated generating operation and obtain:
\[
\begin{align*}
x(5) &= x(5) - x(4) = 12095.09 \quad -- forecasted for 2014 \\
x(6) &= x(6) - x(5) = 12213.93 \quad -- forecasted for 2015
\end{align*}
\]

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; 2017a; 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 | Error |
|--------|--------------|------------------|---------------------|------------------|---------------------|-------|-------|
|        |              |                  |                     |                  |                     |       |       |
| 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% |
| *f*    | --           | 12,095.09        | --                  | 11,894.50        | --                  | --    | --    |
| *f*    | --           | 12,213.93        | --                  | 12,026.00        | --                  | --    | --    |
| *f*    | --           | 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). High 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 |
|---------|--------------------------|--------------------|
| DMU₁    | 3.63%                    | 15.53%             |
| DMU₇    | 1.66%                    | 13.21%             |
| DMU₁₂   | 1.25%                    | 9.32%              |
| DMU₁⁺DMU₁₂ | 4.00%            | 23.15%             |
| DMU₁⁺DMU₁₂ | 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 2014 and 2015

| DMUs | INPUTS (USD Millions) | OUTPUTS (USD Millions) |
|------|-----------------------|------------------------|
|      | (1)Total Asset | (1)Total Income | (1)Total Liabilities | (0)Net Income | (0)Total Revenue |
|      | 2014     | 2015     | 2014     | 2015     | 2014     | 2015     | 2014     | 2015     | 2014     | 2015     |
| DMU1 | 1.162.17       | 1.297.88       | 770.72    | 461.27    | 745.03    | 1.123.91       | 3.751.19       | 4.146.44       | 76.48      | 83.03      |
| DMU2 | 3.382.145.285  | 3.439.07       | 5415.414835 | 539.53    | 784.746552       | 760.581       | 5631.45941       | 572.89      | 108.13       | 114.03     |
| DMU3 | 3.1371.0957    | 3.470.1       | 8624.084045 | 8742.69    | 2413.89553       | 2522.15       | 12095.0885       | 12213.93     | 1870.347483       | 1875.38     |
| DMU4 | 3.4280.55438   | 3.5744.6       | 8528.516234 | 7753.24    | 3039.86947       | 3110.24       | 15818.58351       | 16278      | 1946.403192       | 1957       |
| DMU5 | 3.6480.03396   | 3.7028.2       | 14039.83498 | 14222.7    | 3159.41932       | 3106.65       | 17727.1165        | 17904.14     | 1978.45784       | 1988.92     |

Table 3.13. Forecasted Results of Good-efficiency Companies in 2016 and 2017

| DMUs | INPUTS (USD Millions) | OUTPUTS (USD Millions) |
|------|-----------------------|------------------------|
|      | (1)Total Asset | (1)Total Income | (1)Total Liabilities | (0)Net Income | (0)Total Revenue |
|      | 2016     | 2017     | 2016     | 2017     | 2016     | 2017     | 2016     | 2017     | 2016     | 2017     |
| DMU1 | 1.449.43       | 1.618.68       | 313.15    | 199.61    | 1695.46   | 2557.67       | 4582.35     | 5066.29       | 90.13      | 97.84      |
| DMU2 | 3.558.79       | 3.661.38       | 5605.29   | 5702.71   | 772.603   | 784.814       | 5821.91     | 5919.54       | 120.246    | 126.792    |
| DMU3 | 3.5867.6317   | 3.7321.7       | 8862.93   | 8984.83   | 2292.18   | 2233.73       | 12333.95    | 12455.14      | 1880.42     | 1885.48    |
| DMU4 | 3.7271.1       | 3.8862.9       | 7022.84   | 6733.57   | 3182.23   | 3255.99       | 16750.3     | 17236.4       | 1967.65     | 1978.35    |
| DMU5 | 3.9424.0       | 4.0978.9       | 14463.7   | 14688.1   | 3054.76   | 3003.74       | 18156.2     | 18374.7       | 1999.45     | 2010.02    |

Next, a three-layer neural network model is utilized for the Earning Per Share (EPS) forecasting. The proposed neural network model consists of one input layer, one hidden layer, and one output layer, as shown in Figure 3.1. The inputs to the 5-3-1 neural network include total asset, operating cost, liabilities, net income and revenue. Its output is expected EPS of the companies involved in this research.

![Figure 3.1. A Three-layer Neural Network Model](image)

The first layer denoted as \( \alpha^{(1)} = (\alpha_1^{(1)}, \alpha_2^{(1)}, \alpha_3^{(1)}, \alpha_4^{(1)}, \alpha_5^{(1)})^T \), includes five nodes, and we call it the input layer because its nodes are formed by the covariate/features \( x = (x_1, x_2, x_3, x_4, x_5) \), so that \( \alpha^{(1)} = x \).

The hidden layer of this neural network is denoted as \( \alpha^{(2)} = (\alpha_1^{(2)}, \alpha_2^{(2)}, \alpha_3^{(2)})^T \). Its function is to compute the value of its nodes, and it is not perceived. This hidden layer has the components of \( \alpha^{(2)} \) are formulated by non-linear function applied to a linear combination of the nodes of the input layer, so that where \( g(x) = \frac{1}{1 + e^{-x}} \) is the sigmoid/logistic function.

The output layer to see the EPS estimating results is denoted as \( \alpha^{(3)} = (\alpha_1^{(3)}) \) because it returns the hypothesis function \( h_\theta(x) \) which is again a non-linear function applied to a linear combination of the nodes of the previous layer. Thus, \( a_j^{(i)} \) denotes the elements on layer \( j \), \( a_j^{(i)} \) denotes the \( j \)-th unit in layer \( j \), and \( \theta^{(i)} \) denotes the matrix of parameters controlling the mapping from layer \( j \) to layer \( j+1 \).

This neural network is first trained off-line to learn the dynamics of input and output variables. As mentioned in previous sections, the inputs and outputs are adopted from the past data and forecasted data of GM(1,1). Again, the
accuracy is very important factor to determine the training of this neural network in which each neuron is the reliable parameter tested by MAPE at the excellent level of accuracy. After defining parameters, several scenarios during the learning stage are presented to the network as the inputs. For each scenario, the network computes the predicted outputs based on the defined inputs and outputs. To avoid diverging on the network output, we adopt the sigmoid function of the following equation as the threshold limiter of the neural network:

\[ f(x) = \frac{1}{1 + e^{-x}} \]

Note that \( f(x) \) saturates at 0 and 1 when \( x \) approaches negative and positive infinity, respectively. However, \( f(x) \) holds approximately linear in most of the input space. Such a non-linearity is commonly adopted for the threshold functions (Principe et al., 2000). The results of EPS value from neural network are presented in Table 3.14.

Table 3.14. EPS Forecasted Results of Good-efficiency Companies in 2016 and 2017

| DMUs          | EPS             |
|---------------|-----------------|
|               | 2014 | 2015 | 2016 | 2017 |
| DMU_1         | 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 | 3.6755545 | 3.67475 | 3.67559 |
| DMU_7+DMU_12  | 3.49499994 | 3.5679273 | 3.56755 | 3.56583 |

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).

\[ \text{Earnings per Share (EPS)} = \frac{\text{NetIncome} - \text{Dividends on preferred Stock}}{\text{Average outstanding Shares}} \]

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 3.14 summarizes the results. We also note that these results are the calculations from the forecasting outputs (2014-2017) of GM(1,1) and neural network mentioned earlier.

Table 3.15. Efficiency Scores and Rankings of Virtual Alliance Companies

| DMUs          | Score | Rank | Score | Rank | Score | Rank | Score | Rank |
|---------------|-------|------|-------|------|-------|------|-------|------|
|               | 2014  | 2015 | 2016  | 2017 |
| DMU_1         | 1     | 5    | 4     | 1    |
| DMU_7         | 1.242957 | 2    | 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 3.15, 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 (2014-2017). DMU_3+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 research focuses on the relationship between strategic alliance and firms’ performance of green logistics industry by using GM (1,1), neural network and DEA model. The most important purpose of this study is to help the target company find the right partners for strategic alliance. In this research, DMU_12, one of the green logistics companies (listed in the 75 Green Supply Chain Partners in June, 2014) is employed to test whether the strategic alliance benefits exist if DMU_12 has alliances with other companies in the same industry and give the firms suggestions and the direction of improvement. After careful analyses both past, present and future evaluation in the section 4, the study finds out that the following companies: DMU_3 (Hub Group Inc.) and DMU_7 (Con-way Freight) are the good candidates for DMU_12 to have strategic alliances; in which the DMU_3 is strongly recommended. In addition, the research also indicates a possible ideal alliance partners for DMU_12. That is DMU_7. Strategic alliance is not only good for the DMU_3 but also good for the partners as well.
This is a new studying method in both academic research and practical applications by combining Grey theory, neural network and super-SBM-O-V model. The proposed method of this research not only forecasts some important business factors for green logistics providers, but also provides an accurate and appropriate evaluation of the industry at current situation. That could be useful information helping green logistics enterprises’ top managers to have effective decision making for business strategy (including alliance strategy) in the future. The result after strategic alliance provides a meaningful reference to help many other industries’ manager in finding the future candidates of strategic alliance.

Basing on the results of this study, the researchers conclude clearly alliances model, and methodology which bring up can also apply to the other industries to evaluate the strategic alliances partners’ selection, to enhance the overall competitiveness, and to avoid the wrong strategic alliances.

In actual alliances or union, the enterprises may have different considerations, such as the industry expansion, technology acquisition, market development, etc. As long as we can properly adjust the input and output factors through the method applied and the process established in this study, we can still get results with the reference value.

It also gives better insights in terms of understanding the performance and rankings of an industry. In our limitations of this research, researchers would like to contribute to implement the integrated research methodologies to provide meaningful and helpful results to the development of the industry. We would also suggest that this study could be considered to be a better model of performance analysis among the decision makers of variety of industries.

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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References
Blomqvist, K., Hurmelinna-Laukkanen, P., Nummela, N. and Saarenketo, S. (2008). The role of trust and contracts in the internationalization of technology-intensive Born Globals. Journal of Engineering and Technology Management, 25(1): 123-35.

Cantor, D. E., Morrow, P. C. and Montabon, F. (2012). Engagement in environmental behaviors among supply chain management employees: An organizational support theoretical perspective. Journal of Supply Chain Management, 48(3): 33-51.

Charnes, A., Cooper, W. W. and Rhodes, E. (1978). Measuring the efficiency of decision making units. European Journal of Operational Research, 2(6): 429-44.

Chia-Nan, W. and Ty, N. N. (2013). Forecasting the manpower requirement in Vietnamese tertiary institutions. Asian Journal of Empirical Research, 3(5): 563-75.

Crone, S. F., Hibon, M. and Nikolopoulos, K. (2011). Advances in forecasting with neural networks? Empirical evidence from the NN3 competition on time series prediction. International Journal of Forecasting, 27(3): 635-60.

Curry, B., Morgan, P. and Silver, M. (2002). Neural networks and non-linear statistical methods: an application to the modelling of price–quality relationships. Computers and Operations Research, 29(8): 951-69.

Das, T. K. and Teng, B. S. (2000). A resource-based theory of strategic alliances. Journal of Management, 26(1): 31-61.

Das, T. K. and Teng, B. S. (2001). A risk perception model of alliance structuring. Journal of International Management, 7(1): 1-29.
Giuffrida, M., Mangiaracina, R., Perego, A. and Tumino, A., 2016. "Logistics solutions to support cross border e-commerce towards China: The case of the apparel industry." In Workshop on Business Models and ICT Technologies for the Fashion Supply Chain (pp. 163-177). Springer, Cham.

Hansen, J. V. and Nelson, R. D. (2003). Forecasting and recombining time-series components by using neural networks. Journal of the Operational Research Society, 54(3): 307-17.

Kelly, M. J., Schaan, J. L. and Joncas, H. (2002). Managing alliance relationships: key challenges in the early stages of collaboration. R and D Management, 32(1): 11-22.

Mahmud, R. (2013). Financial statement analysis of Sonali bank limited. Available: http://dspace.bracu.ac.bd/xmlui/handle/10361/3607

McKinnon, A., Browne, M. and Whiteing, A. (2012). *Green logistics: Improving the environmental sustainability of logistics*. Kogan Page Publishers.

Mowery, D. C., Oxley, J. E. and Silverman, B. S. (1996). Strategic alliances and interfirm knowledge transfer. Strategic Management Journal, 17(S2): 77-91.

Nguyen, N. T. (2019). Optimizing factors for accuracy of forecasting models in food processing industry: A context of cacao manufacturers in vietnam. Industrial Engineering and Management Systems, 18(4): 808-24.

Nguyen, N. T. (2020a). Attitudes and repurchase intention of consumers towards functional foods in ho Chi Minh city, Vietnam. International Journal of Analysis and Applications, 18(2): 212-42.

Nguyen, N. T. (2020b). Performance evaluation in strategic alliances: A case of vietnamese construction industry. Global Journal of Flexible Systems Management, 21(1): 85-99.

Nguyen, N. T. and Tran, T. T. (2015). Mathematical development and evaluation of forecasting models for accuracy of inflation in developing countries: a case of Vietnam. Discrete Dynamics in Nature and Society, 15: Available: https://doi.org/10.1155/2015/858157

Nguyen, N. T. and Tran, T. T. (2017a). Optimizing mathematical parameters of Grey system theory: an empirical forecasting case of Vietnamese tourism. Neural Computing and Applications, 31(1): 1-15. Available: https://www.researchgate.net/publication/318160259_Optimizing_mathematical_parameters_of_Grey_system_theory_an_empirical_forecasting_case_of_Vietnamese_tourism

Nguyen, N. T. and Tran, T. T. (2017b). A novel integration of dea, gm (1, 1) and neural network in strategic alliance for the indian electricity organizations. Journal of Grey System, 29(2): 80-101.

Nguyen, N. T., Tran, T. T., Wang, C. N. and Nguyen, N. T. (2015). Optimization of strategic alliances by integrating DEA and grey model. Journal of Grey System, 27(1): 38-56.

Principe, J. C., Euliano, N. R. and Lefebvre, W. C. (2000). *Neural and adaptive systems: fundamentals through simulations*. John Wiley and Sons: New York. 119: 514.

Rogers, D. S. and Tibben-Lembke, R. S. (2001). An examination of reverse logistics practices. *Journal of Business Logistics*, 22(2): 129-48.

Seuring, S. and Müller, M. (2008). From a literature review to a conceptual framework for sustainable supply chain management. *Journal of Cleaner Production*, 16(15): 1699-710.

Spicer, A. J. and Johnson, M. R. (2004). Third-party demanufacturing as a solution for extended producer responsibility. *Journal of Cleaner Production*, 12(1): 37-45.

Stevenson, J. W. (2009). *Operations management*. 10th ednMcGraw-Hill companies.

Taylor, A. (2005). An operations perspective on strategic alliance success factors: An exploratory study of alliance managers in the software industry. *International Journal of Operations and Production Management*, 25(5): 469-90.

Thiell, M., Zuluaga, J. P. S., Montañez, J. P. M. and van Hoof, B., 2011. "Green logistics: Global practices and their implementation in emerging markets.” In *Green finance and sustainability: Environmentally-aware business models and technologies*. IGI Global. pp. 334-57.

Tone, K. (2001). A slacks-based measure of efficiency in data envelopment analysis. European Journal of Operational Research, 130(3): 498-509.

Trinh, H. X. P. and Tran, T. T. (2017). An analyzing case: Numbers of Taiwanese students and their expenditures by using grey system theory to forecast. International Journal of Advanced and Applied Sciences, 4(9): 35-45.

Tryon, R. C. (1929). The interpretation of the correlation coefficient. Psychological Review, 36(5): 419.

Wang, C. N., Nguyen, N. T. and Tran, T. T. (2014). The study of staff satisfaction in consulting center system-a case study of job consulting centers in ho chi minh city, vietnam. *Asian Economic and Financial Review*, 4(4): 472-91.

Zaheer, A., Gulati, R. and Nohria, N. (2000). Strategic networks. Strategic Management Journal, 21(3): 203.