Neural Computing and Applications (2019) 31:7963–7974
https://doi.org/10.1007/s00521-018-3639-2

ORIGINAL ARTICLE

Raising opportunities in strategic alliance by evaluating efficiency of logistics companies in Vietnam: a case of Cat Lai Port

Nhu-Ty Nguyen[1] · **Thanh-Tuyen Tran**[2]

Received: 20 July 2017 / Accepted: 13 July 2018 / Published online: 19 July 2018

Abstract

The current context of Vietnam is that Vietnam is a developing country whose geographical shape is long and dynamic. Its logistics is also in the way of development and promising to have good potential. However, lack experience and technology, small and fragmented operation, fierce price competition among local enterprises, domination from foreign logistics giants are that factors that may hinder the growth of the local sector. It is then believed that cooperation among local firms could promote integration of the supply chain, making it more productive and so increase competitiveness of the industry. The study was conducted to evaluate the efficiency of Vietnamese transportation and logistics firms using Malmquist Productivity Index, crafting a clearer picture of how these firms performed in terms of technical efficiency and innovation. Cat Lai Port being a key role in the industry was taken as a case to analyse strategic alliance opportunities using data envelopment analysis and Grey forecasting. Research findings indicate that half of the samples experienced efficiency progress, half experienced performance regress; most of efficiency improvement came from innovation. The study also found that strategic alliances between Cat Lai Port and some firms potentially improve these firms' efficiency.

Keywords Efficiency · Strategic alliance · Logistics · Malmquist · DEA · GM(1,1)

1 Logistics in Vietnam

Over the past 20 years, Vietnam has attained a strong track record of economic growth. Benefited from favourable geographical location and political stability, it has been experiencing rapid industrialization and stronger global connectivity. The AFTA roadmap of reducing tax to 0 per cent and the rollout of ASEAN Economic Community in 2015 has accelerated the trade of goods between the country and the world. The increases in goods trade are boosting the demand for transportation in terms of volume and service quality. The logistics industry in Vietnam is therefore becoming more promising and projected to develop rapidly through the decade.

Yet, *logistics operations* in Vietnam are costly compared to China, Malaysia, and Thailand, primarily because of the unpredictability in supply chain, making business enterprises carry more inventory than needed [39]. Logistics costs account for up to 20.8% per cent (US$38.85bn) of GDP in Vietnam in 2015 [28]. As stated by Mr. Bui, Deputy General Director of Vietnam National Maritime Bureau [35], the transportation facilities and service quality of the local transportation and logistics companies failed to fully meet the requirements from the traders. *The local industry is, in fact, weak and fragmented.* Most of the transport service providers are small and medium enterprises. There are estimated 1200 logistics and transportation enterprises in Vietnam, accounting for, however, only 20% of the industry's total revenue [26]. As the market opened for foreign firms to establish joint venture with the local in 2007 and 100 per cent foreign-owned logistics business in 2012, the local industry has been rapidly dominated by several foreign shipping giants.

Nhu-Ty Nguyen and Thanh-Tuyen Tran have contributed equally to this work.

✉ Nhu-Ty Nguyen
nhutynguyen@hcmiu.edu.vn

Thanh-Tuyen Tran
copcoi2@gmail.com

1 School of Business, International University – Vietnam National University HCMC, Quarter 6, Linh Trung Ward, Thu Duc District, Ho Chi Minh City, Vietnam

2 Scientific Research Office, Lac Hong University, No. 10 Huynh Van Nghe, Bien Hoa City, Dong Nai Province, Vietnam

Vietnam government has only been concentrating on improving infrastructure, which is reflected in various national modal transport development plans. However, logistics is not only pure transportation system but a well-integrated system of trading and movement of goods. Integration in transportation and logistics has long been proved to be the key to achieve optimized performance. Global carrier shipping alliances like 2M, Ocean Alliances, and The Alliance (see [11]) are typical examples of how resources are pulled together to extend service offerings and geographic coverage. It is believed that the cooperation within the local transportation and logistics enterprises will drastically help improve their performance to compete against foreign firms.

Cat Lai Port is one of the dominant ports of Vietnam. Located in the southern hub, it is the only port that frequently runs on full capacity with the ability to accommodate up to 4.2 million TEUs per year. This study has chosen Cat Lai Port to be the target firm to establish alliances with other transportation and logistics entities since it has much potential in sharing operation, information, technology, and experience with other partners.

The industry has very promising growth, yet the operation is of high cost. There is a large quantity of small local enterprises whose services are fragmented and unsustainable. Fierce competition among local enterprises plus competition from foreign firms whose experience and resources are more abundant are deterring the growth potential of the industry. The study identifies these research questions as the problems to solve and the purposes of the research:

1. Are Vietnamese logistics firms operating efficiently?
2. Which are their sources of (in)efficiency?
3. Can strategic alliances help Cat Lai Port improve its operational efficiency?

2 Research development

2.1 Operational efficiency

Operational efficiency (OE) as defined by Lee and Johnson [18] is the ability to deliver products and services effectively without sacrificing quality. To a well-known definition of Farrell [10] in the context of production efficiency research, technical efficiency (to be distinguished with a locative efficiency) means producing maximum outputs given an amount of inputs and alternatively, using the minimum inputs given an amount of output production [1].

Towards measuring OE, there are absolute and the relative approach [18]. Absolute Operational Efficiency compares actual performance with ideal performance in perfect conditions. This measurement gives accurate insights of the efficiency level the unit achieves over its potential. However, it is not easy to manipulate perfect condition.

$$\mathrm{AOE} = \frac{\text{actual throughput}}{\text{ideal throughput(in perfect condition)}}$$

Relative operational efficiency measurement benchmarks actual performance against the best practices that are observable and that happen under the same operational conditions. The insights into this approach could be practically applied since its desired performance is achievable within the current condition.

$$\mathrm{ROE} = \frac{\text{actual throughput}}{\text{best observed throughput}}(\text{same operational condition})$$

Lee and Johnson [18] incorporate the notion of output/input ratio in productivity measurement to define efficiency.

$$\text{productivity} = \frac{\text{output}}{\text{input}}$$

$$\text{efficiency} = \frac{\text{productivity}}{\text{produtivity of best practice}}$$

Data envelopment analysis (DEA), as employed by this paper, is one among many approaches to evaluate relative operational efficiency using observed inputs and outputs of a set of firms to create a benchmark against which performance of each firm is estimated.

The author would like to remark that the paper will employ input-oriented approach in measuring logistics' firm efficiency. Since the market potential for Vietnamese logistics companies stall given the low competitiveness (e.g., high cost) in product and service offerings, the chance for output maximization is limited. In evaluation of past and current performance, the author believes that it should be seen from the point of how these companies have performed in terms of reducing costs given such amount of output production.

2.2 Strategic alliance

A strategic alliance is interdependence between two or more business parties, in which (1) these parties remain legally independent, (2) they share resources, managerial control, and rewards over the cooperative domains, and (3) they make continuing contributions in one or more strategic areas, such as technology or products [40].

Common motives towards strategic alliance formation include market seeking, utilizing distribution, acquiring skills and technology, which are diversifying into new business, cost and risk sharing, achieving economies of scale, suppressing competition, and overcoming legal barriers [29].

Strategic alliance model proposed by Vyas et al. [36] identifies critical characteristics of a successful alliance: (1) Goal compatibility—partners should move towards similar direction, (2) Synergy—by taking advantages of each partner, joint activities should bring more value than the sum of individuals, (3) Value chain—what complementary value the parties will bring to the alliance, and (4) Balancing contribution—no partner dominates the alliance.

Joint ventures, equity investments cooperatives, R&D consortia, strategic cooperative agreements, cartels, franchising, licensing, and subcontractor networks are some representative forms of strategic alliances. (See [29].) Bowersox [2] showed some best practices of strategic alliance in logistics in the USA, one case of which is the coordinated container rail service of American President Companies with vendors, four railroads and Mexican customs officials to pick up parts and components on just-in-time basis without delay in clearance to have a smooth flow of sequenced parts delivered to Ford Motor's auto assembly plant in Mexico. Some seaports in European also reported benefits from joint traffic management system to exchange information, coordinative marketing and sourcing of services and equipment, and port integration via joint ventures to share assets and governance [12].

2.3 Grey system theory and GM(1,1)

Forecasting is predicting future based on past and present collection of data. In business, estimation of future events can help managers evaluate different scenarios to make decisions and plan resources most effectively. Different tools have been used in forecasting in different areas of natural and social science, depending on the nature of the problem and characteristics of the data set [22, 33]. Grey system theory, originated by Julong [16], is an especially effective statistical approach in data environment characterized by incomplete and uncertain information. Superior to conventional model, Grey forecasting model can give reasonable forecasting results over limited quantities of data. Grey time series forecasting applies GM(1,1) model to predict where and how forecasted events would appear. GM(1,1) establishes a differential equation using a raw data series with only one variable, enabling the maximized density of information in the model (see [17]). GM(1,1) has been applied to a variety of scientific domain such as environment [27], meteorology [14], economics [3], business [8, 15], and social [20].

In order to eliminate the uncertainty of the primitive data, smooth the randomness, the new data sequence is generated from the limited original data via the accumulating generation operation (AGO). After that, the differential equation is solved to obtain the n-step ahead predicted value of system. Finally, by using the predicted value, the inverse accumulation generation operation (IAGO) is applied to find the forecasted value from the original data.

The grey model prediction is a local curve fitting extrapolation scheme. At least four data sets are required to obtain reasonable accuracy.

We have a raw non-negative sequence denoted by:

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

n sample size of the data.

The accumulated generation operation (AGO) is obtained:

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

where

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

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

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

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

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

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

From the AGO sequence $X^{(1)}$, a GM(1,1) model which corresponds to the first order different equation $X^{(1)}(k)$ can be constructed as follows:

$$\frac{\mathrm{d}X^{(1)}(k)}{\mathrm{d}k} = aX^{(1)}(k) = b, \tag{6}$$

where parameter a is developing coefficient and b is grey input.

In practice, a and b are not calculated directly from the above equation. The solution, on the other hand, is obtained by applying the least-squares method. That is,

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

where $X^{(1)}(k+1)$ denotes the prediction X at time point $k+1$ and the coefficient $[a, b]^{\mathrm{T}}$ can be obtained by the ordinary least-squares (OLS) method:

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

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

where Y is the data series, B is the data matrix, and $[a, b]^{\mathrm{T}}$ is the parameter series.

$\hat{X}$ is obtained from (7). Let $\hat{X}^{(0)}$ be the fitted and predicted series:

$$\hat{X}^{(0)} = X^{(0)}(1), \hat{X}^{(0)}(2), \ldots \hat{X}^{(0)}(n), \quad (9)$$

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

Then apply the inverse accumulated generation operation (IAGO):

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] \mathrm{e}^{-ak}(1 - \mathrm{e}^{a}). \quad (10)$$

2.4 Data envelopment analysis (DEA)

Data envelopment analysis (DEA) proposed by Charnes et al. [5] following the frontier line-based measurement originated by Farrell [10] is a prevalent tool to measure efficiency and productivity. A group of decision-making units (DMUs) forms a production productivity set from which the efficient frontier can be determined to measure the relative efficiency of each DMU. DEA technique therefore could provide a reference set or benchmarks against which non-frontier (inefficient) units can be measured and compared [7]. Efficiency is measured with multiple inputs and multiple outputs expressed in linear combinations being converted to single virtual input and output; then the efficiency frontier is determined by the ratio of two linear combinations.

DEA has been developed through time with different modification in models. Non-radial models, representative of which is slacks-based measure (SBM) by Tone [31], allows computation of input excess and output shortfall (slacks). The early models return the same score (equal 1) for all units in the efficient frontier; as a result, they are incapable of discriminating performance of efficient DMUS. The necessity to ranking efficient DMUs then led to the development of several super-efficiency models. Super-SBM model promoted by Tone [30] does this by measuring the nearest distance of the target DMU to the efficient frontier excluding the target DMU.

The application of Grey forecasting and DEA to propose strategic alliances has appeared in several empirical studies in electrical industry [25], online game industry [37], and banking. DEA is run on the predicted data of virtual alliances, which are the sum of predicted input and output data of DMUs paired. The ranking results then help identify which alliances have improved performance compared to performance of individual coordinators.

The Malmquist Productivity Index, based on DEA models, measures the productivity changes over time. The so-called Malmquist Index is originally a quantity index, defined in a consumer theory context. It then has further been studied and developed in the nonparametric framework by several authors [19, 24, 32]. Caves et al. [4] developed the Malmquist Productivity Index by calculating the geometric means of two Malmquist Productivity Indices defined for translog technologies. Färe et al. [9] merged the efficiency measurement presented by the Farrell [10] and the measurement of productivity presented by the Caves et al. [4] to develop the Malmquist Productivity Index which is directly measured from the data of input and output in nonparametric setting using the DEA.

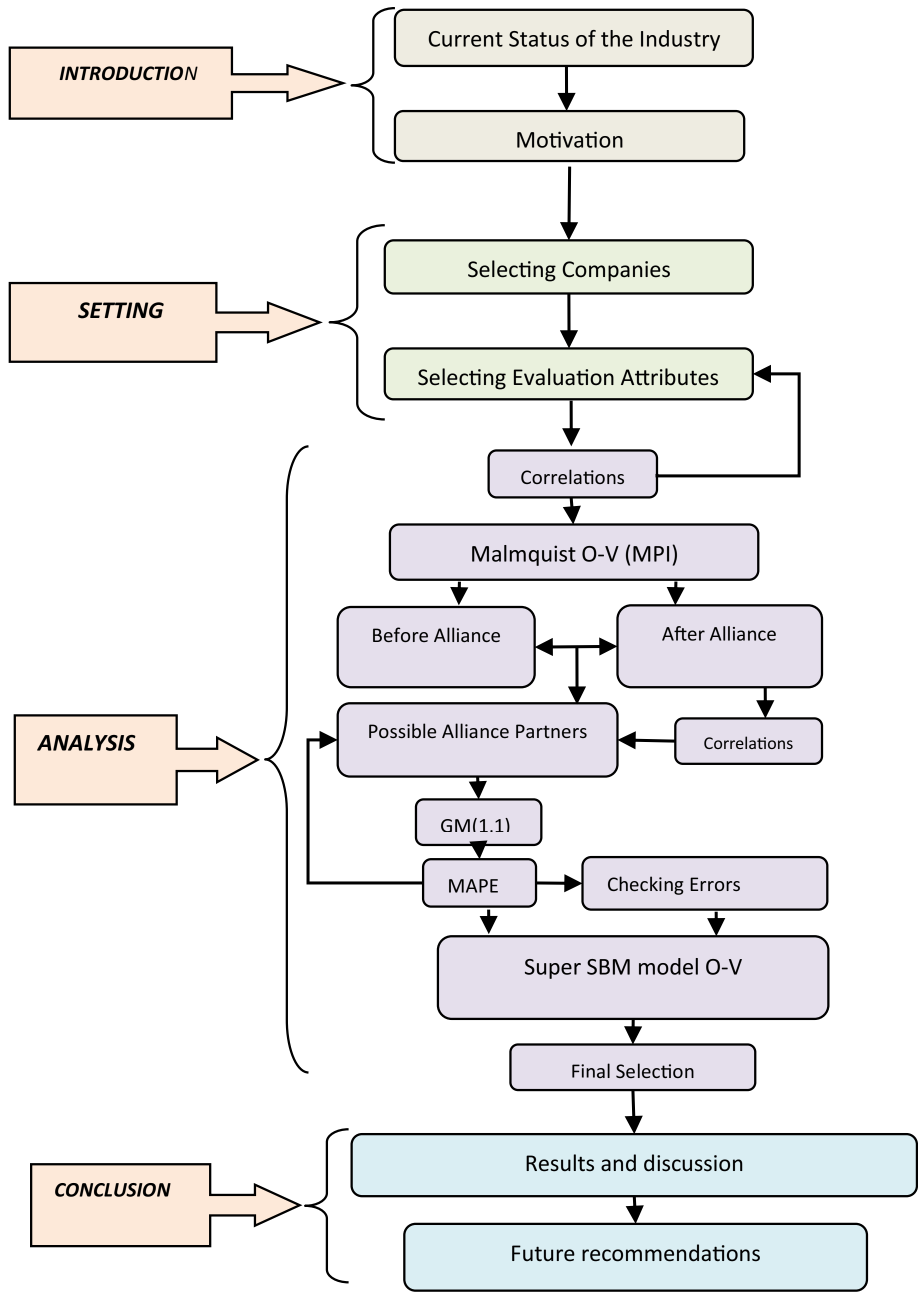
2.5 Research process

Figure 1 illustrates the step-by-step process to conduct the study. The preparation step includes the collection of input and output data of a set of DMUs. This step should be conducted carefully to help reflect the nature of the problem objectively while securing the model assumptions. At stage 2, we examine companies' productivity of over the past 5 years using Malmquist Index measurement. Heading to prediction stage, we apply GM(1,1) to forecast future factor values of DMUs for year 2017 using the data series collected at stage 1; we then apply MAPE to test forecasting accuracy. At this stage, if forecasting errors are high, a review of input and outputs factors is needed to eliminate outliers. All of the input and out factors are forecasted for the future values, which then are re-evaluated by using the Super-SBM model (DEA) for further analysis. We have to test the errors of the values. At the third stage, Pearson correlation test is performed as the setting stage for DEA. Factors are also reviewed if they fail to give desired results. DEA is performed with DEA-Solver 5.0 software by Saitech Company on the forecasted data of original DMUs and virtual alliances. Results of Sects. 2 and 4 will propose direction for efficiency improvement as well as which alliances can be formed between the target DMU and other DMUs.

2.6 Data preparation

Logistics and transportation industry, as of scope of this study, is characterized by certain activities: freight and multi-modal transportation, storage and warehousing, ICD service, maritime cargo handling, custom clearance, shipping agent and brokerage, and other auxiliary services. Since DEA is a benchmarking technique, DMUs set should be a homogeneous group performing similar tasks

Fig. 1 Research Process



under the same market condition [13]. Forty-nine companies listed in stock market in Transportation and Warehousing industry were screened, only 10 of which have solid scope of business relative to our definition; their side business such as real estate, education, direct import–export if any must account for less than 10% of their revenue.

A common rule of thumb is that the quantity of DMUs should be at least twice the number of input and output factors [13]. We first chose *total assets, liability*, and *cost of goods sold* as input factors; and *revenue* and *operating profit* as output factors. We believe these factors well reflect the essential business resources and outcomes of the respective industry.

Data of 10 DMUs (including the target DMU—Cat Lai Port) over 6 consecutive years (2011–2016) are collected from their audited financial reports. Since Grey forecasting requires non-negative data sequence; besides, the handling of negative data in this field is still missing, we will eliminate DMU10 with negative *operating profit* over the whole period and negative data of year 2011 of DMU1. As a result, there remains 9 DMUs, eight of which have appropriate data over 2011–2016 and one of which (DMU1) have appropriate data over 2012–2016.

Table 1 DMU list | * Target DMU

Assigned code	Company name	Stock market code (stock exchange)
DMU1	Gemadept Corporation	GMD (HOSE)
DMU2	Vietnam Ocean Shipping Agency Corporation	VSA (HNX)
DMU3	Doan Xa Port Joint Stock Company	DXP (HNX)
DMU4	Vietnam Container Shipping JSC	VSC (HOSE)
DMU5	Tan Cang Logistics & Stevedoring JSC	TCL (HOSE)
DMU6	Dinh Vu Port	DVP (HOSE)
DMU7	Hai An Transport & Stevedoring JSC	HAH (HOSE)
DMU8*	Cat Lai Port	CLL (HOSE)
DMU9	Hai Minh Corporation	HMH (HNX)

From this point, we will be running Malmquist for nine companies over 5-year data (2012–2016). Grey forecasting is performed for DMU1 using 5-year data (2012–2016) and for the remaining DMUs using 6-year data (2011–2016). Data envelopment analysis on virtual alliances is then run on the forecasted data of year 2017 (the results from Grey forecasting).

Table 1 shows the list of nine DMUs involved in our analysis.

3 Research results

3.1 Performance evaluation

Table 2 shows the Malmquist Productivity Indices of companies over 5-year period and their sources of efficiency. Half of the set experienced progress; half remaining experienced regress in efficiency. Most of the companies have their catch-up capability unchanged or degraded. The sources of efficiency, on the other hand, come mostly from technological innovation.

Only two DMUs (5 and 7) reflect their improvement in efficient operation (catch-up effect > 1). Meanwhile, most efficiency gain is attributed to technology application (DMU2, DMU3, DMU6, DMU7, DMU9 with frontier shift effect > 1).

Our target DMU8* exhibit regress in both technical efficiency (catch-up = 0.9723) and innovation (0.9826).

Company with the most progressed efficiency, DMU6 has significant improvement in frontier shift (1.2568), while the catch-up capability keeps steady (1.000).

3.2 Forcasted data of year 2017

Grey forecasting is performed on input and output data of 9 DMUs to return the forecasted value of year 2017. Tables 3 and 4 show the forecasted data by two different methods (i.e. Grey forecasting and moving average) to see the differences between them

Table 2 Malmquist Productivity Index from 2012 to 2016 *Target DMU

	Catch-up	Frontier shift	Malmquist Index
DMU1	1	0.9866	0.9866
DMU2	1	1.0346	1.0346
DMU3	1	1.0080	1.0080
DMU4	0.9993	0.9362	0.9355
DMU5	1.0018	0.9445	0.9505
DMU6	1	1.2568	1.2568
DMU7	1.0143	1.0041	1.0184
DMU8*	0.9723	0.9826	0.9550
DMU9	1	1.0164	1.0164
Average	0.9986	1.0189	1.0180
SD	1.0143	1.2568	1.2568

DMU2, DMU3, DMU6, DMU7, and DMU9 record positive efficiency change (MI > 1)

DMU8* (Cat Lai Port) and the remaining DMU1, DMU4, DMU5 experienced efficiency loss during 2012–2016 (MI < 1)

We also perform inverse forecasting to return forecasted data of year 2011–2016 (year 2012–2016 for DMU1), then compare these predicted values with original data to test forecasting reliability.

Mean absolute per cent error (MAPE) is used to measure forecasting accuracy in a fitted time series value [21]:

$$\mathrm{MAPE} = \frac{1}{n}\sum \frac{|\mathrm{Actual} - \mathrm{Forecast}|}{\mathrm{Actual}} \times 100(28)$$

n is the number of forecasting steps

MAPE results indicate 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 [6, 21, 23, 34]. We also try to make some comparisons for better insights of GM(1,1) applicable to this topic. We use the moving

Table 3 Forecasted data of year 2017 ($1000) by GM(1,1)

	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating profit
DMU1	484,681.43	134,056.71	211,332.34	192,802.49	31,712.69
DMU2	30,527.17	38,475.73	12,585.60	42,642.66	1880.29
DMU3	15,275.50	3304.84	934.96	5145.65	2035.62
DMU4	137,044.89	30,969.38	55,487.14	50,221.98	14,742.46
DMU5	38,215.36	25,074.84	10,748.54	32,151.30	5396.04
DMU6	53,259.65	16,130.77	5953.97	30,974.63	16,258.36
DMU7	57,131.97	15,269.72	26,807.81	30,419.25	9477.90
DMU8*	34,131.18	10,035.50	4340.54	14,890.83	4680.85
DMU9	13,512.10	4614.23	710.53	7371.33	1753.94

Table 4 Forecasted data of year 2017 ($1000) by Ma

	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating profit
DMU1	493,681.14	142,135.32	221,457.1	201,238.6	32,567.56
DMU2	31,023.17	39,475.73	13,425.12	42,642.66	1456.6
DMU3	14,158.12	3526.74	934.52	5145.65	2018.96
DMU4	132,123.20	31,258.24	56,348.21	50,221.98	15,486.21
DMU5	38,485.32	24,568.96	11,235.42	32,456.21	5458.21
DMU6	51,253.12	14,587.26	58,969.89	31,485.59	15,638.56
DMU7	57,131.97	16,587.52	26,807.81	30,419.25	9578.63
DMU8*	312,345,23	11,253.12	4340.54	15,789.63	4536.89
DMU9	23,512.10	4857.25	711.23	7454.21	1758.24

average (MA) of three to make forecasting. The moving average demonstrates good trend when its forecasts with lower level of error (see Table 5). 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 Table 5. 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).

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 6 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

Table 5 Sample forecasting results and errors

Series	Original (1)	GM prediction (2)	Residual error (2-1)	MA Prediction (3)	Residual error (3-1)	Error $\frac{\lvert(1-2)\rvert}{2} \times 100\%$	Error $\frac{\lvert(1-3)\rvert}{3} \times 100\%$
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

Table 6 MAPE

	MAPE (%) of GM(1,1)	MAPE (%) of MA
DMU1	8.00	12.3
DMU2	7.86	14.21
DMU3	12.06	25.12
DMU4	7.38	10.58
DMU5	6.31	9.58
DMU6	3.20	5.36
DMU7	18.28	52.23
DMU8*	12.15	14.10
DMU9	17.77	30.12
Average MAPE	10.33	19.29

only 3.2 and 18.28% 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 10.3%; at this category, it takes to 19.29% 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 6):

Table 6 presents MAPE of forecasted data of year 2011–2016 (year 2012–2016 for DMU1). Average MAPE = 10.33% indicates "Good" accuracy. Grey method is therefore a reliable predicting tool and forecasted data of year 2017 will be brought to further stage for alliance performance analysis.

4 Alliance performance

4.1 Correlation test

Data envelopment analysis (DEA) assumes isotonicity relations between the analysed factors, i.e. an increase in any input should not lead to a decrease in any output [13]. As a result, Pearson correlation test is performed as a precondition of DEA.

Tables 7 and 8 show that there are strong positive correlations among factors (coefficient $r > 0.8$, p value ≤ 0.05, significance level alpha = 0.05). Thus, data is validated to enter DEA.

4.2 Virtual alliances

Target DMU8* Cat Lai Port is paired with each of the remaining DMUs to form virtual alliance. The sum of input and output factors demonstrates data of these alliances (see Wang et al. [38]).

We denote DMU8j as the virtual alliance company between DMU8 and DMUj (Tables 9 and 10).

4.3 Alliance performance

DEA returns scores to rank performance of each DMU. Potential virtual alliances are those with:

- Score > 1 indicating efficient units
- Ranking higher than of its component companies.

DMU81 encounters infeasible solution problem. Infeasible linear programme is a common issue and is a special research area in DEA. The author will omit handling of this issue in this paper and exclude alliance DMU81 off the research conclusion (Tables 11 and 12).

Table 7 Correlation matrix (year 2016)

Variables	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating income
Total asset	1	0.961	0.998	0.980	0.883
Cost of goods sold	0.961	1	0.967	0.994	0.807
Liabilities	0.998	0.967	1	0.982	0.858
Net revenue	0.980	0.994	0.982	1	0.862
Operating income	0.883	0.807	0.858	0.862	1

Table 8 Correlation matrix (year 2017)

Variables	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating profit
Total asset	1	0.963	0.997	0.983	0.913
Cost of goods sold	0.963	1	0.967	0.994	0.836
Liabilities	0.997	0.967	1	0.984	0.889
Net revenue	0.983	0.994	0.984	1	0.887
Operating profit	0.913	0.836	0.889	0.887	1

Table 9 List of DMUs and virtual alliances (year 2016—thousand US dollars)

	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating profit
DMU1	444,343.81	120,109.15	185,629.30	164,625.87	25,162.36
DMU2	27,214.02	33,896.41	11,701.35	37,906.39	1334.06
DMU3	14,537.99	2883.05	892.61	4672.05	2115.94
DMU4	105,243.10	30,129.22	38,715.86	47,505.44	13,636.87
DMU5	36,733.27	29,644.73	10,943.81	36,047.97	5007.78
DMU6	46,959.46	14,569.34	6859.47	27,441.62	13,871.88
DMU7	42,419.65	10,133.88	17,201.98	21,403.93	6482.03
DMU9	12,619.52	4209.70	972.32	5090.55	1464.48
DMU8*	29,580.36	7700.90	4291.77	12,629.58	4426.23
DMU81	473,924.17	127,810.05	189,921.07	177,255.45	29,588.59
DMU82	56,794.38	41,597.31	15,993.11	50,535.97	5760.29
DMU83	44,118.35	10,583.95	5184.37	17,301.63	6542.17
DMU84	134,823.47	37,830.12	43,007.63	60,135.02	18,063.10
DMU85	66,313.63	37,345.63	15,235.58	48,677.55	9434.01
DMU86	76,539.83	22,270.24	11,151.23	40,071.20	18,298.11
DMU87	72,000.02	17,834.78	21,493.75	34,033.51	10,908.26
DMU89	42,199.89	11,910.60	5264.09	17,720.13	5890.71

Table 10 List of DMUs and virtual alliances (year 2017—thousand US dollars)

	Total asset	Cost of goods sold	Liabilities	Net revenue	Operating profit
DMU1	484,681.43	134,056.71	211,332.34	192,802.49	31,712.69
DMU2	30,527.17	38,475.73	12,585.60	42,642.66	1880.29
DMU3	15,275.50	3304.84	934.96	5145.65	2035.62
DMU4	137,044.89	30,969.38	55,487.14	50,221.98	14,742.46
DMU5	38,215.36	25,074.84	10,748.54	32,151.30	5396.04
DMU6	53,259.65	16,130.77	5953.97	30,974.63	16,258.36
DMU7	57,131.97	15,269.72	26,807.81	30,419.25	9477.90
DMU9	13,512.10	4614.23	710.53	7371.33	1753.94
DMU8*	34,131.18	10,035.50	4340.54	14,890.83	4680.85
DMU81	518,812.61	144,092.22	215,672.88	207,693.32	36,393.55
DMU82	64,658.35	48,511.23	16,926.14	57,533.49	6561.15
DMU83	49,406.68	13,340.35	5275.50	20,036.48	6716.47
DMU84	171,176.07	41,004.89	59,827.68	65,112.81	19,423.31
DMU85	72,346.54	35,110.35	15,089.08	47,042.14	10,076.89
DMU86	87,390.84	26,166.27	10,294.51	45,865.47	20,939.21
DMU87	91,263.15	25,305.23	31,148.35	45,310.08	14,158.75
DMU89	47,643.29	14,649.73	5051.07	22,262.16	6434.79

Table 13 summarizes the author's proposal on which alliances should be formed. Virtual alliance DMU86 and DMU87 both have score > 1 and ranking higher than rankings of its component companies alone. In other words, performance of these companies is improved through the alliances. Hence, we recommend target DMU8* to form alliance with DMU6 and DMU7.

In year 2016, the alliance DMU82 only benefits DMU8* but not DMU2 (unbalanced alliance). However, DEA ranking in year 2017 indicates the alliance DMU82 may benefit both parties. Thus, we conclude that an alliance between DMU8* and DMU2 is potential.

On the other hand, performance of the alliance DMU85 degrades from 1.019 (efficient) in year 2016 to 0.895 (inefficient) in year 2017. The cooperation between DMU8* and DMU5 is therefore risky.

Performance of the alliances DMU84, DMU89, and DMU83 is all below efficiency level (score < 1), thus they are not recommended.

Table 11 Performance ranking of alliances (year 2016)

Rank	DMU	Score	Is the alliance performance efficient and better than its component companies?
1	DMU86	2.586	Yes
2	DMU3	1.361	
3	DMU6	1.217	
4	DMU2	1.148	
5	DMU82	1.127	No
6	DMU9	1.074	
7	DMU7	1.043	
8	DMU85	1.019	Yes
9	DMU87	1.010	Yes
10	DMU81	1.000	Unconcluded
11	DMU5	0.971	
12	DMU1	0.965	
13	DMU84	0.953	No
14	DMU8*	0.824	
15	DMU83	0.811	No
16	DMU89	0.803	No
17	DMU4	0.779	

Table 12 Performance ranking of alliances (year 2017)

Rank	DMU	Score	Is the alliance performance efficient and better than its component companies?
1	DMU86	2.972	Yes
2	DMU9	1.432	
3	DMU82	1.337	Yes
4	DMU6	1.306	
5	DMU2	1.205	
6	DMU3	1.155	
7	DMU7	1.013	
8	DMU87	1.006	Yes
9	DMU81	1.000	Unconcluded
10	DMU1	0.970	
11	DMU85	0.895	No
12	DMU5	0.885	
13	DMU89	0.805	No
14	DMU84	0.788	No
15	DMU83	0.727	No
16	DMU8*	0.714	
17	DMU4	0.648	

5 Conclusion

Logistics in Vietnam is in tough yet promising stage. Our geographic location in the international routes of goods flow has so much potential to be leveraged. The recovery of global economy and deeper business integration of the country with the world, the shift of manufacturing hub from China towards South East Asia has facilitated goods trade in the region. Consequently, everyone wants part of the pie. The invasion of foreign carriers and logistics companies has yet to eat up a major part of the market. Thousands of small enterprises were established with fragmented service. Some major local players, who are most potential to represent the local industry struggle in between: foreign competitors have better technology, experience and relationship with large production corporation; small local logistics enterprises try to attract clients by dumping the fees, creating price pressure for the whole market. Our service is costly because we have so many players yet fail to make the most out of individual resources. Therefore, we need an evaluation of our strength, weakness, and potential to cooperate and help improve mutual efficiency.

Table 13 Alliance performance summary

Virtual alliance	Comments
DMU86	Good
DMU82	Potential
DMU87	Good
DMU81	Unconcluded
DMU85	Risky
DMU84	Bad
DMU89	Bad
DMU83	Bad

The study has pointed out the sources of (in)efficiency of local firms, among which some have better innovation (represented by the frontier shift effects) and most have no significant improvement in technical efficiency (the degree to which a company can catch up with the frontier companies). Our target company, Cat Lai Port, is falling behind both in terms of innovation and technical efficiency. Strategic alliance between Cat Lai Port and Dinh Vu Port, Vietnam Ocean Shipping Agency, HaiAn Transport & Stevedoring, and Tan Cang Logistics would help improve the firm's performance. Mutual benefits can be gained through technology transfer, information exchange, cooperative marketing, shared resources, leveraged governmental relationship, increased bargaining power with suppliers, widen geographical coverage, linkage of service offerings, etc.

Each of these companies has its own strength and shortage leaving many opportunities to complement and support each other. The cooperation between logistics companies plays a key role to promote a coherent integration in the supply chain and to increase competitiveness of the local industry.

The paper sheds lights for a decision-making approach that involves not only qualitative evaluation, but also quantitative evidence. Performance of strategic alliances from operational perspective, with insights taken further to forecasted future, will provide managers with more information to be considered when making decisions.

Strategic alliance between Vietnamese logistics companies is, however, not something happens overnight. The integration within an industry requires management efforts of enterprises as well as direction and support from the authorities. The study has helped boosting the option into consideration by giving evidence that the opportunity to improve performance efficiency is promising through strategic alliances.

6 Limitation

The size of the study is relatively small, considering the number of companies involved in the study compared with the number of companies in the industry. Missing data also led to elimination of some major companies. Limited time and resources did not allow the author to investigate further into non-financial information.

7 Research recommendation

The author would like to propose further research studies that help promote deeper insights for management decision and policy making. A bigger sample size of research is to representatively evaluate the whole local logistics industry. Data represent input and output production may subject to physical units than monetary market value to avoid price effects. It seems that most local companies want to expand internationally, so a study involving logistics companies in the region may fill this gap.

Acknowledgements The authors would like to thank Ms. Nguyen Hai Ngoc, an undergraduate student from the bachelor program in Business Administration, School of Business, International University – Vietnam National University, HCMC for her editorial assistance.

Compliance with ethical standards

Conflict of interest The authors declare that there is no conflict of interests regarding the publication of this paper.

References

1. Arena P, Fazzino S, Fortuna L, Maniscalco P (2003) Game theory and non-linear dynamics: the Parrondo paradox case study. Chaos Solitons Fractals 17(2–3):545–555
2. Bowersox DJ (1989) Leading edge logistics—competitive positioning for the 1990s. Council of Logistics Management, Oak Brook, Illinois. https://hbr.org/1990/07/the-strategic-benefits-of-logistics-alliances. Accessed June 2017
3. Camelia D (2015) Grey systems theory in economics–bibliometric analysis and applications' overview. Grey Syst Theory Appl 5(2):244–262
4. Caves DW, Christensen LR, Diewert WE (1982) The economic theory of index numbers and the measurement of input, output, and productivity. Econ J Econ Soc 50(6):1393–1414
5. Charnes A, Cooper WW, Rhodes E (1979) Measuring the efficiency of decision-making units. Eur J Oper Res 3(4):339
6. Chia-Nan W, Ty NN (2013) Forecasting the manpower requirement in Vietnamese tertiary institutions. Asian J Empir Res 3(5):563–575
7. Cook WD, Seiford LM (2009) Data envelopment analysis (DEA)—thirty years on. Eur J Oper Res 192(1):1–17
8. Delcea C, Popa CDS, Bolos M (2015) Consumers' decisions in grey online social networks. J Grey Syst 27(4):12–28
9. Färe R, Grosskopf S, Norris M, Zhang Z (1994) Productivity growth, technical progress, and efficiency change in industrialized countries. Am Econ Rev 84(1):66–83
10. Farrell MJ (1957) The measurement of productive efficiency. J R Stat Soc Ser A (General) 120(3):253–290
11. Flexport (2016) What the new ocean carrier alliances mean to your freight. https://www.flexport.com/blog/what-are-ocean-alliances/. Accessed Apr 2017
12. Fraunhofer (2016) Port cooperation between European seaports—fundamentals, challenges and good practices. http://www.guengl.eu/uploads/publications-documents/CMLReportPortCooperationvFINAL.PDF. Accessed Apr 2017
13. Golany B, Roll Y (1989) An application procedure for DEA. Omega 17(3):237–250
14. Gong Z, Forrest JYL (2014) Special issue on meteorological disaster risk analysis and assessment: on basis of grey systems theory. Nat Hazards 71(2):995–1000
15. Hsu CI, Wen YH (2000) Application of grey theory and multiobjective programming towards airline network design. Eur J Oper Res 127(1):44–68
16. Julong D (1982) Grey control system. J Huazhong Univ Sci Technol 3:9–18
17. Julong D (1989) Introduction to grey system theory. J Grey Syst 1(1):1–24
18. Lee CY, Johnson AL (2012) Operational efficiency. The handbook of industrial and systems engineering. http://polab.imis.ncku.edu.tw/Book%20Chapter/Operational%20Efficiency.pdf. Accessed May 2017
19. Malmquist S (1953) Index numbers and indifference surfaces. Trabajos de estadística 4(2):209–242
20. Mao M, Chirwa EC (2006) Application of grey model GM(1,1) to vehicle fatality risk estimation. Technol Forecast Soc Change 73(5):588–605
21. Nguyen N-T, Tran T-T (2015) Mathematical development and evaluation of forecasting models for accuracy of inflation in developing countries: a case of Vietnam. Discrete Dyn Nat Soc 2015:858157. https://doi.org/10.1155/2015/858157
22. Nguyen NT, Tran TT (2016) Facilitating an advanced product layout to prioritize hot lots in 450 mm wafer foundry in the semiconductor industry. Int J Adv Appl Sci 3(6):14–23
23. Nguyen NT, Tran TT (2017) Optimizing mathematical parameters of Grey system theory: an empirical forecasting case of Vietnamese tourism. Neural Comput Appl 28:1–15. https://doi.org/10.1007/s00521-017-3058-9
24. Nguyen NT, Tran TT (2017) A novel integration of DEA, GM (1,1) and neural network in strategic alliance for the Indian electricity organizations. J Grey Syst 29(2):80–101

25. Nguyen NT, Tran TT, Wang CN, Nguyen NT (2015) Optimization of strategic alliances by integrating DEA and grey model. J Grey Syst 27(1):38–56
26. Oxford Business Group (2016) Vietnam loading up on logistics. http://www.oxfordbusinessgroup.com/news/vietnam-loading-logistics. Accessed Apr 2017
27. Pai TY, Hanaki K, Ho HH, Hsieh CM (2007) Using grey system theory to evaluate transportation effects on air quality trends in Japan. Transp Res Part D Transp Environ 12(3):158–166
28. Stoxplus (2016) Vietnam logistics market 2016 report. https://biinform.com/Reports/DBB-vietnam-logistic-market-2016-report-.html. Accessed Apr 2017
29. Todeva E, Knoke D (2005) Strategic alliances and models of collaboration. Manag Decis 43(1):123–148
30. Tone K (2002) A slacks-based measure of super-efficiency in data envelopment analysis. Eur J Oper Res 143:32–41
31. Tone K (2001) A slacks-based measure of efficiency in data envelopment analysis. Eur J Oper Res 130(3):498–509
32. Tran TT (2016) Evaluating and forecasting performance using past data of an industry: an analysis of electronic manufacturing services industry. Int J Adv Appl Sci 3(12):5–20
33. Tran TT (2017) Forecasting strategies and analyzing the numbers of incoming students: case in Taiwanese vocational schools. Int J Adv Appl Sci 4(9):86–95
34. Trinh HXP, Tran TT (2017) An analyzing case: numbers of Taiwanese students and their expenditures by using grey system theory to forecast. Int J Adv Appl Sci 4(9):35–45
35. VCCINews (2013) Creating momentum for Vietnam's logistics to take off. http://vccinews.com/news_detail.asp?news_id=29618. Accessed Apr 2017
36. Vyas NM, Shelburn WL, Rogers DC (1995) An analysis of strategic alliances: forms, functions and framework. J Bus Ind Market 10(3):47–60
37. Wang CN, Tsai JH, Teng HC (2008) An approach on alliance for online game industry. In: 3rd International conference on innovative computing information and control, ICICIC'08. IEEE
38. Wang CN, Nguyen NT, Tran TT (2015) Integrated DEA models and grey system theory to evaluate past-to-future performance: a case of Indian electricity industry. Sci World J 2015:638710. https://doi.org/10.1155/2015/638710
39. World Bank (2014) Efficient logistics: a key to Vietnam's competitiveness. http://www.worldbank.org/en/news/feature/2014/01/07/efficient-logistics-a-key-to-vietnams-competitiveness. Accessed May 2017
40. Yoshino MY, Rangan S (1995) Strategic alliances: an entrepreneurial approach to globalization. Harvard University Press, Cambridge, p 5