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Integrating the EBM Model and LTS(A,A,A) Model to Evaluate the Efficiency in the Supply Chain of Packaging Industry in Vietnam

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Abstract: In recent decades, Vietnamese labeling and packaging has been widely recognized as being one of the fastest developing industries in Vietnam, supported by the tremendous demand of domestic production and the exportation of its packaged goods. The emerging packaging technology trends and the participation of foreign direct investment (FDI) companies have led to fierce competition between all packaging enterprises in Vietnam. This paper aims to calculate the productivity performance of 10 packaging companies in Vietnam from the past to the future by combining the additive Holt-Winters (LTS(A,A,A)) model to predict key variables in the financial statement for the next 4 years (2020–2023) and an epsilon-based measure of efficiency (EBM) model of data envelopment analysis (DEA) to define the developing trend, efficiency, and ranking of packaging operations. The empirical results will assist packaging enterprises to identify their positions, suggest feasible solutions to overcome shortcomings and catch up with the global trends, and propose superior partnerships for manufacturers, which have packaging service demands and support investment decisions for investors. Overall, all the enterprises in the packaging industry have high productivity. In particular, SIVICO JSC is identified as the most efficient packaging company in Vietnam, as it continuously maintains the first ranking over the observation time, followed by Agriculture Printing & Packing JSC and Bien Hoa Packaging Company. In the past, Tan Dai Hung Plastic JSC was identified as the most unproductive unit, while in the future term, the inefficient decision-making units (DMUs) are Tan Tien Plastic Packaging JSC, Sai Gon Packaging JSC, Dong A JSC, and PetroVietnam Packaging JSC. The suggestion for incompetent enterprises is changing the value of inputs proportionally to optimize for better performance.

Keywords: data envelopment analysis (DEA); additive Holt-Winters model (LTS(A,A,A)); epsilon-based measurement (EBM); packaging industry

MSC: 60K10; 62-07; 62P20

check for updates

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1. Introduction

Although packaging is an auxiliary industry for many manufacturing industries, it plays a key role, contributing significantly to the development of the economy. It is also widely considered to be one of the most important parts of logistic systems. The purpose of the earliest and most basic packaging was containing products, serving the stages of transportation, preservation, and display. The second benefit of packaging is protecting products from damage, deformation, theft, or reduction of quality due to external and environmental impacts such as air, humidity, water, and light. Furthermore, providing information on products on stamps, labels, or the cover is a legal requirement for packaging to help consumers better understand the product before making a purchasing decision.

Furthermore, packaging has long been recognized as the silent salesperson and has been the focus of much recent regulation [1]. It contributes to product positioning and brand identity. It is also a marketing and sales support tool. Product packaging with innovative designs and unique colors outstanding and suitable for brand identity publications will easily impress consumers and help them associate and remember products and brands more. Research and packaging design is a vital part of the product development strategy of most businesses that cannot be replaced.

Understanding the important role of packaging, as stated by the Vietnam Packaging Association (VINPAS), over the last 10 years, the packaging industry has been recognized as one of the fastest growing economic sectors in both size and the number of enterprises established in Vietnam [2]. Currently, Vietnam has more than 900 packaging factories, and the numbers of companies is still increasing, about 70% of which are concentrated in the southern provinces [3]. The Association of Vietnam Retailers (AVR) explained the first reason behind this development. The population of Vietnam is over 97 million, leading to the rise of domestic demand in the food and beverage industry, as well as for industrial and pharmaceutical product packaging [4]. The Vietnamese food market is on an upward trend and is expected to grow annually by 13.05% (compound annual growth rate (CAGR) 2021–2025) [5]. Besides that, Vietnam is one of the 17 countries with the highest pharmaceutical growth rate in the world, with a market size of about USD 5.1 billion (as stated by IMS Health) [6]. Specifically, in the packaging industry, the proportion of food packaging is approximately one third to a half, while the percentage for electronics packaging is 5–10% and pharmaceutical and chemistry packaging is estimated to be 5–10% [4].

Moreover, recently, the urbanization process has been developing quickly, along with the appearance of a series of foreign supermarkets that invested in Vietnam such as Big C, Aeon, and Lotte Mart. In addition, the habit of using packaged products has given the packaging industry many development opportunities. In addition, the high export market requirement in packing services is stimulating the development of this industry. The Vietnam packaging industry has a high average growth rate of 15–20% per year [5]. In recent years, the attractiveness of the packaging industry in Vietnam has been proven, as many overseas manufacturers have selected Vietnam as an ideal destination to supply machines, devices, and goods and to invest in building factories. The market for packaging materials can be divided into a series of main segments, including paper and cardboard, plastic, metal, glass, wood, textiles, and other suitable materials such as foam and leather. Based on the statistical data from Thongke [7], Figure 1 summarizes the levels of some imported input materials for packaging production in Vietnam from 2010 to 2019.

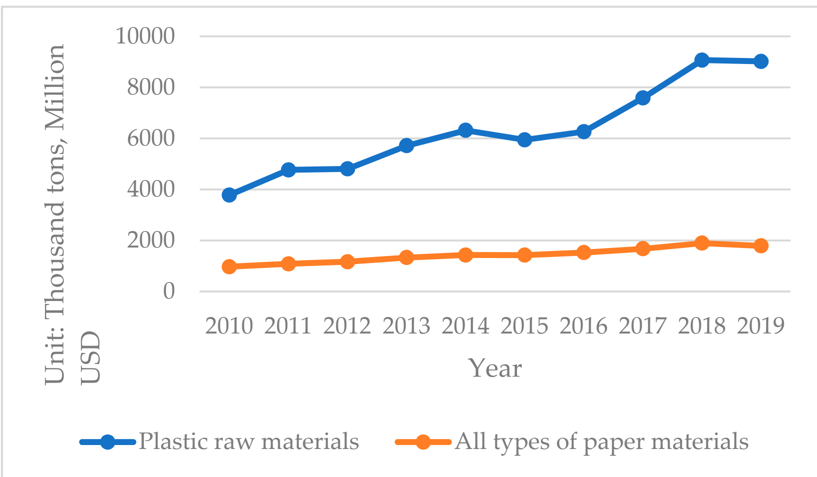

Figure 1. Import levels of some input materials for packaging production in Vietnam in 2010–2019 (Source: thongke.idea.gov.vn [7]).

In addition, in 2015, greenhouse gas (GHG) emissions from plastics accounted for 3.5 percent of the global annual GHG emissions [8], and in 2018, Laura Parker emphasized that around 40 percent of the plastic created was for the packaging industry, which means this industry would also be responsible for the world's pollution [9]. Particularly, plastic packaging in Vietnam achieved a growth rate of 25 percent per year and accounted for the highest proportion in structural plastic (38–39%) [10]. In 2019, the total consumption of paper material reached 3818 million tons, while the percentage of paper packaging production attained was over 80% [10].

The packaging industry is undoubtedly considered a potential industry with high growth rate in Vietnam, but according to the National Steering Committee for Clean Water—Ministry of Natural Resources and Environment [11], the paper manufacturing industry that includes the paper packaging industry is one of the most serious environmental polluting industries today, especially for water resources.

To face concerns about environmental pollution with a high amount of plastic waste, the global packaging operation is looking forward to producing active, intelligent [12], and green packaging in the future. Some preliminary work was carried out in 2001, showing that various executives perceive how influential a strategy on how associated social responsibility affects the social and financial performance of an enterprise [13]. Following the global trend, Vietnamese consumers are gradually switching to using green packaging to ensure their health and safety.

These packaging technologies are also known as the trend of environmentally friendly and sustainable development packaging. The solutions are integrating packaging with Internet of things (IoT) technology, recycling materials, reusable packaging products, and using fast decomposition packaging. All these actions aim to reduce hazardous waste in the environment, sustain materials, expand product storage life, and improve safety, management, and cost-effectiveness. At the same time, governments have been aware of and set out regulations to improve the environment. These commitments were agreed upon by worldwide governments. This tendency enhances tough technological competition among all enterprises in the packaging industry. Therefore, the biggest challenge now for this industry is not only finding customers but also investing in technological innovation that has the minimum impact on the environment by using eco-friendly materials and manufacturing processes to compete and catch up with the ever-growing production and sustain business. When the production process is not optimized, the waste of raw materials, fuel, and emissions will also create significant environmental impacts.

Moreover, in the new development context, Vietnam joined the World Trade Organization (WTO) in 2007 and attracted many foreign companies and corporations to come to Vietnam to seek investment opportunities. At this time, the Vietnam government has also allowed 100% foreign-owned companies to operate in the packaging industry [14]. Considering some aspects of competitiveness and production materials, foreign direct investment (FDI) enterprises have shown superiority. Their machines and technology are very modern, have closed production lines, are mostly automated so their costs are low, and their productivity is very high. Vietnamese packaging enterprises also revealed many shortcomings, such as a lack of vision, unclear long-term strategy, poor governance, low productivity, lack of high-quality human resources, weak financial positions, and so on. In addition, the market still requires businesses in the industry to constantly research and create unique and more effective personalization and interaction. There is a major concern that the profit margins of packaging companies will be reduced more than before due to the increase in production costs, and the obstacle to technology transfer is one factor that inhibits the development of the green packaging market. Besides that, the number of consumers aware of the need to use green packaging is still not in the majority, so it is not enough for packaging companies to completely switch to supplying green packaging. If packaging enterprises do not utilize their competitive advantages and update the technology to adapt to growth trends, they will go backward and lose customers. To initiate a sustainable strategy in an operation, different administration systems, such as commodity expense, capital budgeting, information, and performance assessment, must be composed and defined [13].

According to all these facts mentioned above, the purpose of this study is to identify and evaluate the performance and ranking of 10 packaging companies in Vietnam in each period from 2012 to 2023, by integrating the additive Holt-Winters (LTS(A,A,A)) forecasting model in Tableau and an epsilon-based measure of efficiency (EBM) in data envelopment analysis (DEA). Due to the fact that financial reporting plays an important role in the process of strategic decision-making, specifically decisions of an investment nature [15], while all the packaging companies are trying to meet the market demands and sustain development and increase their competitive advantages or minimize weaknesses, the financial performance forecasting analysis in this study can show how financial variables change over time and hence support packaging companies to make strategic decisions, whether they should align their budgets or determine expenses to invest in new technology, materials, processes, and consultancy to adapt to global trends, because green supply chain management (GSCM) practices in the packaging industry contain the risks of high investment costs and low returns [16]. Besides that, the results will also assist manufacturers, which need packaging services to find the most suitable partners and investors, who need to make investment decisions in this industry. This investigation is expected to add substantially to the understanding of applying EBM to DEA, the model which can give the score and ranking for each decision-making unit (DMU) performance in the experiment years and its implementation, contributing to the specific solution to improve the efficiency for the identified company.

There are five parts in this paper, and they are as follows. Section 1 is an overview of the study that includes the packaging industry background, motivation, objectives, and the process of the research. Section 2 reviews the literature of the packaging industry, the additive Holt-Winters model (LTS(A,A,A)), and an epsilon-based measure of efficiency (EBM) in DEA, proposes the data sources and figures out the input and output that would be applied for the methods. Section 3 presents the empirical results, indicates assessed values, and calculates and discusses the outcomes. Section 4 provides the conclusions, describes some elements that may affect the findings, and recommends future studies.

2. Theoretical Foundations and Methodology

2.1. Literature Review

As mentioned above, packaging plays an important role in every industry. It is not only the thing that is protecting the products, but also the tool that is supporting overall sales. Package design has a huge impact on the decision-making stage of customers. Nielsen demonstrated that more than 60% of buyers try a new product just because the package attracts their eye, and over 40% will consume a product continuously because of its impressive design [17]. Nowadays, traditional packaging is not sufficient to meet the need of the development of consumer experience expectations over time and increasing product complexity. Moreover, recently, national and international have aimed to promote a circular economy and reduce the carbon footprint of manufactured products [18]. Hence, with the growth trend of smart packaging in the Industry 4.0 era, in 2018, Dirk Schaefer and Wai M. Cheung conducted a general overview of smart packaging and defined its underlying base technologies with opportunities and challenges, hence finding out the solutions for smart packaging to minimize its shortcomings and to get its full potential [19]. Gareth R.T. White et al. investigated the decision's complication around the interorganizational green packaging design in an automotive manufacturer. The author noticed that despite the enterprise generating considerable attempts to enhance its environmental effectiveness, the most important aspects in the form of packaging are the operational matters [20]. In this study, the performance of packaging companies in Vietnam is measured by integrating the LTS(A,A,A) model and the EBM model.

The Holt-Winters (HW) theory was one of the favorable variants of the exponential smoothing (ES) forecasting method variations, first introduced by Holt [21]. It is a well-known concept that is used to predict the future data value and performance of an undefined system in diversified interdisciplinary fields, capable of accommodating the changing trends and seasonal adjustments based on a selection of time interval data [22]. The HW model includes mathematical equations that are calculated to create accurate forecasts. It divides into two forms based on the nature of the seasonal element. The first variant is the additive method, suitable for obtaining the seasonality changes in data that are stable during the series, and the second is the multiplicative method which, on the contrary, is suitable for catching up the seasonality changes in data that are raised all over the observation time [23]. For example, in 2015, Eimutis Valakevicius and Mindaugas Brazenas used the seasonal Holt-Winters model to forecast the exchange rate volatility [24]. Vicky Chrystian Sugiarto et al. applied the HW method to predict goods demands from consumers for enterprise resource planning at a sales and distribution module [25]. Furthermore, Maciej Szmit and Anna Szmit proposed a modified HW version to forecast the anomaly detection of network traffic [26]. The HW method is integrated and can be used in Tableau, an analytic forecasting platform that was created from a computer science project at Stanford in 2003 [27]. Tableau is a beneficial business intelligence (BI) platform that supports analysis and gives data visualization for organizations from diverse fields and countries to utilize their decision-making procedures. Tableau accommodates with most data forms and gives out-of-the-box combinations with a diversified range of big data platforms, including Hadoop. Tableau integrates with R, the BI statistical language that many data experts manipulate for progressive analytics [28]. There are different Tableau manners that have been introduced for linear and branching time point-based temporal logics [29]. One of the most practical functions in Tableau is predicting future data by applying exponential smoothing throughout the past statistics. It contains multiplicative and additive methods and enables highly precise results [30]. Its application was reported in the study of Anita S. Harsoor and Anushree Patil, who proposed sales forecasting for Walmart by using the Holt-Winters method in Tableau [30]. In order to forecast the future value of all subjects, this research will conduct the additive Holt-Winters method (LTS (A,A,A)) in the Tableau software.

Data envelopment analysis (DEA) is a decision-making support method that was first introduced in 1978 by Charnes, Cooper, and Rhodes [31], based on the fundamental theory of the nonparametric method for assessing the technical efficiency of Farrel [32], whose domain of inquiry is a group of decision-making units (DMUs) which can obtain multiple inputs and declare multiple outputs [33]. Over four decades, DEA was developed for various models and was utilized by a large number of worldwide researchers and scholars in multiple fields. Since the first Charnes, Cooper, and Rhodes (CCR) model was introduced, there have been many upgraded DEA models which shortened the limitations of previous models, such as the variable returns-to-scale Banker, Charnes, and Cooper (BBC) model (1984) [34], which improved the shortcomings of the constant returns to scale of the CCR model, the slacks-based measure (SBM) considering the change in proportion between the inputs and outputs, and directly dealing with the slacks gap (Tone, 2001) [35]. A highlighted case study confirmed the usefulness of the fuzzy analytic network process (FANP) and data envelopment analysis (DEA), which includes the CCR model, BCC model, and SBM model in order to rank and evaluate the suppliers in the rice supply chain, through the efforts of Wang, C.N et al. in 2018 [36]. DEA normally has two assessments of technical efficiency with different attributes: radial and nonradial [37]. To solve the issue related to radial and nonradial models concerning the proportionality between the input and output changes, the epsilon-based measure (EBM) model was invented in 2010 by K. Tone and M. Tsutsui [37], which has both radial and non-radial attributes in an undetermined structure. In 2018, Chia-Nan Wang, Jen-Der Day, and Thi-Kim-Lien Nguyen used the EBM model and gray forecasting to assess the efficiency of 10 third-party logistics providers [38]. Li Yang, Ke-Liang Wang, and Ji-Chao Geng assessed China's regional ecological energy efficiency and energy saving and pollution abatement potentials with the exploited EBM model [39]. QiangChen et al. applied the EBM model for marketization and calculated the water resource utilization efficiency based on provincial panel data in China during the span of 2008–2013 [40].

2.2. Method of Research

2.2.1. Research Process

This research applied the additive Holt-Winters model to predict the future values of performance indicators in financial statements and the EBM model to estimate the performance of each DMU. The final analysis results show the efficiency and inefficiency of 10 packaging companies for every year during the period from 2012 to 2023. The process was divided into even stages, shown in Figure 2:

- Stage 1: With the background knowledge about the packaging industry, the authors defined the importance of assessing the performance of packaging companies and identified the research objectives, target, and scope;
- Stage 2: Based on the overview of the background of previous studies of the packaging industry and the LTS(A,A,A) and EBM methods, the authors found that the research topic was new and necessary. Hence, the researcher established the methodology of the study;
- Stage 3: All suitable packaging companies were chosen from Vietstock [41] to meet the research target, and the models were designed after reviewing the theory of the additive Holt-Winters method and the EBM model. The study collected ten packaging companies;
- Stage 4: Input and output factors were selected to assess the performance of packaging companies. If the input and output indicators were not appropriate, they would be replaced by other factors;
- Stage 5: The study used the series of historical collected data to forecast the future values by using the additive Holt-Winters model. The results of the forecasting data would be examined by the mean absolute percent error (MAPE) indicator. If the MAPE index was accurate and appropriate, the next step would be applied, but if not, the data and factors would need to be retested;
- Stage 6: Following the previous step, an epsilon-based measurement model in DEA would be conducted to measure the performance of 10 enterprises from 2012 to 2023. The Pearson's coefficient would be tested to define the correlation among the input and output variables. According to the EBM model, the Pearson's coefficient was adjusted and formulated by the values of affinity and diversity. The suitable index would need to be between 0 and +1;
- Stage 7: The authors analyzed the performance and ranking of all DMUs from the past to the future. The recommendations for unproductive units to improve their effectiveness based on the EBM model results would be represented. Then, the empirical results and conclusions would be discussed.

2.2.2. Data Sources

There are many companies in the packaging industry, and each company has different sizes, technology, and target products. It is quite difficult to access all companies' data when not all of them provide public financial reports. Firms that have negative values in their financial statements were also not selected for this study. This research aims to calculate the productivity performance of packaging industry companies in Vietnam. Therefore, the authors collected 10 packaging companies in Vietnam that were listed in Vietstock [41] from 2012 to 2019. The name of each DMU is shown in Table 1.

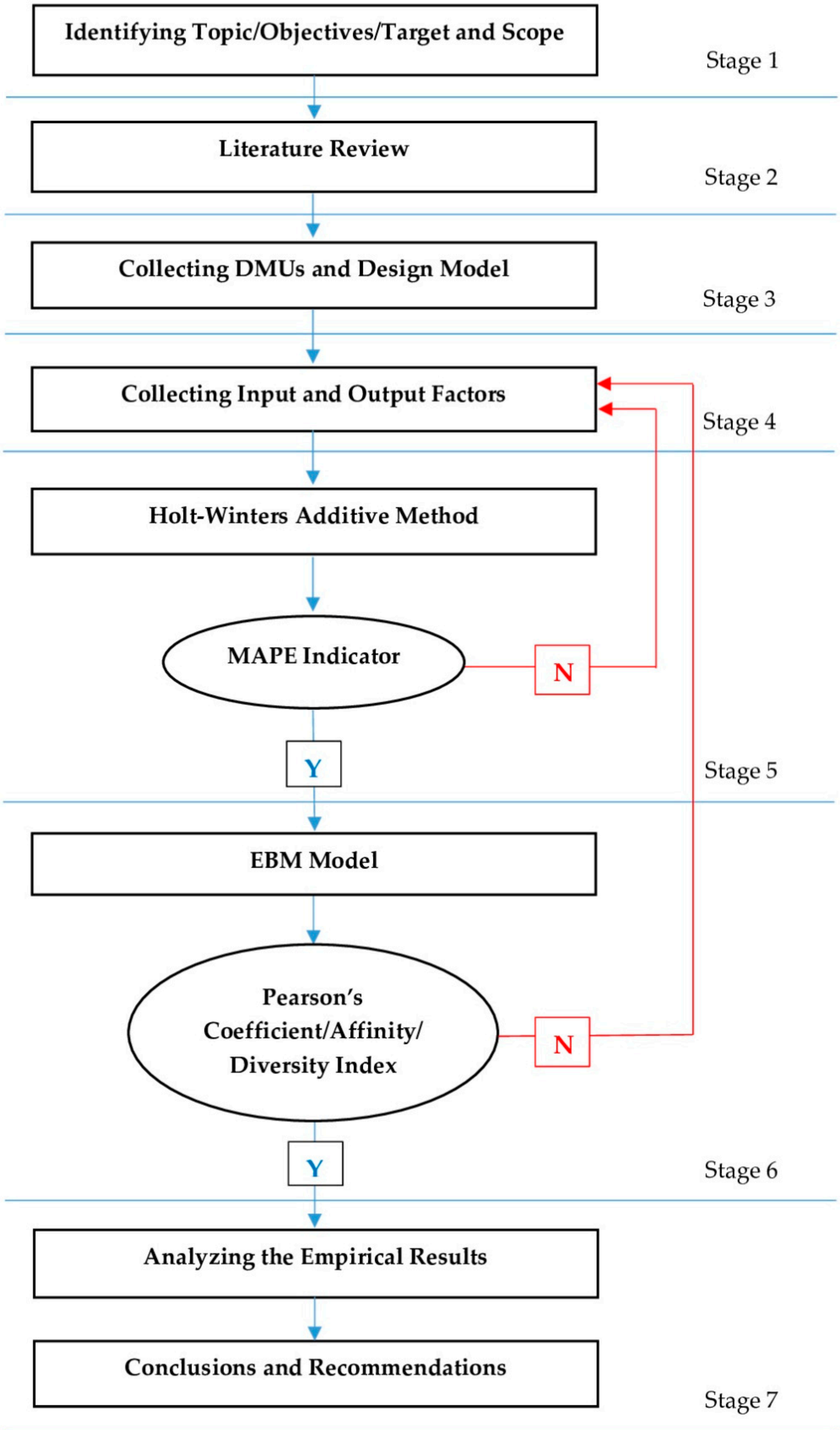

Figure 2. Research framework.

Table 1. List of packaging companies.

DMUs	Company Name	Headquarters
DMU1	Agriculture Printing & Packing Joint Stock Company	Hanoi, Vietnam
DMU2	Tan Tien Plastic Packaging JSC	Ho Chi Minh City, Vietnam
DMU3	Sai Gon Packaging Joint Stock Company	Ho Chi Minh City, Vietnam
DMU4	Bien Hoa Packaging Company	Dong Nai Province, Vietnam
DMU5	SIVICO JSC	Hai Phong City, Vietnam
DMU6	Tan Dai Hung Plastic Joint Stock Company	Ho Chi Minh City, Vietnam
DMU7	Dam Phu My Packaging Joint Stock Company	Vung Tau City, Vietnam
DMU8	Dong A Joint Stock Company	Khanh Hoa Province, Vietnam
DMU9	Do Thanh Technology Corporation	Ho Chi Minh City, Vietnam
DMU10	PetroVietnam Packaging JSC	Bac Lieu City, Vietnam

Source: Vietstock.vn [41].

Finding the input and output factors plays an important role for applying DEA. One of the most beneficial features of DEA is allowing users to choose the variable inputs and outputs. However, these elements must correspond. Experiments on the pricing strategy in the European packaging industry were performed in 2017 by Niklas L.Hallberg, which revealed how asset specificity and routines impacted the pricing strategy and finally enterprise effectiveness [42]. In an economic value-added tree, according to Pohlen and Goldsby, performance indicators including the cost of goods sold, expenses, net profit, sales, fixed assets, and working capital were affected by supply chain activities [43]. Besides that, Roland T. Rust et al. highlighted that the cost determination focused on the efficiency of the operation's processes [44].

Regarding the purpose of the research, this study selected input and output factors for 10 packaging companies during the period from 2012 to 2019 to estimate their performance as mentioned below.

Input variables:

The total assets (TA) was defined as the total amount of assets owned by a person, group, or operation.

The cost of goods sold (CGS) presented the direct costs attributable to the production of the goods sold in a company.

The operating expenses (OE), also called operating expenditures or opex, were the ongoing costs for running a product, business, or system.

Output variables:

The revenue (RE) was the income that a business had from its normal business activities, usually from the sale of goods and services to customers.

The gross profit (GP) was the profit that an operation made after subtracting the cost of goods sold from its revenue.

2.3. *Mathematical Modeling*

2.3.1. Additive Holt-Winters Method

The additive Holt-Winters method is one of the most favorable forecasting tools among the HW methods, in which the seasonal component is indicated in constant terms in the scale in the time series. The LTS(A,A,A) method has been widely adopted by researchers due to its ease of comprehension, moderate data storage conditions, and ability to be effortlessly automated [22]. This research will exploit the Tableau software to obtain the additive Holt-Winters prediction values for 10 packaging companies in Vietnam from 2020 to 2023, based on the historical data from 2012 to 2019.

Let us indicate that X_0 is the units of packaging enterprises, calculated by applying the primary time series $T_1, T_{t+1}, \ldots, T_{t+n}$ (with $t = 0, 1, 2, \ldots n$) and the evaluated prediction values $P_1, P_{t+1}, \ldots, P_{t+n}$ (with $t = 0, 1, 2, \ldots n$).

The sequence of examination for the primary time series and forecasting values begins at $t = 0$ as the first period. The standard formula for exponential smoothing is formulated by

$$\begin{array}{l} P_0 = T_0 \\ P_1 = \alpha \times T_1 + (1-\alpha) \times P_{t-1} \\ 0 \leq \alpha \leq 1 \end{array} \tag{1}$$

In the additive Holt-Winters method, the overall approach form is described as

$$\begin{array}{l} P_1 = \alpha \times (T_t - S_{t-k}) + (1-\alpha) \times (P_{t-1} + R_{t-1}) \\ R_t = \beta \times (P_1 - P_{t-1}) + (1-\beta) \times R_{t-1} \\ S_t = \gamma \times (T_t - P_t) + (1-\gamma) \times S_{t-k} \end{array} \tag{2}$$

The forecasted value of the data elements T_t is given by

$$T_t = P_{t-1} + R_{t-1} + S_{t-k} \tag{3}$$

The prediction for the next period n is identified by

$$T_t(n) = P_t + n \times R_t + S_{t+n-k} \tag{4}$$

where α, β, and γ correspond to the smoothing constants for the level of the series $(0 \leq \alpha \leq 1, 0 \leq \beta \leq 1, 0 \leq \gamma \leq 1)$, k is the rate of occurrence span of the seasonality, T_t is the particular value at the past time series t, P_t is the approximate smoothing of the deseasonalized level at the termination of span t, R_t is the approximate smoothing of the trend factor at the termination of span t, S_t is the approximate smoothing of the seasonal factor at the termination of span t, n is the number of spans in the forecasting lead time, and t is the time indicator.

Actually, the gap between the predicted data value and the actual data value always remains. As proposed by Stekler [45,46], an ideal forecast can be sorted out through calculation of the root mean square errors (RMSEs) and mean absolute percentage errors (MAPEs). Both are the most favorable prediction estimation measures used [47,48]. The RMSE is the square root of the second sample moment of the differences between the forecasted and observed values [49] and is non-negative. The lower the RMSE, the better the regression model is. The RMSE and is defined by [50]

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(P_t - T_t)^2} \tag{5}$$

The mean absolute percent error (MAPE) is an index that is used to define the accuracy of the forecasting values. It gives an intuitive interpretation in terms of the relative error and can be commonly used in many cases [48,51]. It expresses the accuracy as a percentage. The MAPE indicator is interpreted as

$$MAPE = \frac{100}{n}\sum_{t=1}^{n}\left|\frac{T_t - P_t}{T_t}\right| \tag{6}$$

where: T_t is the actual value in time t and P_t is the forecasted value in the time t.

The forecasting values estimated by the additive Holt-Winters method must be examined by the MAPE indicator. If the MAPE index is lower than 50%, it means the predicted value is appreciable. Conversely, if it is higher than 50%, it means the forecasting values have a lot of noise, and then another forecasting model can be retested. The MAPE index was divided into four categories as presented in Table 2.

Table 2. The parameters of the mean absolute percent error (MAPE).

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

2.3.2. An Epsilon-Based Measure (EBM) Model

An Epsilon-Based Measure of Efficiency

According to DEA, there are two different measurement types for technical efficiency: radial and nonradial. The radial measurement only focuses on the proportionate change of the input or output and ignores the appearance of slacks. In contrast, the nonradial measurement faces slacks directly and is not concerned with the proportion of inputs and outputs changing. As a result, both can lead to inappropriate evaluation in some cases. The epsilon-based measure (EBM) was invented as a solution for this shortcoming. The model combines both radial and nonradial features. Two parameters, one scalar and one vector, are contained in this framework, determined by affinity index with regards to the inputs and outputs. These two parameters are defined to integrate the radial and nonradial models into a unified model to assess the efficiency of DMUs.

By indicating the input-oriented EBM (EBM I-C) for $DMU_0 = (x_0, y_0)$, we then calculate it as

$$\gamma^* = \min_{\theta,\lambda,s^-} \theta - \varepsilon_x \sum_{i=1}^{s} \frac{w_i^- s_i^-}{x_{i0}} \quad (7)$$

This is subject to

$$\theta x_0 - X\lambda - s^- = 0$$
$$Y\lambda \geq y_0, \lambda \geq 0, s^- \geq 0$$

where the weight (relative importance) of input (i) is w_i^- and $\sum\limits_{i=1}^{s} w_i^- = 1\left(w_i^- \geq 0 \forall i\right)$ and ε_x is the parameter that integrates the radial θ and nonradial slacks terms.

Diversity Index and Affinity Index

Generally, in DEA, the Pearson's correlation plays an essential role in clarifying the relationship between two variables. It translates the initial data to estimate the correlation. If the Pearson's index is high, it means the two variables associate with each other. On the other side, if the correlation coefficient is low, it means the input and output relation is unappropriated. The value of the Pearson's correlation coefficient ranges from −1 to +1.

In addition, the weight is also one of the most important factors in DEA. The weight determines how much the input will impact the output [52]. If the weight is close to 0, it shows that there is no change in the output even if the input changes. Nonpositive weights indicate the opposite relationship between the input and output, such that if the input grows, the output will decline.

Regarding the EBM model, the values of $_x$ and w_i have a major impact on estimating the efficiency of DMUs. However, instead of using the Pearson's correlation coefficient as another model, the EBM model will use the affinity index between two vectors.

Let $a \in R_+^n$ and $b \in R_+^n$ be two non-negative vectors with a dimension n. They display the examined values for a definite input component in n DMUs. S (a,b) is the affinity index between two vectors a and b with the following features:

$S(a,a) = 1(\forall_a)$ Identical
$S(a,b) = S(a,b)$ Symmetric
$S(ta,b) = S(a,b)/(\forall t > 0)$ Units-invariant

$$1 \geq S(a,b) \geq 0/(\forall a,b)$$

Let us define

$$
\begin{aligned}
c_j &= \ln \tfrac{b_j}{a_j}\ (j = 1, \ldots, n) \\
\bar{c} &= \tfrac{1}{n} \sum_{j=1}^{n} c_j \\
c_{max} &= \begin{matrix} max \\ j \end{matrix} \ \{c_j\}, c_{min} = \begin{matrix} min \\ j \end{matrix} \ \{c_j\}
\end{aligned}
\tag{8}
$$

The diversity index of vectors (*a*,*b*) as the deviation of $\{c_j\}$ from the average $\bar{c}$ will be identified as follows:

$$
\begin{gathered}
D(a,b) = \tfrac{\sum_{j=1}^{n} |c_j - \bar{c}\ |}{n(c_{max} - c_{min})} = 0\ if\ c_{max} = c_{min} \\
\text{And}:\ 0 \leq D(a,b) = D(b,a) \leq \tfrac{1}{2}
\end{gathered}
\tag{9}
$$

$D(a,b) = 0$ only if vector a and vector b are proportional.

If we denote the affinity index between vector a and vector b as *S*(*a*,*b*), then

$$
S(a,b) = 1 - 2D(a,b) \tag{10}
$$

If $1 \geq S(a,b) \geq 0$, *S*(*a*,*b*) is accomplished with properties (7) and (8).

In DEA, the Pearson's correlation coefficient (*P*(*a*,*b*)) will be calculated by the following equation:

$$
P(a,b) = \frac{\sum_{j=1}^{n} (a_j - \bar{a})(b_j - \bar{b})}{\sum_{j=1}^{n} (a_j - \bar{a})^2 (b_j - \bar{b})^2} \tag{11}
$$

where: $\bar{a}$ and $\bar{b}$ are the average of a_j and b_j, respectively.

However, in the EBM model, the affinity index will replace the Pearson's correlation coefficient (*P*(*a*,*b*)). As mentioned above, the Pearson's index range is $-1 \leq P(a,b) \leq 1$. Thus, when analyzing the fundamental factor, there is no assurance for the principal vector only including positive components. Therefore, it will be adjusted to $0 \leq P(a,b) \leq 1$.

3. Results

3.1. Additive Holt-Winters Forecasting

3.1.1. Forecasting's Results

In this section, through the data of 10 packaging companies from the period of 2012–2019 that were collected, the additive Holt-Winters additive model in Tableau will be applied to calculate the future data from 2020 to 2023. From the past data sequence, in applying the method, forecasting values for the inputs and outputs of all 10 DMUs from 2012 to 2023 are described in Tables A1 and A2.

3.1.2. Forecasting Accuracy

According to the additive Holt-Winters forecasting model, there is a difference that exists between the predicted data value and the actual data value. In this research, the authors utilized the root mean square error (RMSE) and mean absolute percent error (MAPE) to calculate the accuracy of the forecasting values.

Table 3 illustrates the RMSE index per DMU. It can be seen from the table that all RMSE results were positive values and could be accepted.

As mentioned in Table 2, for the MAPE parameter, if the MAPE index was under 20%, it meant the accuracy of the forecasted value was highly appreciable. Table 4 identifies the average MAPE of each DMU.

It is apparent from Table 4, all DMUs had MAPE indexes under 36%, and their mutual average was 10.56%. As such, all DMU predicted values had good accuracy and were close to the actual values. Furthermore, all predicted values for all DMUs from 2020 to 2023 in Table A2 were non-negative values and acceptable to use in EBM analysis.

Table 3. Root mean square error of the decision-making units (DMUs).

DMU	TA	COGS	OE	RV	GP
DMU10	9299	22,475	1142	24,231	3622
DMU9	4583	9399	1183	10,882	3641
DMU8	15,812	8755	2242	10,464	2786
DMU7	23,760	42,656	2533	45,992	3609
DMU6	48,677	28,471	5974	30,089	7180
DMU5	13,996	12,353	1833	18,976	8786
DMU4	49,316	107,923	4705	93,504	31,286
DMU3	19,964	25,163	3066	29,994	6167
DMU2	176,835	139,673	24,194	114,024	36,453
DMU1	42,930	53,109	13,693	61,806	13,769

Table 4. The average MAPEs of the DMUs.

DMU	TA	CGS	OE	RE	GP
DMU10	8.30%	16.90%	7.40%	16.20%	14.80%
DMU9	2.40%	8.10%	9.30%	7.80%	36.00%
DMU8	11.20%	3.20%	9.80%	3.20%	6.60%
DMU7	15.60%	15.50%	7.70%	13.90%	6.90%
DMU6	6.80%	3.40%	10.90%	3.40%	11.90%
DMU5	12.00%	7.90%	10.90%	8.30%	14.70%
DMU4	5.90%	7.50%	4.10%	6.10%	13.60%
DMU3	12.10%	13.10%	9.50%	12.10%	14.50%
DMU2	17.10%	9.40%	15.60%	6.60%	18.30%
DMU1	9.20%	8.00%	15.80%	8.10%	10.20%
Average			10.56%		

3.1.3. Smoothing Coefficients

According to the condition of smoothing coefficients in the additive Holt-Winters method, an acceptable α, β, γ index ranged from 0 to 1. The three smoothing constants were applied to forecast the future performance of packaging enterprises. The results of the alpha, beta and gamma that are shown in Table A3 confirmed our data were appreciable when their values were accounted for from 0 to 0.5.

3.2. Assessing the Performance of DMUs

In this part, the EBM-I-C (input-oriented under constant returns-to-scale assumption) in DEA will be applied to assess the efficiency of each packaging company, based on the historical data (2012–2019) in Table A1 and forecasted data (2020–2023) in Table A2 obtained from the additive Holt-Winters forecasting results. The efficiency of each year will be presented in Tables 8 and 9 below.

One of the biggest concerns before assessing the efficiency of the DMUs through EBM was defining whether the data value was positive. Besides that, the relation between the input and output data was isotonic. The correlation coefficient would be used to define the relationship among two variables, and it would be ranged from -1 to +1. If the index was near +1, it meant the two variables had a strong correlation. In contrast, if the correlation coefficient was close to -1, it meant the input and output correspondence was low. Table A4 presents the Pearson's correlation coefficient of the DMUs for each year. As can be observed from the results, the correlation coefficient minimum was 0.6889. This means all the data variables were closely connected and acceptable to run EBM.

As stated in the EBM model, two parameters that combine the radial and nonradial models were established by an affinity index. The affinity index between two vectors was calculated to replace the Pearson's correlation coefficient. Their appropriated values had to meet the requirement $0 \leq P(a, b) \leq 1$.

The diversity index of the vectors was determined as the deviation of variables and $0 \leq D(a,b) = D(b,a) \leq 1/2$. It was only equal to 0 when the two vectors were proportional. Both the affinity and diversity indicators were utilized to assure that the correspondence of the input and output variables was suitable for evaluating the efficiency of the DMUs with

EBM. It can be seen from Tables 5 and 6 the data variables satisfied the condition of the EBM model.

Table 5. Affinity index.

	TA	**CGS**	**OE**	**TA**	**CGS**	**OE**
Year		2012			2013	
TA	1	0.56183	0.50585	1	0.69466	0.54117
COGS	0.56183	1	0.62592	0.69466	1	0.69653
OPEX	0.50585	0.62592	1	0.54117	0.69653	1
Year		2014			2015	
TA	1	0.58307	0.58106	1	0.58916	0.64542
COGS	0.58307	1	0.66894	0.58916	1	0.3793
OPEX	0.58106	0.66894	1	0.64542	0.3793	1
Year		2016			2017	
TA	1	0.46081	0.41815	1	0.51481	0.43663
COGS	0.46081	1	0.50503	0.51481	1	0.54862
OPEX	0.41815	0.50503	1	0.43663	0.54862	1
Year		2018			2019	
TA	1	0.43808	0.36851	1	0.49053	0.58637
COGS	0.43808	1	0.61053	0.49053	1	0.55946
OPEX	0.36851	0.61053	1	0.58637	0.55946	1
Year		2020			2021	
TA	1	0.40351	0.4343	1	0.42414	0.30355
COGS	0.40351	1	0.47663	0.42414	1	0.55016
OPEX	0.4343	0.47663	1	0.30355	0.55016	1
Year		2022			2023	
TA	1	0.38145	0.42825	1	0.46037	0.36986
COGS	0.38145	1	0.46722	0.46037	1	0.57605
OPEX	0.42825	0.46722	1	0.36986	0.57605	1

Table 6. Diversity index.

	TA	**CGS**	**OE**	**TA**	**CGS**	**OE**
Year		2012			2013	
TA	0	0.21908	0.24708	0	0.15267	0.22941
COGS	0.21908	0	0.18704	0.15267	0	0.15173
OPEX	0.24708	0.18704	0	0.22941	0.15173	0
Year		2014			2015	
TA	0	0.20847	0.20947	0	0.20542	0.17729
COGS	0.20847	0	0.16553	0.20542	0	0.31035
OPEX	0.20947	0.16553	0	0.17729	0.31035	0
Year		2016			2017	
TA	0	0.26959	0.29092	0	0.2426	0.28168
COGS	0.26959	0	0.24749	0.2426	0	0.22569
OPEX	0.29092	0.24749	0	0.28168	0.22569	0
Year		2018			2019	
TA	0	0.28096	0.31574	0	0.25473	0.20681
COGS	0.28096	0	0.19473	0.25473	0	0.22027
OPEX	0.31574	0.19473	0	0.20681	0.22027	0
Year		2020			2021	
TA	0	0.29824	0.28285	0	0.28793	0.34823
COGS	0.29824	0	0.26168	0.28793	0	0.22492
OPEX	0.28285	0.26168	0	0.34823	0.22492	0
Year		2022			2023	
TA	0	0.30928	0.28588	0	0.26981	0.31507
COGS	0.30928	0	0.26639	0.26981	0	0.21198
OPEX	0.28588	0.26639	0	0.31507	0.21198	0

The weight of the inputs and outputs and the epsilon indicator played an essential role in eliminating the EBM score for each DMU. A weight index defines the proportional effect the input will have on the output. Table 7 indicates that the entirety of the weight indexes were positive. In this case, this means that changing the input factors would have an impact on the outputs, and if the values of the input increased, the values of the output would grow.

Table 7. Weight to input or output.

Year	TA	CGS	OE
2012	0.32093	0.34465	0.33442
2013	0.32474	0.35017	0.32509
2014	0.32246	0.33894	0.3386
2015	0.36319	0.31142	0.32539
2016	0.32258	0.34353	0.3339
2017	0.32247	0.34689	0.33063
2018	0.29778	0.35773	0.34448
2019	0.33084	0.32498	0.34418
2020	0.32334	0.33465	0.34201
2021	0.29858	0.36348	0.33795
2022	0.32227	0.33315	0.34458
2023	0.30633	0.35596	0.3377

The results of the epsilon for the EBM through the years in Table A5 satisfied the condition $0 \leq$ epsilon index ≤ 1. The efficiencies of 10 packaging enterprises were obtained based on the factors of weight and epsilon for EBM. Tables 8 and 9 indicate the efficiency scores for the DMUs from the past to the future.

Table 8. The efficiency scores for DMUs in the past years (2012–2019).

DMUs	2012	2013	2014	2015	2016	2017	2018	2019
DMU1	0.89705	0.96757	0.9784	0.99872	1	1	1	0.93651
DMU2	1	1	0.87235	0.92132	1	1	1	1
DMU3	0.86749	0.90359	0.89433	0.87861	0.89172	0.91656	0.92816	0.88593
DMU4	0.88807	0.8649	0.94419	0.99352	1	1	1	1
DMU5	1	1	1	1	1	1	1	1
DMU6	0.77576	0.82786	0.95611	0.89414	0.98359	0.97447	0.8957	0.86206
DMU7	0.85263	0.85531	0.99586	1	1	1	0.95107	0.87843
DMU8	1	1	1	1	1	0.95604	0.93866	0.91156
DMU9	0.68077	0.73016	0.821	0.77799	0.85843	0.842	0.87313	0.86069
DMU10	0.77112	0.8618	0.94475	0.92874	0.91311	0.92236	0.9592	0.89168

Table 9. The efficiency scores for DMUs in the prediction years (2020–2023).

DMUs	2020	2021	2022	2023
DMU1	1	1	1	1
DMU2	1	0.96085	0.94435	0.95079
DMU3	0.96805	0.91031	0.99711	0.93022
DMU4	1	1	1	1
DMU5	1	1	1	1
DMU6	0.88965	0.91612	0.88826	0.91979
DMU7	0.92741	0.93248	0.91575	0.92693
DMU8	0.91389	0.91726	0.8986	0.91106
DMU9	0.93047	0.93126	0.97919	0.96635
DMU10	0.92496	0.93115	0.91512	0.92765

In general, all the enterprises in the packaging industry had high productivity, while there was no company with an efficiency score below 0.681 in the observation time from

2012 to 2023. As reported by Tables 8 and 9, there were five DMUs with efficiency scores increasing over time from the past to the future. Specifically, they were DMU1, DMU4, DMU5, and DMU9. In contrast, only DMU8 showed a downward trend compared with the first period; however, its efficiency index remained high. Other DMUs presented the fluctuation trend over the same time span. Figure 3 indicates the ranking positions of all companies from past to future (2012–2023).

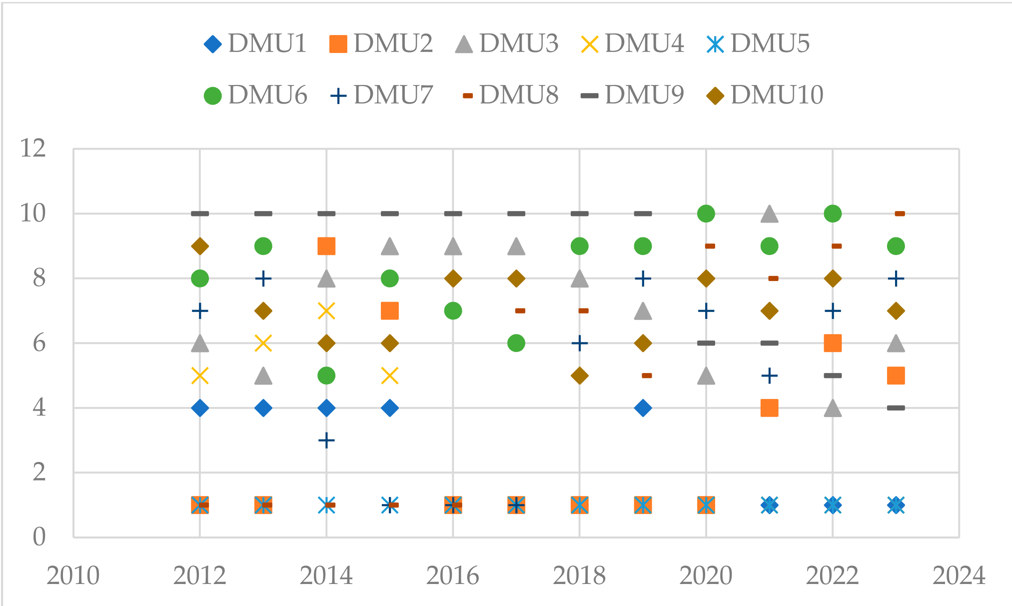

Figure 3. Ranking positions of the DMUs.

Once a DMU gained the first ranking, that meant its theta index (θ) needed to be equal or closest to one, and all slacks for each variable needed to be the lowest and nearest to zero. Conversely, if the slack was high and the theta index was far from one, the DMU could not reach a high position. In the case where θ was higher than one, this meant the DMU was inefficient, and the values of the inputs needed to change accordingly to increase the efficiency and values of the outputs. Table A6 describes theta (θ) and slack (s) in the solution for each unit.

It is interesting to note that in the past data sequence, DMU6 was the most inefficient unit, even with high efficiency scores of 0.95611 (in 2014), 0.98359 (in 2016), and 0.97447 (in 2017) while compared with the efficient unit (score = 1). Particularly, DMU6 had the theta θ = {1.044; 1.064; 1.005} (>1) in 2014, 2016, and 2017, respectively. The input value, theta and slack (s1, s2, and s3) indicators of DMU6 in 2014 in Tables A1 and A6 were picked as a sample for the ideal suggestion emphasized for the inefficient unit. All input indexes were multiplied by θ = 1.044 without the slack. Furthermore, the total assets was reduced by the slack s1 = 384,480. The estimated input for the total assets was 650,097 × 1.044 − 384,480 = 294,221.268. Calculated accordingly, the optimal cost of goods sold was 692,997 × 1.044 − 71,033.5 = 652,455.368, and 47,851 × 1.044 − 0 = 49,956.444 for the operating expenses. DMU6 was advised to reduce the amount of total assets from 650,097 to 294,221.268 and the cost of goods sold from 692,997 to 652,455.368 and increase the operating expenses from 47,851 to 49,956.444 to have better performance.

It is apparent from Table A6 that the incompetent DMUs in each period were different. Except for DMU6 mentioned above, DMU7 was unproductive in 2014, and so was DMU4 in 2015. In the future term, DMU2, 3, 8 and 10 were predicted to be inefficient. With a few exceptions, the years 2015, 2016, and 2017 illustrated that DMU7 got pretty good scores and rankings. In another year, DMU7 showed fluctuating results in its efficiency score, ranking around the fifth to eighth positions. DMU2 showed a high performance, but it was unstable. In 2012 and 2013, it had the highest rank at first with the score also being one. One year later, its position dropped significantly to ninth and seventh in 2014 and 2015. Between 2016 and 2010, it gained the first ranking with a score of one again. From 2021 to 2023, with its forecast value, it was predicted to fall to the fourth, sixth, and fifth positions, respectively. As can be seen from Tables 8 and 9 and Figure 3, compared with the other DMUs, based on the efficiency score and ranked in the order of DMU3, DMU6, and DMU10, these three DMUs were determined to be the most ineffective enterprises. In the same period, three companies' scores fluctuated below one, and their ranks stayed around the last positions. As opposed to the developing companies, DMU8 was the most efficient enterprise from the initial years. It obtained the first position with the highest point of one in the first five years (2012–2016). Nevertheless, they could not remain stable from 2017 to 2023. It was predicted to be in the last group of low efficiency, with DMU8 falling to the last two positions—the ninth and tenth ranking—in 2022 and 2023 with scores of 0.8986 and 0.9110, respectively. The projected input values that were recommended for each inefficient DMU would not be the same based on the efficiency score, theta, and slack index calculations. However, in general, following the estimated instructions as with DMU6, we can see the common solutions for these DMUs were lowering the input values' total assets and operating expenses to improve the values of the outputs, including the revenue and gross profit.

Overall, DMU5 started with the highest score of one, and it ranked first in 2012 and continuously maintained the same the same level until 2023. Its theta was always equal to one and the slacks were zero. DMU5 was defined as the most efficient unit over time. Following that, DMU1 presented steady growth for the whole time. Its position was fourth from 2012 to 2015. One year after, it increased rapidly to be the first leader among the DMUs. In 2019, its position fell to the fourth ranking again with a score of 0.9365. Then, it reversed positions to first with the highest score for the next four years. DMU4 denoted a slight change in its score and position for the first four years, from 2012 to 2015. Noticeably, its beginning position was fifth with a score of 0.888 and ranked sixth, seventh, and fifth in 2013, 2014, and 2015, respectively. It was even mentioned that it was inefficient in 2015 based on the theta and slack indexes. However, starting from 2016, it climbed to the dominant position together with DMU5 with an efficiency score of one and a ranking of first.

DMU9's score substantially grew within 12 years, but due to it having the lowest score (0.6807) from the beginning, it still held the last ranking (tenth) among ten packaging companies between the year 2012 and 2019. Their position only changed from sixth to fourth, with a score from 0.9312 to 0.9663 from 2020 to 2023, respectively.

3.3. Discussion

The development potential of the packaging industry is expanding. However, Vietnamese packaging companies are facing a lot of pressure and great competition from many FDI enterprises. Specifically, following the global packaging trends combined with high technology and eco-friendly practices together with the COVID-19 pandemic, packaging enterprises need to deal with changes in consumer behavior. When customers turn to attain their fundamental priorities, which are food, shelter, water, and healthcare and pharmaceutical products, they are not focused on luxury order desires [53]. In terms of the packaging materials, packaging companies all faced common difficulties under the impact of the crisis, such as breaking the supply chain in business, difficulty in approaching new customers, and not being able to implement a sales plan. However, packaging businesses also have many opportunities such as Vietnam's e-commerce scale, which will continue to grow [54]. Under the EU–Vietnam Free Trade Agreement (EVFTA), the import tax on Vietnam's plastic bags into the EU market will be removed, creating a significant competitive advantage for the packaging industry [55].

To have a deeper understanding not only of the investment and cooperation opportunities, but also the performance effectiveness of each firm in the packaging industry in

Vietnam, based on the historical financial statements of 10 determined packaging companies from 2012 to 2019, this research evaluated the developing trends from the past, present, and future of all units by integrating the additive Holt-Winters model and epsilon-based measurement (EBM) of DEA. Throughout the analysis, manufacturer managers can find the most suitable company to collaborate with to sustain their business strategy and catch up with global trends. According to the empirical results, generally, all packaging companies had productivity from medium to high. DMU1, DMU4, and DMU5 were evaluated as the three most efficient units and ideal suppliers which reached the first rank and remained at it over time. In contrast, DMU3, DMU6, and DMU8 presented fluctuations and a downward trend and kept the last positions. Formulated on the calculation of feasible solutions of EBM, the inefficient and unstable units could change the input value for better performance of the output value. Besides that, they should have policies to improve their competitiveness in quality, reduce waste in the production process, attach value to maintaining long-term relationships with large customers, strengthen after-sales and customer care services, adjust the selling prices reasonably while ensuring profit, and finally invest in technical machinery and equipment to meet the strict requirements from the market.

This section may be divided by subheadings. It should provide a concise and precise description of the experimental results, their interpretation, as well as the experimental conclusions that can be drawn.

4. Conclusions

The packaging industry has an important role in a developing economy, especially in Vietnam, where the demand for producing products is increasing day by day, leading to an increase in the need for packaging. Packaging's values are not only protecting products, but also its role as a sales and marketing tool. Along with the Fourth Industrial Revolution and high customer requirements, packaging companies are under pressure to deal with challenges to improve their core competencies through technology and associated services as suppliers. However, to adapt with the growth trends, which are being fast, flexible, convenient, good, cheap, and environmentally friendly, changing technology will be a big task for companies when it requires strong capital ability. With uncertain circumstances, financial forecasting and performance evaluation are necessary for packaging companies.

This research aimed to construct the efficiency and developing trends of 10 packaging operations from the past to the future by integrating the additive Holt-Winters model, an extended variation of Holt's exponential smoothing that captures seasonality in Tableau and the EBM of DEA. Based on the collected original data from 2012 to 2019 for the packaging companies, the LTS(A,A,A) approach was employed to forecast the value of the data for the next four years (2019–2023), with the chosen inputs and outputs being total assets, cost of goods sold, operating expenses, revenues, and gross profit. The mean absolute percent error (MAPE) estimated the accuracy of the forecasting values. With the MAPE under 10.56%, the predicted data value in this research had good accuracy. Subsequently, the EBM model was applied to assess the decision-making unit (DMU) productivity by giving efficiency scores with rankings and then providing suggestions through the calculation of the theta and slack indexes for incompetent companies in order to improve their performance. The empirical results will first assist packaging company's managers in defining their positions in the market and making long-term sustainable advancement decisions. Secondly, it will be valuable support for investors and manufacturers for choosing the best supplier for their business and making investment decisions. This finding also validates the usefulness of the Holt-Winters forecasting model and epsilon-based measure of efficiency (EBM) in data envelopment analysis (DEA), as the model can measure the performance of a decision-making unit (DMU) and contribute solutions for companies over the observation period, specifically for cases in the packaging industry. These frameworks' combination can be adopted in multiple fields and different projects.

Although the research was successful, some limitations still remain. Since a company's strategic decision-making process and performance can be defined and affected by diversified variations, including internal and external factors not be presented in a financial statement such as human resources and environmental factors, the study estimated the efficiency of packaging companies based on input and output indicators in financial reports. Accordingly, future investigations can address greater clarity on the links between other factors and their effects on the performance of the industry. The research models that were applied in this study are not the only methods for predicting and assessing the productivity of decision-making units. Future research can employ other frameworks and models to achieve their objectives and have a comparative measurement. Besides that, because many firms have not published their financial reports, the sample size was limited and less comparative. Hence, future studies can expand the research target and scope in other regions and other industries.

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Appendix A

Table A1. Historical data of all DMUs from 2012 to 2019.

DMUs	TA	CGS	OE	RE	GP	TA	CGS	OE	RE	GP
			2012					2013		
1	225,416	340,331	38,933	416,943	76,612	274,489	464,002	40,906	560,700	96,698
2	668,890	1,395,761	54,114	1,492,420	96,659	1,056,549	1,380,548	74,396	1,502,907	122,358
3	160,851	259,660	26,390	298,989	39,329	158,167	263,520	37,208	311,871	48,350
4	549,662	728,958	65,569	851,749	122,791	610,872	854,393	81,818	1,003,373	148,980
5	52,861	94,134	9817	124,178	30,044	74,832	108,153	8925	143,966	35,813
6	613,666	575,399	52,258	607,377	31,978	659,919	639,476	48,231	697,931	58,455
7	85,926	112,173	19,925	139,762	27,589	117,109	153,832	23,847	187,198	33,367
8	85,821	195,900	16,682	224,146	28,246	98,168	199,944	16,068	228,837	28,892
9	130,541	61,722	8149	63,934	2212	135,051	89,090	7923	93,198	4107
10	75,970	63,329	10,801	74,106	10,777	90,478	121,727	11,578	142,961	21,233
			2014					2015		
1	341,105	519,131	50,759	627,524	108,392	397,805	629,962	58,670	762,977	133,015
2	1,178,560	1,349,670	124,823	1,514,504	164,834	813,781	1,199,197	127,930	1,392,908	193,711
3	154,407	195,163	23,177	227,823	32,660	128,275	185,389	25,771	213,096	27,707
4	669,385	975,754	85,333	1,130,701	154,947	758,795	1,170,064	93,132	1,341,383	171,319
5	114,886	115,157	11,523	154,670	39,513	153,226	152,150	18,119	219,307	67,156
6	650,097	692,997	47,851	741,824	48,827	534,730	658,109	53,171	707,016	48,907
7	109,409	190,702	26,730	228,455	37,752	124,503	253,216	29,901	294,832	41,616
8	99,367	220,428	16,878	250,700	30,272	130,624	247,714	20,324	283,429	35,715
9	147,895	96,769	8907	107,445	10,676	149,944	102,962	13,251	123,154	20,193
10	94,615	133,418	12,483	156,913	23,496	85,418	120,657	14,001	144,477	23,820

Table A1. *Cont.*

DMUs	TA	CGS	OE	RE	GP	TA	CGS	OE	RE	GP
			2016					2017		
1	491,379	714,851	82,110	882,745	167,894	554,368	804,222	79,506	978,153	173,931
2	925,723	1,176,364	90,554	1,405,264	228,901	1,089,353	1,300,812	83,663	1,459,899	159,087
3	125,184	146,857	26,553	179,511	32,654	136,676	155,664	29,137	194,254	38,590
4	749,980	1,199,774	95,752	1,381,740	181,966	936,962	1,370,666	107,416	1,554,386	183,719
5	164,648	119,490	16,115	167,652	48,161	199,119	140,997	18,421	196,151	55,153
6	599,823	649,998	42,523	702,107	52,109	643,818	674,064	41,945	735,337	61,273
7	142,893	245,138	28,506	286,394	41,255	196,875	347,340	35,998	396,111	48,770
8	156,247	263,115	24,429	303,369	40,255	196,681	277,142	27,955	324,829	47,688
9	157,994	104,988	12,415	125,975	20,987	158,356	104,128	13,035	122,352	18,224
10	116,449	125,837	17,292	153,299	27,461	121,774	159,485	18,877	186,927	27,442
			2018					2019		
1	653,755	976,249	94,511	1,164,601	188,352	792,415	1,073,852	135,016	1,309,529	235,677
2	1,247,892	1,566,783	90,360	1,704,119	137,337	1,348,780	1,536,620	101,103	1,763,523	226,903
3	154,904	168,339	24,290	204,135	35,796	184,592	176,278	27,793	216,420	40,142
4	922,925	1,594,683	113,093	1,780,171	185,488	904,496	1,404,516	112,349	1,703,555	299,039
5	218,140	149,617	17,891	194,421	44,804	227,599	143,197	22,743	195,523	52,326
6	662,377	645,763	53,968	713,685	67,922	666,365	710,317	57,558	781,061	70,744
7	237,719	396,920	40,416	447,932	51,012	219,920	312,037	38,074	356,255	44,218
8	212,062	292,097	33,075	340,094	47,998	214,670	314,913	33,194	364,964	50,052
9	177,527	124,191	13,163	143,492	19,301	168,725	140,759	16,597	166,938	26,179
10	135,686	204,770	20,944	236,603	31,833	138,740	196,867	20,361	223,738	26,870

Table A2. Forecasting data of all DMUs from 2020 to 2023.

			2020					**2021**		
DMU	**TA**	**CGS**	**OE**	**RE**	**GP**	**TA**	**CGS**	**OE**	**RE**	**GP**
DMU1	850,040	1,196,789	138,220	1,440,914	245,096	950,126	1,281,480	147,732	1,558,944	267,450
DMU2	1,374,361	1,597,270	105,622	1,823,640	204,782	1,368,105	1,554,814	117,317	1,821,797	232,070
DMU3	175,830	129,146	19,810	168,189	32,505	188,005	126,189	26,516	167,267	34,539
DMU4	996,251	1,637,435	118,693	1,876,436	260,157	1,066,083	1,780,077	129,827	2,038,766	288,901
DMU5	261,082	156,042	22,871	204,316	48,378	288,472	181,496	25,529	246,528	65,084
DMU6	680,308	706,044	54,344	780,796	65,853	645,751	720,639	54,991	808,669	78,104
DMU7	251,207	405,412	41,817	458,543	53,231	274,346	453,014	44,925	510,812	57,963
DMU8	241,088	331,934	37,875	384,130	54,348	262,890	347,643	38,781	406,668	57,687
DMU9	181,861	135,863	16,041	164,526	29,677	184,060	150,650	17,949	184,694	35,383
DMU10	153,283	207,356	23,097	239,495	35,705	155,938	226,242	24,245	263,363	34,249
			2022					2023		
DMU1	1,007,751	1,404,417	163,168	1,690,329	286,882	1,007,751	1,489,108	172,680	1,808,358	309,237
DMU2	1,484,175	1,651,786	116,115	1,902,359	228,986	1,477,920	1,609,330	127,809	1,900,516	256,274
DMU3	179,243	99,386	17,891	136,472	30,548	191,418	96,429	24,597	135,549	32,582
DMU4	1,096,442	1,838,949	129,923	2,110,224	295,616	1,166,274	1,981,591	141,057	2,272,553	324,360
DMU5	308,559	171,025	26,133	224,616	53,591	335,949	196,478	28,791	266,828	70,297
DMU6	689,501	729,578	56,184	812,369	71,837	654,944	744,173	56,830	840,242	84,088
DMU7	293,641	470,269	46,726	528,806	58,764	316,780	517,871	49,834	581,076	63,496
DMU8	281,545	365,746	43,462	426,143	61,167	303,347	382,355	44,367	448,680	64,505
DMU9	193,144	150,899	18,021	185,439	36,204	195,343	165,686	19,929	205,607	41,910
DMU10	171,279	235,558	26,251	271,358	40,154	173,935	254,475	27,399	295,226	38,698

Table A3. Forecasting parameters of all DMUs from 2020 to 2023.

DMU	TA			CGS			OE			RE			GP		
	α	β	γ	α	β	γ	α	β	γ	A	β	γ	α	β	γ
DMU10	0.5	0	0	0.1	0.5	0	0.5	0	0	0.1	0.5	0	0	0	0.5
DMU9	0.2	0.5	0	0.2	0.5	0	0.1	0.5	0	0.1	0.5	0	0	0.2	0
DMU8	0.5	0	0	0.5	0	0.1	0.5	0	0.5	0.5	0	0.2	0.5	0	0
DMU7	0.5	0	0	0.1	0.5	0	0.2	0.4	0	0.1	0.5	0	0	0.5	0
DMU6	0.1	0	0	0	0	0	0.3	0	0	0	0	0	0.1	0.5	0
DMU5	0.2	0.4	0	0	0.5	0	0.1	0.5	0	0	0	0	0	0	0
DMU4	0.1	0.5	0	0.1	0.5	0	0.1	0.5	0	0.2	0.4	0	0.2	0	0.1
DMU3	0.5	0	0.5	0	0	0	0	0	0	0.5	0	0	0.1	0	0
DMU2	0.1	0.5	0	0.5	0	0.2	0	0	0	0.5	0	0.4	0	0.1	0
DMU1	0.5	0	0.5	0.5	0	0.5	0.5	0	0.1	0.5	0	0.5	0.5	0	0

Table A4. Pearson's correlation coefficient from 2012 to 2020.

	TA	CGS	OE	RE	GP	TA	CGS	OE	RE	GP
Year			2012					2013		
TA	1	0.8995	0.9214	0.8983	0.6889	1	0.9765	0.8682	0.9682	0.7643
COGS	0.8995	1	0.8203	0.9984	0.7635	0.9765	1	0.9108	0.9986	0.8525
OPEX	0.9214	0.8203	1	0.8389	0.8564	0.8682	0.9108	1	0.9267	0.9441
REV	0.8983	0.9984	0.8389	1	0.7983	0.9682	0.9986	0.9267	1	0.8792
GP	0.6889	0.7635	0.8564	0.7983	1	0.7643	0.8525	0.9441	0.8792	1
Year			2014					2015		
TA	1	0.9795	0.9572	0.9716	0.8403	1	0.9852	0.9584	0.9809	0.8849
COGS	0.9795	1	0.9861	0.9989	0.9175	0.9852	1	0.9742	0.9986	0.9208
OPEX	0.9572	0.9861	1	0.9896	0.9445	0.9584	0.9742	1	0.9775	0.9317
REV	0.9716	0.9989	0.9896	1	0.9349	0.9809	0.9986	0.9775	1	0.9400
GP	0.8403	0.9175	0.9445	0.9349	1	0.8849	0.9208	0.9317	0.9400	1
Year			2016					2017		
TA	1	0.9719	0.9023	0.9687	0.8896	1	0.9758	0.8901	0.9701	0.8555
COGS	0.9719	1	0.9614	0.9983	0.9261	0.9758	1	0.9615	0.9989	0.9163
OPEX	0.9023	0.9614	1	0.9710	0.9641	0.8901	0.9615	1	0.9709	0.9696
REV	0.9687	0.9983	0.9710	1	0.9463	0.9701	0.9989	0.9709	1	0.9342
GP	0.8896	0.9261	0.9641	0.9463	1	0.8555	0.9163	0.9696	0.9342	1
Year			2018					2019		
TA	1	0.9587	0.8824	0.9522	0.8058	1	0.9717	0.8562	0.9619	0.8640
COGS	0.9587	1	0.9599	0.9990	0.8972	0.9717	1	0.9187	0.9986	0.9431
OPEX	0.8824	0.9599	1	0.9701	0.9716	0.8562	0.9187	1	0.9307	0.9491
REV	0.9522	0.9990	0.9701	1	0.9161	0.9619	0.9986	0.9307	1	0.9595
GP	0.8058	0.8972	0.9716	0.9161	1	0.8640	0.9431	0.9491	0.9595	1
Year			2020					2021		
TA	1	0.9624	0.8729	0.9599	0.8710	1	0.9596	0.9141	0.9634	0.9185
COGS	0.9624	1	0.9367	0.9993	0.9484	0.9596	1	0.9497	0.9991	0.9629
OPEX	0.8729	0.9367	1	0.9472	0.9789	0.9141	0.9497	1	0.9597	0.9811
REV	0.9599	0.9993	0.9472	1	0.9588	0.9634	0.9991	0.9597	1	0.9716
GP	0.8710	0.9484	0.9789	0.9588	1	0.9185	0.9629	0.9811	0.9716	1
Year			2022					2023		
TA	1	0.9543	0.8796	0.9540	0.8892	1	0.9475	0.8951	0.9518	0.9145
COGS	0.9543	1	0.9365	0.9994	0.9598	0.9475	1	0.9459	0.9992	0.9689
OPEX	0.8796	0.9365	1	0.9465	0.9761	0.8951	0.9459	1	0.9562	0.9782
REV	0.9540	0.9994	0.9465	1	0.9685	0.9518	0.9992	0.9562	1	0.9769
GP	0.8892	0.9598	0.9761	0.9685	1	0.9145	0.9689	0.9782	0.9769	1

Table A5. Epsilon for the EBM in each year.

Year	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	2023
Epsilon Indicator	0.43475	0.35458	0.3885	0.45829	0.53821	0.49927	0.52371	0.45406	0.56151	0.57004	0.57388	0.52865

Table A6. Theta and slack(s) index of inputs for all DMUs.

	θ	s1	s2	s3	θ	s1	s2	s3	θ	s1	s2	s3
DMUs		**TA**	**CGS**	**OP**		**TA**	**CGS**	**OP**		**TA**	**CGS**	**OP**
		2012				2013				2014		
DMU1	0.929	31,857.3	0	3195.4	0.976	0	0	3041.67	0.995	0	0	6376.4
DMU2	1	0	0	0	1	0	0	0	0.879	61674.2	0	0
DMU3	0.880	13,990.3	0	0	0.950	0	0	14,933.2	0.922	0	0	4962.6
DMU4	0.924	141,796	0	0	0.882	17,388.9	0	9979.64	0.945	0	0	717.87
DMU5	1	0	0	0	1	0	0	0	1	0	0	0
DMU6	0.833	250,021	0	0	0.859	176,739	0	0	1.044	384,480	71,033.5	0
DMU7	0.945	21,662.3	0	7770.2	0.914	9755.52	0	10,195.4	1.067	0	12,693.5	12,587
DMU8	1	0	0	0	1	0	0	0	1	0	0	0
DMU9	0.785	75,288.1	0	1344.4	0.786	57,690.6	0	448.829	0.872	60,551.9	0	0
DMU10	0.887	35,843.9	0	3722.6	0.882	5517.84	0	1352.41	0.953	0	0	749.08
		2015				2016				2017		
DMU1	1	0	0	503.37	1	0	0	0	1	0	0	0
DMU2	0.938	0	0	14,575	1	0	0	0	1	0	0	0
DMU3	0.922	0	0	7567.8	0.990	23,990.9	0	9586.41	1	9019.53	0	12,853
DMU4	1.034	163,592	40128	0	1	0	0	0	1	0	0	0
DMU5	1	0	0	0	1	0	0	0	1	0	0	0
DMU6	0.953	184,021	9580	0	1.064	175,678	103,835	0	1.005	98,118.2	21,995.2	0
DMU7	1	0	0	0	1	0	0	0	1	0	0	0
DMU8	1	0	0	0	1	0	0	0	0.964	5435.88	0	536.3
DMU9	0.830	38,383	0	821.22	1	73,793.2	0	4178.29	0.863	20,932.3	0	0
DMU10	0.953	0	0	2306	1	24,775.6	0	4807.43	0.964	11,407.2	0	2997.1
		2018				2019				2020		
DMU1	1	0	0	0	1	57,216.4	0	45,477.8	1	0	0	0
DMU2	1	0	0	0	1	0	0	0	1	0	0	0
DMU3	1	17,622	0	7283.9	1	54,888.6	0	12,343	1.051	45,456.5	0	3759.5
DMU4	1	0	0	0	1	0	0	0	1	0	0	0
DMU5	1	0	0	0	1	0	0	0	1	0	0	0
DMU6	0.990	285,762	0	8089.8	0.907	189,408	0	669.823	0.965	241,965	0	3054.2
DMU7	1	2253.92	0	10,630	0.941	17,857.2	0	12,343.9	0.987	4486.41	0	12,268
DMU8	0.976	16,061.5	0	4681.9	0.955	11,340.6	0	7647.54	1.005	36,412.6	0	12,651
DMU9	0.969	91393.4	0	1104.2	0.978	76344	0	5219.01	0.994	63710.1	0	0
DMU10	1	7665.27	0	3713.5	0.937	11,205.9	0	4322.7	0.992	20,175.1	0	5160.4
		2021				2022				2023		
DMU1	1	0	0	0	1	0	0	0	1	0	0	0
DMU2	1.023	446,999	0	4009.5	1.009	508,648	8349.4	0	1.030	546,525	0	13,645
DMU3	1.061	54,696.9	0	13,954	1.066	26,314.5	0	3772.2	1.066	57,073.2	0	12,006
DMU4	1	0	0	0	1	0	0	0	1	0	0	0
DMU5	1	0	0	0	1	0	0	0	1	0	0	0
DMU6	0.980	209,830	0	2383.2	0.970	246,953	0	4501.22	0.985	213,602	0	3797.4
DMU7	0.985	2990.18	0	11,701	0.980	12,985.1	0	13,230.1	0.978	11,725.8	0	12,690
DMU8	1.021	55,483.7	0	13,686	1.010	59,100.6	0	15,919	1.021	78,770.5	0	16,905
DMU9	1.002	39,098.6	0	3220	0.993	14,513	0	0	0.997	11,595.1	0	2335.1
DMU10	1.016	20,777	0	7871.2	0.991	23,287.3	0	6794.24	1.012	24,443	0	9392.2

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