Research Article

Applying EBM Model and Grey Forecasting to Assess Efficiency of Third-Party Logistics Providers

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A third-party logistics (TPL) provider's outsourcing mode is developed to support the economic activities for various industries. The aim of this research is to assess the efficiency of 10 large TPL providers from past to future by integrating the GM (1,1) model in grey forecasting and an epsilon-based measure model (EBM) in data envelopment analysis (DEA). The GM (1,1) model is utilized to formulate a forecast data in the future over period from 2018 to 2022. Then, via EBM model, past–current–future data are used for computing efficiency of these providers. The empirical values show that 115 cases comprise 79 efficiency cases and 36 inefficiency cases. CHRW, ECHO, and UPS get strong efficiency and keep a stable efficiency score in whole term. EXPD and KRRYF do not achieve efficiency during the period from 2013 to 2022. Excluding CHRW, ECHO, and UPS, seven TPL providers demonstrate upward trend and downward trends in every term. The increasing and decreasing variation index of 10 third-party logistics providers will help customers to select the best TPL providers.

1. Introduction

Industrial growth is enhancing international trade processes to demand world commerce with the aim of exchanging raw materials, semiproducts, and goods. With the past and current conditions, establishing logistics is a crucial factor, as it connects production and consumption to implement and control the flow of goods, services, and relative information [1, 2]. Logistics display competences of transportation by providing a supply chain to help customers reduce inventory and shorten transportation time, and so on in which the shipping service of TPL providers is reliable, as they can make the provision of fast pace and vary service to companies from all sectors [3]. Logistics is a strategic role in a firm's success that ensures successful supply chain management [4]; notably, it can directly manage physical information [5]. As a result of competitive business environments, TPL appeared in the 1970s and 1980s when companies outsourced logistical operations to TPL; thus, it designed integrated service between warehousing and transportation [6, 7].

Customers typically prefer utilizing high-quality logistics to reduce transportation costs. TPL receives basic equipment, technology, and information to meet market demands [8]. It collects inbound shipments or outbound shipments from factories at the same time to merge in their distribution centers via information analysis system; then, they will be transferred to the final destination by an alternative transportation route on time [9, 10].

As a characteristic of TPL and based on user replies, TPL providers can reduce inventory and stock out costs and also help users to better navigate through the web of government regulations and obtains customs clearance to avoid unnecessary delays [11]. Besides, the leverage technology helps integrate information systems into systematic inventory management; the integrated factors are a fulfillment service with supply chain management that offers visible data [12]. As a result, TPL have a collaborative relation [13] and reputation to uphold for customers worldwide; it also supports augmenting positive relationships with exporters among competitive markets [14]. When receiving goods from

a supplier, logistics not only take care of delivery of products, storage, loading, labelling, distribution, and unloading but also utilize the appropriate software to transmit milestones to the client.

In trade activity, TPL plays a key role in the logistics activities among outsourcing company, the marketplace, and the customer, with the function of integrating the supply; thus, this alliance will maintain effective outsourcing progress [15], inasmuch as logistics outsourcing can cut down on charges, increase flexibility, and direct delivery [16, 17]. The goal of a TPL provider builds multiple distribution functions and optimization of inventory [18]. From the criteria, TPL can define that it is a provider of an outsourced logistics service that encompasses the relative activities of delivering a product. Van Laarhoven claimed that “third-party Logistics are activities carried out by a logistics service provider on behalf of shipper and consisting of at least transportation” [19]. Selecting the right TPL is critical for wholesalers, companies, and retailers in order to maintain a supply chain [20]. Therefore, this research offers deep analysis of TPL providers from past to future to define the efficiency and inefficiency of TPL providers through their key financial factors.

Integrated capabilities between outsource and information transmission are noted to minimize the total delivery costs [6, 21]. With the aim of evaluating the efficiency in an operating process, the study integrates EBM and grey models to assess and predict the performance of TPL providers from past to future. Data envelopment analysis is an excellent analysis tools for multi models, including CCR, BBC, SBM, and dynamic SBM, to calculate and analyze financial reports or statistical data of humans, economies, and so on [22]. Koopmans and Farrell calculated the efficiency when using decision-making units (DMU) for analyzing original models; performance was conducted by the ratio between output and input of each of DMU [23, 24]. The EBM model composes the radial (technical) efficiency and the nonradial (value-dependent) efficiency [25], so that the research applies it into calculating the efficiency of TPL providers in each of periods.

A grey model is a forecast option with a biased exponential model that depends on a serial number of historical data to estimate the accuracy value, and the accumulation technique is a the accumulated generating operation (AGO), which is also used for obtaining methodical regularity and effectively reducing noise in discrete time-series data [26, 27]. The GM (1,1) model, which consists of group difference equations, is one of the more useful grey forecasting models. The prediction values are based on historical time-series in which the minimum number of data is four, and the data must be in consecutive order.

The study consists of four sections. Section 1 introduces the theory of TPL providers and overviews of grey forecasting and DEA. Section 2 proposes the input and output factors of the objectives, figures out proposal research, and sets up methodology with the equation of the GM (1,1) and EBM models. Section 3 shows estimated values and empirical analysis results. Section 4 summarises important marks.

2. Materials and Methods

2.1. Data Collection. According to the principle of DEA, the data comprises input variables and output variables. Based on the researching objective of determining the performance of TPL providers from the previous period to the future, with the list of top 50 TPLs on logisticsmgmt.com [28], the study selected input and output factors of 10 large third-party logistics providers during the period from 2012 to 2017 when their input and output variables were listed by the source of tmxmoney.com [29]. Input variables such as assets, current assets, current liabilities, and capitalization, along with output variables such as revenue and gross profit, are key points in the financial report of every company that assesses the efficiency of an operation process.

Input Variables. Assets (AS): Property, equipment, tangible assets, and intangible assets owned by an enterprise.

Current assets (CA): Cash and cash equivalents, short-term investment, and stock inventory.

Current liabilities (CL): Outstanding checks, compensation, current portion of debt, accounts payable, and other similar debts are values that the logistics must be paid within one year.

Capitalization (CP): The total amount investment expenses to establish the structure and operation business.

Output Variables. Revenue (RE): The value of goods and services from the transportation, products, and handling is held by a logistics service.

Gross profit (GP): Profit appears when the revenue deducts the cost of goods sold.

2.2. Proposal Research. The study utilizes GM (1,1) to forecast the future status and EBM model to evaluate the efficiency in each term. The final analysis result shows the efficiency and inefficiency of 10 TPL providers of every year during the period from 2012 to 2022. Figure 1 describes five stages in the research process as follows:

Stage 1. With the desirable knowledge of deep logistics, the authors determine the study objective of TPL providers. Based on the methodology, the input factors and output factors are chosen to apply into formulating the performance of TPL providers.

Stage 2. Overview the theory of TPLs, GM (1,1), and EBM model and provide the background of previous study of TPLs, GM (1,1), and EBM.

Stage 3. As criterion of foreseeing additional TPL providers, the study uses the series of historical collected data for predicting the future data by GM (1,1) model in grey forecasting. The prediction values must be tested by MAPE indicator. If the MAPE index is unsuitable, the objective must be retested.

Stage 4. Accordingly, the principle of DEA, Pearson's coefficient of all input and output variables, must be isotonic under the condition from -1 to +1. If they are unappreciated, they will be reselected. Besides, Pearson's coefficient in the EBM

FIGURE 1: Research Process.

model will be utilized by formulating the value of diversity and affinity. Pearson's coefficient is adjusted from 0 to +1. The EBM model calculates the score, theta, and slack to determine the efficiency and inefficiency of each company in every term.

Stage 5. Conduct some key points. By approaching GM (1,1) and the EBM model, the analysis result reveals their performance to seek out values from past to future.

2.3. Grey Forecast Model. GM (1,1) model is a grey forecasting model which bases on the historical data with time-series at least four years, it uses for predict further time-series with multiple inputs and outputs. GM (1,1) model only forecasts data when the primal data is a positive value and employed accordingly below steps:

Step 1. With the primal data

$$A^{(0)} = (A^{(0)}(1), A^{(0)}(2), \dots, A^{(0)}(n)) \quad n \geq 5 \quad (1)$$

Step 2. Depending on the $A^{(0)}(1)$ calculates time-series A^1

$$A^1 = (A^{(1)}(1), A^{(1)}(2), \dots, A^{(1)}(n)) \quad n \geq 5$$

$$A^{(1)}(k) = \sum_i^k A^{(0)}i \quad (k = 0, 1, \dots, n)$$

$$\text{Subject to } A^{(1)}(1) = A^{(0)}(1) \quad \text{if } k = 0$$

$$A^{(1)}(2) = A^{(0)}(1) + A^{(0)}(2) \quad \text{if } k = 1$$

$$A^{(1)}(n)$$

$$= A^{(0)}(1) + A^{(0)}(2) + \dots + A^{(0)}(n)$$

$$\text{if } k = n$$

(2)

Step 3. After having A^1 series it will create the mean equation $Z^{(1)}$

$$Z^{(1)}(k) = Z^{(1)}(1), Z^{(1)}(2), \dots, Z^{(1)}(k)$$

$$(k = 1, 2, \dots, n)$$

$$Z^{(1)}(k) = \frac{1}{2} (A^{(1)}(k) + A^{(1)}(k-1))$$

$$(k = 1, 2, \dots, n)$$

$$\begin{aligned}
Z^{(1)}(2) &= \frac{1}{2} (A^{(1)}(1) + A^{(1)}(2)) \quad (k=2) \\
Z^{(1)}(3) &= \frac{1}{2} (A^{(1)}(2) + A^{(1)}(3)) \quad (k=3)
\end{aligned} \tag{3}$$

Step 4. Find out a and b

$$A^{(1)}(k) + a \times Z^{(1)}(k) = b \quad (k=2, 3, \dots, n) \tag{4}$$

Changing the linear equation into the form of a matrix as below:

$$\begin{aligned}
S &= \begin{bmatrix} -Z^{(1)}(2) & 1 \\ \dots & \dots \\ -Z^{(1)}(k) & 1 \end{bmatrix} \quad (k=2, 3, \dots, n) \\
B_N &= \begin{bmatrix} A^{(0)}(2) \\ \dots \\ A^{(0)}(k) \end{bmatrix} \quad (k=2, 3, \dots, n) \\
\widehat{ST} &= \begin{bmatrix} -Z^{(1)}(2) & -Z^{(1)}(3) & \dots & -Z^{(1)}(k) \\ 1 & 1 & 1 & 1 \end{bmatrix} \\
&\quad (K=2, 3, \dots, n)
\end{aligned} \tag{5}$$

And then,

$$\widehat{\theta} = \begin{bmatrix} \frac{a}{b} \end{bmatrix} = (S^T S)^{-1} S^T B_N \tag{6}$$

Step 5. Calculate the whitening equation of the different equation:

$$\frac{dA^{(1)}}{dt} + a \times A^{(1)} = b \tag{7}$$

Step 6. This goes with

$$\begin{aligned}
\widehat{A}^{(1)}(k+1) &= \left[A^{(0)}(1) - \frac{b}{a} \right] e^{-ak} + \frac{b}{a} \\
&\quad (k=0, 1, 2, \dots, n)
\end{aligned} \tag{8}$$

Step 7. Find out the prediction value

$$\begin{aligned}
\widehat{A}^{(0)} &= \widehat{A}^{(0)}(1), \widehat{A}^{(0)}(2), \dots, \widehat{A}^{(0)}(n) \\
&\quad (n=0, 1, 2, \dots, s)
\end{aligned} \tag{9}$$

where $\widehat{A}^{(0)}(1) = A^{(0)}(1)$

$$\begin{aligned}
\widehat{A}^{(0)}(k+1) &= \left[A^{(0)}(1) - \frac{b}{a} \right] e^{-ak} (1 - e^a) \\
&\quad (k=0, 1, 2, \dots, n)
\end{aligned} \tag{10}$$

TABLE 1: Parameter of MAPE.

Value	Qualify
MAPE<10%	Excellent
10%<MAPE<20%	Good
20%<MAPE<50%	Reasonable
MAPE>50%	Poor

Step 8. Estimating the MAPE (mean absolute percent error)

$$\begin{aligned}
MAPE &= \frac{100}{n} \sum_{t=1}^n \left| \frac{A^{(0)}(k) - \widehat{A}^{(0)}(k)}{\widehat{A}^{(0)}(k)} \right| \\
&\quad (k=0, 1, 2, \dots, n)
\end{aligned} \tag{11}$$

MAPE indicator is applied to measure the accuracy of forecasting value in statistics and the parameter of MAPE is given as in Table 1.

As in Table 1, the forecasting data is accepted when its MAPE indicator is under 50%. In contrast, the MAPE indicator is upper 50%, the data is unappreciated, and it must be re-examined by another prediction model.

2.4. Epsilon-Based Measure Model

2.4.1. Epsilon-Based Measure of Efficiency. Tone discussed that EBM model could test the robustness and stability of efficiency measure of DMUs relating with the parametric change of multiplier variables. It has two parameters one scalar and one vector. When having n DMU₀, s inputs a_{ij} ($i=1, 2, \dots, s$), z output b_{ij} ($i=1, 2, \dots, z$) and then it will denote DMU_j by (a_j, b_j) ($j=1, \dots, n$) with $a_j \in R_s$ and $b_j \in R_z$. Input and output data matrices by $A = (a_{ij}) \in R_s \times n$ and $B = (b_{ij}) \in R_z \times n$. Radial and non-radial models are ϵ_a and ϵ_b . The result of the principal component analysis defines the weights w^- and w^+ . EBM model describes the following:

$$\begin{aligned}
E = \theta^* &= \min_{\theta, \lambda, s^-} \theta - \epsilon_a \sum_{i=0}^s \frac{w_i^- s_i^-}{a_0} \\
\text{Subject to } &\theta a_0 - A\lambda - s^- = 0, \\
&B\lambda \geq 0, \\
&\lambda \geq 0, \\
&s^- \geq 0
\end{aligned} \tag{12}$$

Whereas the weight of input (i) is w_i^- and $\sum_{i=0}^s w_i^- = 1$ ($w_i^- \geq 0$), the radial θ and nonradial slacks terms are combined by ϵ_a .

TABLE 2: Historical Statistic Data of 10 TPL providers from 2013 to 2017 (USD in Millions).

Years	AS	CA	CL	CP	RE	GP
Max	36212	13387	7131	17298	55438	41735
Min	245	167	79	159	884	156
Average	6302.9	2828.7	1761.2	2989	12191.1	5075.3
SD	10123.61	3725.79	2020.51	4829.3	15280.21	12245.38
Max	35440	11218	8621	11997	58232	43474
Min	316	186	127	182	1173	164
Average	6231.2	2607.7	1926.6	2463.7	12408.7	5222.4
SD	9868.29	3082.73	2403.75	3256.71	15975.36	12769.6
Max	38311	13208	10696	13786	58363	45416
Min	747	261	137	592	1512	177
Average	6524.7	2724.2	2056.8	2759.3	12228.1	5439.1
SD	10695.16	3621.4	3003.78	3729.14	16010.8	13342.21
Max	40377	13849	11730	12799	60906	47084
Min	767	268	168	562	1716	192
Average	7061.6	2930.3	2313.8	2743	12600.8	5693.6
SD	11233.95	3782.79	3276.59	3427.48	16676.99	13820.88
Max	45403	15548	12708	21278	65872	49438
Min	838	348	234	570	1943	339
Average	8027.4	3408.4	2689.4	3816.3	14152.8	6152.3
SD	12616.41	4247.49	3545.04	5878.02	17979.62	14457.22

TABLE 3: Historical input and output factors of CHRW from 2013 to 2017.

Years	(I)AS	(I)CA	(I)CL	(I)CP	(O)RE	(O)GP
2013	2803	1664	1270	1440	12752	1009
2014	3214	2105	1576	1547	13470	1069
2015	3184	1731	1449	1650	13476	1217
2016	3688	2008	1846	1758	13144	1213
2017	4236	2511	1987	2176	14869	1189

$$\begin{aligned}
D = \theta^* &= \max_{v,u} \quad ub_0 \\
\text{Subject to} \quad &va_0 = 1, \\
&-va + uB \leq 0, \\
&v \geq 0, \\
&u \geq 0
\end{aligned} \tag{13}$$

with $s - \epsilon R_m$ being the input slack. The primal-dual is E and D. If setting the optimal solution of E is θ^* , λ^* , s^*

when DMU (a_0, b_0) fulfil $\theta^* = 1$ and $s^{*-} \neq 0$ it is weak efficiency;

when DMU (a_0, b_0) fulfil $\theta^* = 1$ and $s^{*-} = 0$ it is strong efficiency;

when DMU (a_0, b_0) fulfil $\theta^* \neq 1$, it doesn't have efficiency.

2.4.2. Diversity Index and Affinity Index. According to the normal way, Pearson's correlation coefficient translates the full original data. However, EBM model does not present the translation of original which established an affinity index between two input vectors instead of Pearson's correlation

coefficient [25]. $S(x,y)$ lets the affinity index between the vector x and vector y with the properties as follows:

- (P1) $S(x,y) = 1$
- (P2) $S(x,y) = S(y,x)$
- (P3) $S(tx,y) = S(x,y)$ ($t > 0$)
- (P4) $1 \geq S(x,y) \geq 0$

Let the diversity index is to be $H(x,y)$ and it is denoted by

$$H(x,y) = \frac{\sum_{j=1}^n |e_j - \bar{e}|}{n(e_{\max} - e_{\min})} = 0 \quad \text{when } e_{\max} = e_{\min}$$

$$\text{Subject to } e_j = \ln \frac{y_j}{x_j} \quad (j = 1, \dots, n)$$

$$\bar{e} = \frac{1}{n} \sum_{j=1}^n e_j \tag{14}$$

$$e_{\max} = \max_j \{e_j\}$$

$$e_{\min} = \min_j \{e_j\}$$

Note that $0 \leq H(x,y) = H(y,x) \leq 1/2$

TABLE 4: Prediction value of CHRW (2018-2022).

Year	(I)AS	(I)CA	(I)CL	(I)CP	(O)RE	(O)GP
2018	4,592	2,525	2,174	2,356	14,758	1,261
2019	5,089	2,729	2,397	2,645	15,190	1,299
2020	5,640	2,950	2,643	2,970	15,634	1,338
2021	6,250	3,189	2,915	3,334	16,092	1,378
2022	6,926	3,447	3,215	3,743	16,563	1,419

TABLE 5: Average MAPE of DMUs.

DMUs	Average MAPE	DMUs	Average MAPE
CHRW	0.30159 %	JBHT	0.34119 %
DSDVY	0.58396 %	KHNGY	0.17893 %
ECHO	0.61847 %	KRRYF	0.42077 %
EXPD	0.13804 %	PLWTF	0.32993 %
HUBG	0.42406 %	UPS	0.34136 %
Average of all MAPEs = 0.36783 %

FIGURE 2: The Variation Index.

The affinity index is set as below:

$$S(x,y) = 1 - 2H(x,y)$$

If $1 \geq H(x,y) \geq 0$, $H(x,y)$ is suitable with the properties (P1), (P2), (P3), and (P4).

And Pearson's correlation of diversity and affinity is given as

$$r(x,y) = \frac{\sum_{j=1}^n (x_j - \bar{x})(y_j - \bar{y})}{\sqrt{\sum_{j=1}^n (x_j - \bar{x})^2 \sum_{j=1}^n (y_j - \bar{y})^2}} \quad (15)$$

$$\text{Subject to } \bar{x} = x_j$$

$$\bar{y} = y_j$$

According to the normal rule of Pearson's correlation coefficient, it ranges $-1 \leq r(x,y) \leq +1$ [30]. In this case, the principal component analysis is not guaranteed that the principal vector consists of non-negative component so that it is adjusted $0 \leq r(x,y) \leq +1$.

3. Results and Discussion

3.1. Data Analysis. From the data of 10 TPL providers, as shown in Section 2.1, the research combines the GM(1,1)

model to predict the operating process from 2018 to 2022 and the EBM model to figure out the performance from 2013 to 2022. The 10 TPL providers include C.H. Robinson Worldwide (CHRW); DSV A/S ADR (DSDVY); Echo Global Logistics (ECHO); Expeditors International (EXPD); Hub Group (HUBG); J.B. Hunt Transport Services (JBHT); Kuehne & Nagel International (KHNGY); Kerry Logistics Network (KRRYF); Panalpina Welttransport (PLWTF); United Parcel Service (UPS).

Table 2 summarizes the input and output variables of 10 TPL providers from 2013 to 2017. AS, CA, CL, CP, RE, and GP are positive elements. The significant values are highly appreciated using the GM (1,1) model for estimating and the EBM model for formulating the performance.

3.2. Forecasting Result. The prediction value is derived after utilizing the past series variables for calculation. From the historical data, the data of CHRW are selected as an example.

Based on the grey forecast model in Section 2.3, the research applies the steps of GM(1,1) into calculating the prediction values of CHRW through the data in the Table 3.

Setting the primal data $A^{(0)}$

$$A^{(0)} = (2,803; 3,214; 3,184; 3,688; 4,236) \quad (16)$$

Formulating A^1 series

$$A^1 = (2,803; 6,017; 9,201; 12,889; 17,125) \quad (17)$$

Generating the mean sequence Z^1

$$Z^{(1)}(k) = (4,410; 7,609; 11,045; 15,007) \quad (18)$$

Finding out a and b

$$\begin{aligned} 3,214 + a \times 4,410 &= b \\ 3,184 + a \times 7,609 &= b \\ 3,688 + a \times 11,045 &= b \\ 4,236 + a \times 15,007 &= b \end{aligned} \quad (19)$$

Transposing the linear equation

$$S = \begin{bmatrix} -4,410 & 1 \\ -7,609 & 1 \\ -11,045 & 1 \\ -15,007 & 1 \end{bmatrix},$$

TABLE 6: Diversity Index.

Years		AS	CA	CL	CP
AS	2013	0	0.23549	0.29498	0.21076
CA		0.23549	0	0.26058	0.22181
CL		0.29498	0.26058	0	0.35295
CP		0.21076	0.22181	0.35295	0
AS	2014	0	0.25888	0.33341	0.26642
CA		0.25888	0	0.21107	0.21795
CL		0.33341	0.21107	0	0.26828
CP		0.26642	0.21795	0.26828	0
AS	2015	0	0.22336	0.24709	0.25315
CA		0.22336	0	0.29144	0.21161
CL		0.24709	0.29144	0	0.24507
CP		0.25315	0.21161	0.24507	0
AS	2016	0	0.23408	0.25065	0.25973
CA		0.23408	0	0.31959	0.23724
CL		0.25065	0.31959	0	0.26114
CP		0.25973	0.23724	0.26114	0
AS	2017	0	0.25314	0.2601	0.2453
CA		0.25314	0	0.22821	0.25334
CL		0.2601	0.22821	0	0.24903
CP		0.2453	0.25334	0.24903	0
AS	2018	0	0.25547	0.2417	0.23668
CA		0.25547	0	0.23378	0.25901
CL		0.2417	0.23378	0	0.23754
CP		0.23668	0.25901	0.23754	0
AS	2019	0	0.28869	0.24919	0.23179
CA		0.28869	0	0.21551	0.27191
CL		0.24919	0.21551	0	0.23552
CP		0.23179	0.27191	0.23552	0
AS	2020	0	0.27091	0.2363	0.25264
CA		0.27091	0	0.23656	0.28843
CL		0.2363	0.23656	0	0.23542
CP		0.25264	0.28843	0.23542	0
AS	2021	0	0.23389	0.21274	0.23686
CA		0.23389	0	0.19268	0.27759
CL		0.21274	0.19268	0	0.21808
CP		0.23686	0.27759	0.21808	0
AS	2022	0	0.23079	0.21104	0.233
CA		0.23079	0	0.17374	0.27662
CL		0.21104	0.17374	0	0.21739
CP		0.233	0.27662	0.21739	0

$$B_N = \begin{bmatrix} 3,214 \\ 3,184 \\ 3,688 \\ 4,236 \end{bmatrix},$$

$$\hat{S}^T = \begin{bmatrix} -4,410 & -7,609 & -11,045 & -15,007 \\ 1 & 1 & 1 & 1 \end{bmatrix}$$

(20)

The value of a and b is given as

$$\hat{\theta} = \begin{bmatrix} a \\ b \end{bmatrix} = (S^T S)^{-1} S^T B_N = \begin{bmatrix} -0.1027576 \\ 2,602.479 \end{bmatrix} \quad (21)$$

Calculating the whitening equation

$$\frac{dA^{(1)}}{dt} - 0.08186 \times 3,214 = 2,602.479 \quad (22)$$

TABLE 7: Affinity Index.

Years		AS	CA	CL	CP
AS	2013	1	0.52902	0.41003	0.57848
CA		0.52902	1	0.47883	0.55637
CL		0.41003	0.47883	1	0.29411
CP		0.57848	0.55637	0.29411	1
AS	2014	1	0.48224	0.33318	0.46716
CA		0.48224	1	0.57786	0.56411
CL		0.33318	0.57786	1	0.46344
CP		0.46716	0.56411	0.46344	1
AS	2015	1	0.55328	0.50582	0.4937
CA		0.55328	1	0.41713	0.57677
CL		0.50582	0.41713	1	0.50985
CP		0.4937	0.57677	0.50985	1
AS	2016	1	0.53183	0.4987	0.48053
CA		0.53183	1	0.36083	0.52553
CL		0.4987	0.36083	1	0.47772
CP		0.48053	0.52553	0.47772	1
AS	2017	1	0.49372	0.47979	0.5094
CA		0.49372	1	0.54357	0.49333
CL		0.47979	0.54357	1	0.50195
CP		0.5094	0.49333	0.50195	1
AS	2018	1	0.48905	0.51661	0.52664
CA		0.48905	1	0.53244	0.48199
CL		0.51661	0.53244	1	0.52493
CP		0.52664	0.48199	0.52493	1
AS	2019	1	0.42262	0.50161	0.53642
CA		0.42262	1	0.56897	0.45618
CL		0.50161	0.56897	1	0.52896
CP		0.53642	0.45618	0.52896	1
AS	2020	1	0.45819	0.5274	0.49472
CA		0.45819	1	0.52687	0.42315
CL		0.5274	0.52687	1	0.52915
CP		0.49472	0.42315	0.52915	1
AS	2021	1	0.53222	0.57451	0.52627
CA		0.53222	1	0.61464	0.44481
CL		0.57451	0.61464	1	0.56383
CP		0.52627	0.44481	0.56383	1
AS	2022	1	0.53842	0.57791	0.53399
CA		0.53842	1	0.65252	0.44675
CL		0.57791	0.65252	1	0.56521
CP		0.53399	0.44675	0.56521	1

Seeking the prediction

$$= \left[2,803 - \frac{2,602.479}{-0.08186} \right] e^{0.08186 \times 0} (1 - e^{-0.08186}) \quad (24)$$

$$\begin{aligned} \widehat{A}^{(1)}(1) &= \left[2,803 - \frac{2,602.479}{-0.08186} \right] e^{0.08186 \times 0} + \frac{2,602.479}{-0.08186} \\ &= 2,803 \end{aligned} \quad (23)$$

Conducting the prediction value

$$\widehat{A}^{(0)}(k+1)$$

The forecasting result is given in the Table 4.

The prediction values of DMUs are shown in Tables 10 and 11, and the values are tested by MAPE indicator in Table 4.

Accordingly, the principle of MAPE is shown in Table 1, with the results shown in Table 5. The average MAPE indication of each TPL provider receives qualification, as

TABLE 8: Weight to input/output.

Years	AS	CA	CL	CP
2013	0.262621	0.267338	0.216236	0.253805
2014	0.228585	0.272134	0.242624	0.256657
2015	0.252846	0.252934	0.237963	0.256258
2016	0.259103	0.248377	0.236821	0.255699
2017	0.24647	0.252485	0.25186	0.249184
2018	0.249585	0.246069	0.254578	0.249769
2019	0.244283	0.242928	0.26103	0.251759
2020	0.250183	0.241032	0.262642	0.246144
2021	0.25053	0.246415	0.263813	0.239241
2022	0.249089	0.248673	0.265069	0.237169

TABLE 9: Efficiency score.

DMU	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
CHRW	1	1	1	1	1	1	1	1	1	1
DSDVY	1	0.962	0.707	0.753	0.859	0.851	0.896	0.958	1	1
ECHO	1	1	1	1	1	1	1	1	1	1
EXPD	0.578	0.667	0.754	0.762	0.76	0.812	0.836	0.856	0.888	0.924
HUBG	0.946	1	0.98	1	0.99	1	1	1	1	1
JBHT	1	0.9742	1	1	0.93	1	1	0.998	1	1
KHNGY	1	0.9114	1	1	1	1	1	1	1	1
KRRYF	0.31	0.385	0.34	0.407	0.4113	0.432	0.456	0.485	0.526	0.57
PLWTF	0.942	0.965	1	1	1	1	1	1	1	1
UPS	1	1	1	1	1	1	1	1	1	1

the values are lower than 0.61847%, and their common average is 0.36783%. That means they reach the high accuracy prediction with the excellent qualifications under 10%. As a result, the GM (1,1) is an appropriate model to use for predicting of TPL providers from 2018 to 2022. The data in Tables 10 and 11 indicate that they are positive and absolutely suitable to utilize in the EBM model.

3.3. Measurement of Efficiency. To assess the operation process of TPL providers, the research proposes the EBM model in DEA to determine the efficiency of TPL providers in the past–current–future. The data in the analysis must be R^+ ; the research implements a small analysis step to ensure all data are higher than 0. Tables 12 and 13 denote that no input data or output data are under 0.

In addition, following the rule of DEA, the relationship of input and output factors is isotonic before implementing the performance count. The condition of correlation coefficient ranges from -1 to +1 and has a good linear relation when close to 1. Tables 12 and 13 denote that Pearson's correlation coefficients are from 0.91014 to 1. These values achieve the qualification level and receive a strong linear relation. Therefore, the data are used for estimating the efficiency of the EBM model.

New vectors are built up in the EBM model; however, the vectors must be positive. The affinity index of vectors is presented to replace Pearson's correlation. Their values are

satisfied with the condition $[0 \leq r(x,y) \leq +1]$ when the largest eigenvalue and eigenvector of affinity matrix are from 0 to 1.

Table 6 shows diversity is from 0 to 0.35295. Table 7 gives an affinity of 0.29411 to 1. Both approach the largest eigenvalue and eigenvector and ensure the rationale of the affinity index is determined. Input variables are calculated by the input-oriented model under the constant returns-to-scale (CSR) assumption. From that point, the results of epsilon for EBM and weight to input/output are computed as follows:

Epsilon for EBM

Epsilon for EBM of 2013 = 0.521603

Epsilon for EBM of 2014 = 0.515902

Epsilon for EBM of 2015 = 0.490042

Epsilon for EBM of 2016 = 0.520046

Epsilon for EBM of 2017 = 0.496313

Epsilon for EBM of 2018 = 0.487955

Epsilon for EBM of 2019 = 0.496962

Epsilon for EBM of 2020 = 0.506061

Epsilon for EBM of 2021 = 0.45633

Epsilon for EBM of 2022 = 0.44635

Epsilons for EBM during the term of 2013-2022 are positive with their results under 0.44635 so they are significant.

TABLE 10: Forecasting values over the period 2018–2020 (USD in millions).

DMUs	Year	(I)AS	(I)CA	(I)CL	(I)CP	(O)RE	(O)GP
CHRW	2018	4592	2525	2174	2356	14758	1261
DSDVY		7515	3598	2937	3087	13718	4000
ECHO		1109	412	280	776	2301	404
EXPD		3085	2532	1076	1989	6692	927
HUBG		1794	684	574	1059	4060	578
JBHT		4846	1531	920	3296	7446	1270
KHNGY		7529	5017	4760	2209	18460	2651
KRRYF		5322	1569	1439	3076	4318	576
PLWTF		1729	1461	1008	562	4874	1667
UPS		48589	17183	14580	23595	67575	51452
CHRW	2019	5089	2729	2397	2645	15190	1299
DSDVY		8965	4329	3516	3935	16254	4895
ECHO		1372	496	350	948	2688	465
EXPD		3189	2653	1124	2048	6750	961
HUBG		1997	712	658	1197	4227	894
JBHT		5323	1810	1013	3776	7857	1273
KHNGY		7919	5304	5260	2185	18905	2753
KRRYF		5985	1718	1777	3320	4947	631
PLWTF		1703	1444	1015	531	4540	2719
UPS		52683	19003	16419	28696	70509	53673
CHRW	2020	5640	2950	2643	2970	15634	1338
DSDVY		10696	5208	4208	5016	19258	5990
ECHO		1696	597	438	1159	3141	534
EXPD		3297	2780	1174	2109	6808	996
HUBG		2222	741	754	1354	4401	1385
JBHT		5848	2139	1115	4326	8291	1277
KHNGY		8330	5608	5813	2161	19360	2859
KRRYF		6731	1880	2194	3583	5667	691
PLWTF		1678	1428	1022	503	4229	4432
UPS		57122	21016	18491	34900	73571	55990

Weight to Input/Output. Based on the epsilon for EBM and weight to input/output, as shown in Table 8, the efficiencies of TPL providers are presented in Table 9. According to Table 9 and the theta's rule, the empirical analysis results denote that CHRW and UPS achieved a strong efficiency during all terms when their scores and theta always obtain 1 and their slacks attain 0. ECHO receives strong efficiency as the scores and theta of ECHO is 1, and its slack is 0 as well, except 2015 when its slack of current assets and capitalization are 0.000075 and 0.000177, respectively. KHNGY with its score and theta as 1 and its slack as 0 has a strong efficiency during 2013 and from 2015 to 2022. The year 2014 is exclusive without efficiency because the score is lower than 1, and the slack is different with 0. PLWTF shows strong efficiency from 2017 to 2022, with score and theta as 1 and slack as 0; it has a weak efficiency in 2015–2016 with score as 1, and the theta is different 0. All scores, theta, and slack of PLWTF are unqualified in 2013–2014 so it does not have efficiency. JBHT obtains a strong efficiency in 2013, 2015–2016, 2018–2019, and 2021–2022; the others years do not receive efficiency because of unqualified indicators. HUBG

demonstrates strong efficiency in 2014, 2016, and 2019–2022 and a weak efficiency in 2018 with score and theta as 1 and slack as difference 0. DSDVY has a strong efficiency in 2013 and 2021–2022, it does not obtain efficiency in others years. EXPD and KRRYF are TPL providers that show inefficiency during the 2013–2022 term.

The operating performance of TPL providers from past to future is identified by the analyzed values after integrating the GM (1,1) and EBM models. The relative efficiency of a comparable DMU, with its input and output factors, is defined by DEA [31]. The research quantifies the scores of 115 cases of 10 TPL providers through the EBM model. The empirical analysis result in Table 9 denotes 19 efficiency and 35 inefficiency cases; 35 inefficient cases should be improved efficiency by reducing the input variables and increasing the output variables.

Figure 2 illustrates the operating efficiency of 10 TPL providers from past to future. CHRW, ECHO, and UPS are excellent TPL providers and obtain stable enduring performance over the whole term. The PLWTF index increases slightly from 0.942 to 1 from 2013 to 2015 and obtains a

TABLE 11: Forecasting values over the term of 2021–2022 (USD in millions).

DMUs	Year	(I)AS	(I)CA	(I)CL	(I)CP	(O)RE	(O)GP
CHRW	2021	6250	3189	2915	3334	16092	1378
DSDVY		12760	6266	5036	6394	22818	7330
ECHO		2097	718	548	1417	3670	614
EXPD		3409	2914	1226	2172	6866	1033
HUBG		2472	772	864	1531	4581	2144
JBHT		6425	2528	1227	4957	8749	1281
KHNGY		8762	5929	6423	2138	19827	2969
KRRYF		7570	2058	2709	3868	6493	757
PLWTF		1653	1411	1028	476	3939	7226
UPS		61936	23243	20824	42445	76766	58407
CHRW	2022	6926	3447	3215	3743	16563	1419
DSDVY		15223	7539	6028	8150	27036	8971
ECHO		2594	864	686	1732	4287	706
EXPD		3524	3053	1281	2237	6926	1071
HUBG		2751	804	990	1732	4769	3320
JBHT		7058	2988	1350	5679	9232	1284
KHNGY		9216	6269	7098	2114	20305	3083
KRRYF		8514	2252	3345	4174	7438	829
PLWTF		1628	1395	1035	450	3670	11782
UPS		67155	25705	23451	51620	80100	60928

TABLE 12: Pearson's correlation coefficient (2013–2015).

	Year	AS	CA	CL	CP	RE	GP
AS	2013	1	0.9813	0.9475	0.996	0.9767	0.9926
CA		0.9813	1	0.98	0.9734	0.9866	0.9584
CL		0.9475	0.98	1	0.9252	0.9792	0.9101
CP		0.996	0.9734	0.9252	1	0.9642	0.9913
RE		0.9767	0.9866	0.9792	0.9642	1	0.9586
GP		0.9926	0.9584	0.9101	0.9913	0.9586	1
AS	2014	1	0.9699	0.9705	0.9918	0.9818	0.9929
CA		0.9699	1	0.9933	0.9593	0.9864	0.9444
CL		0.9705	0.9933	1	0.9511	0.9895	0.9446
CP		0.9918	0.9593	0.9511	1	0.9658	0.9801
RE		0.9818	0.9864	0.9895	0.9658	1	0.9673
GP		0.9929	0.9444	0.9446	0.9801	0.9673	1
AS	2015	1	0.9856	0.9827	0.9954	0.9796	0.9954
CA		0.9856	1	0.9969	0.9712	0.9893	0.9748
CL		0.9827	0.9969	1	0.966	0.9917	0.9694
CP		0.9954	0.9712	0.966	1	0.9655	0.9893
RE		0.9796	0.9893	0.9917	0.9655	1	0.9706
GP		0.9954	0.9748	0.9694	0.9893	0.9706	1

balanced value over the remaining time. KHNGY is dropped in 2014, but it resumes again as soon as 2015 and maintains sustainable efficiency from 2016 to 2022. DSDVY, HUBG, and JBHT show smooth fluctuation in each term; specifically, HUBG during the term of 2013–2017 has one rising year and one falling year; JBHT is one falling year and then maintaining balance in performance value in two consecutive years; the result is repeated during all terms; the variation

index of DSDVY slumps with the score indicator from 1 down to 0.707 within three continual years from 2013 to 2015; it rises slowly as the index increases lightly within six sequent years from 2016 to 2021. EXPD and KRRYF always show upward movement, but they have not obtained efficiency because their indicators are under 1. For that reason, most providers demonstrate downward and upward trends in each term, excluding CHRW, ECHO, and UPS.

TABLE 13: Pearson's correlation coefficient (2016–2022).

Year	AS	CA	CL	CP	RE	GP
2016	AS	1	0.9849	0.9834	0.9916	0.9947
	CA	0.9849	1	0.9962	0.9671	0.9736
	CL	0.9834	0.9962	1	0.9608	0.9709
	CP	0.9916	0.9671	0.9608	1	0.9821
	RE	0.9841	0.9913	0.9948	0.9651	0.9758
	GP	0.9947	0.9736	0.9709	0.9821	1
	GP	0.9947	0.9736	0.9709	0.9821	0.9758
2017	AS	1	0.9813	0.9766	0.9955	0.9931
	CA	0.9813	1	0.9956	0.9633	0.9652
	CL	0.9766	0.9956	1	0.9538	0.9565
	CP	0.9955	0.9633	0.9538	1	0.9915
	RE	0.9829	0.9923	0.9909	0.9676	0.9702
	GP	0.9931	0.9652	0.9565	0.9915	1
	GP	0.9931	0.9652	0.9565	0.9915	0.9702
2018	AS	1	0.9856	0.9806	0.9954	0.993
	CA	0.9856	1	0.9957	0.9685	0.9732
	CL	0.9806	0.9957	1	0.9585	0.9643
	CP	0.9954	0.9685	0.9585	1	0.9911
	RE	0.9843	0.9935	0.9927	0.9689	0.9727
	GP	0.993	0.9732	0.9643	0.9911	1
	GP	0.993	0.9732	0.9643	0.9911	0.9727
2019	AS	1	0.9868	0.981	0.9952	0.991
	CA	0.9868	1	0.9949	0.9699	0.9736
	CL	0.981	0.9949	1	0.9583	0.9635
	CP	0.9952	0.9699	0.9583	1	0.9904
	RE	0.9848	0.9943	0.9924	0.9692	0.971
	GP	0.991	0.9736	0.9635	0.9904	1
	GP	0.991	0.9736	0.9635	0.9904	0.971
2020	AS	1	0.9877	0.9814	0.9949	0.9873
	CA	0.9877	1	0.9938	0.9712	0.9715
	CL	0.9814	0.9938	1	0.9582	0.9605
	CP	0.9949	0.9712	0.9582	1	0.988
	RE	0.9851	0.9949	0.9918	0.9688	0.9664
	GP	0.9873	0.9715	0.9605	0.988	1
	GP	0.9873	0.9715	0.9605	0.988	0.9664
2021	AS	1	0.9884	0.9818	0.9945	0.9795
	CA	0.9884	1	0.9922	0.9723	0.965
	CL	0.9818	0.9922	1	0.9581	0.9534
	CP	0.9945	0.9723	0.9581	1	0.9823
	RE	0.9849	0.9951	0.9905	0.9677	0.9566
	GP	0.9795	0.965	0.9534	0.9823	1
	GP	0.9795	0.965	0.9534	0.9823	0.9566
2022	AS	1	0.9888	0.982	0.9939	0.963
	CA	0.9888	1	0.9901	0.973	0.9491
	CL	0.982	0.9901	1	0.9579	0.9371
	CP	0.9939	0.973	0.9579	1	0.9693
	RE	0.9841	0.9949	0.9884	0.9652	0.9362
	GP	0.963	0.9491	0.9371	0.9693	1
	GP	0.963	0.9491	0.9371	0.9693	0.9362

4. Conclusions

TPL providers are responsible for logistics services with outsourcing activities to support enterprises for delivering the products fluently. The research integrates an EBM model in DEA and a GM (1,1) model in grey forecasting to present the efficiency progress of 10 TPL providers from the past to future. The major aims of this research are to show foreseeing

future values, determining the efficient and inefficient terms of enterprises, and pointing out operating trends of companies.

The GM (1,1) model is applied into computing the accuracy-predicting values of TPL providers over the term from 2018 to 2022 based on historical time-series during the term from 2013–2017. Key financial indicators, e.g., assets, current assets, current liabilities, capitalization, revenue, and

gross profit, are used for forecasting and analyzing a company's productivity. The forecasting data discover a future operating status of 10 TPL providers.

Furthermore, the actual and estimated values are employed to compute the efficiency over the whole term via EBM model. Analysis results reveal the performance valuations of TPL providers during the period from 2013 to 2022. Moreover, the study describes an efficient picture of TPL providers from the previous to future term that supports TPL providers in understanding their operation process and strategic growth to implement a successful business plan; in addition, customers have a good overview of TPL companies to choose the best suitable TPL provider.

Although this study explores the performance of TPL providers, limitations remain. First, the study only demands us to define efficiency and inefficiency without ranking TPL providers in each year, so that further research can create more models to rank. Second, the published input and output variables may not offer enough information, e.g., number of containers, employees, etc., for examining the operation process. Thus, the next study will research more of these factors.

Appendix

See Tables 10–13.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors have no conflicts of interest regarding the publication of this paper.

Authors' Contributions

Chia-Nan Wang guided the analysis method and edited the content; Jen-Der Day guided the research direction and found the solutions; Thi-Kim-Lien Nguyen designed research framework, analysed the empirical result, and wrote the paper.

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