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Chia-Nan Wang, Tien-Muoi Le, Han-Khanh Nguyen, Hong Ngoc-Nguyen

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Chia-Nan Wang [1], Tien-Muoi Le [1,2,*], Han-Khanh Nguyen [3] and Hong Ngoc-Nguyen [1,4]

1 Department of Industrial Engineering and Management, National Kaohsiung University of Science and Technology, Chien Kung Campus 415 Chien Kung Road, Kaohsiung 807, Taiwan; cn.wang@kuas.edu.tw
2 Department of Science Technology and International Cooperation, Hung Yen University of Technology and Education, Khoai Chau district 17817, VietNam
3 Faculty of Economics, Thu Dau Mot University, Number 6, Tran Van On Street, Phu Hoa Ward, Thu Dau Mot City 820000, VietNam; khanhnh@tdmu.edu.vn
4 Department of Industrial Engineering and Management, National Kaohsiung University of Science and Technology, Chien Kung Campus 415 Chien Kung Road, Kaohsiung 807, Taiwan; nguyenhongngocnkust@gmail.com
* Correspondence: letienmuoiutehy@gmail.com; Tel.: +886-968-934-321

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Abstract: Thailand's economy is developing rapidly, with energy being a significant factor in this development. This study uses a variety of models to assess the performance of Thailand's energy industry in two different phases, the first being from 2013 to 2017 and the second from 2018 to 2020. The Malmquist model-one of data envelopment required input and output data that showed Thailand's productivity index and the rate-of-change ratio, which is used to assess technical changes, change efficiency, and productivity changes of the 12 listed companies in energetic generation and distribution in Thailand. To calculate future indicators, the forecast data are generated by applying the Grey model (1,1) GM(1,1). Accuracy prediction is determined by the mean absolute percentage error (MAPE). The results show that the magnitude of the change in efficiency during the first period is stable, and some major changes in the technical level of some companies may be observed. In the future, the performance of most companies has increased steadily, but performance has been outstanding. This research provides insights into Thailand's energy over the past few years, and predictions of future performance may be used as a reference for more purposes.

Keywords: Thai energy; optimization; evaluation; performance

1. Introduction

Over the last four decades, Thailand has made remarkable progress in social and economic development, moving from a low-income country to an upper-income country in less than a generation. As such, Thailand has been one of the widely cited development success stories, with sustained strong growth and impressive poverty reduction, particularly in the 1980s. Thailand's economy grew at an average annual rate of 7.5% in the boom years of 1960 to 1996, and 5% following the Asian financial crisis of 1999–2005, creating millions of jobs that helped pull millions of people out of poverty. According to the World Bank, Thailand made progress in becoming a high-income country in 2011 and is now the second-largest economy in Southeast Asia. The average national growth rate from 2005 to 2015 was 3.5%. However, the political crisis of 2013 to 2014 slowed the country's economy and dropped to 0.9% in 2014. Since then, Thailand has recovered. The growth rate in the first half of 2017 was 3.5%, which exceeded market expectations and is expected to increase by 3.6% in 2018 [1].

Thailand consumes a large volume of energy, which includes oil and electricity. According to the World Energy Outlook report, due to the strong growth of the urban population and industrial economy,

energy demand in Southeast Asia has increased by about 66% [2]. In contrast, the decline in domestic supply has prompted Southeast Asian countries to shift from energy exports to energy importers. For coal, natural gas, oil, and electricity, energy is the main source of growth for end-users and rising consumption, which has become a challenge for the region. To correct this situation, further policy updates and infrastructure investment are needed. Domestic energy suppliers are under pressure to increase production and seek new resources. These activities require a solid financial background and expertise. To ensure adequate energy supply for the economy, some companies are obliged to import energy from other countries. In addition, such investments introduce cultural difficulties, because these companies must cooperate or cooperate with partners from different backgrounds, making them more difficult. The companies are familiar with the proprietary trading activities popular in Southeast Asia.

On the other hand, Thailand's power sector has model similar to those of other countries in the region. There are differences in terms of management boards, which are managed by the Ministry of Energy and National Energy Policy Council (NEPC). For one thing, the electricity sector in Thailand is mainly passed down from generation to generation, i.e., Electricity Generating Authority of Thailand (EGAT). More recently, part of the collective energy was given to EGAT's direct customers, the Metropolitan Electricity Authority (MEA), and other parts of the Provincial Electricity Authority (PEA). In addition, there are generator sets called Very Small Power Producers (VSPPs) that do not trade with EGAT, but sell electricity directly to MEA and PEA. Between generation and distribution, EGAT also acts as a transmission tool. Finally, energy will reach end-users through the MEA and PEA networks. Thanks to an agreement with EGAT, the Thai energy industry is considered one of the safest private companies in Thailand. It purchases electricity through private operators under the PPA to ensure the electricity supply in their industry.

In June 2015, the Energy Policy and Planning Office issued the latest power development plan (PDP) for 2015–2036, forecasting a steady increase in electricity and energy demand. The PDP 2015 was formulated in line with the social and economic development direction addressed by the office of National Economic and Social Development Board (NESDB). The average growth of projected long-term Thai gross domestic product (GDP) estimated by the NESDB was 3.94%. With the integration of the PDP 2015 and the Energy Efficiency Development Plan (EEDP) to foster energy efficiency, the expected energy saving would be 89,672 GWh in the year 2036 [3]. Moreover, renewable energy, for instance, municipal waste, biomass, biogas, wind, and solar power generation, will be encouraged according to the accelerated experiential dynamic psychotherapy (AEDP). Investments in the transmission and distribution system will accommodate renewable energy and smart-grid development.

According to the Ministry of Energy, the country's primary energy consumption was 75.2 Mtoe (million tonnes of oil equivalent) in 2013, an increase of 2.6% over the previous year. According to British Petroleum, energy consumption was 115.6 Mtoe in 2013. These energy companies are operating in the electricity, oil, gas, coal, and renewable energy sectors.

According to Thailand's Power Development Plan for 2015–2036, the country intends to build 20 additional gas-powered electricity-generating stations (17,728 MWe), nine "clean coal" power stations (7390 MWe), and 14,206 MW of renewable energy, including hydro, a large proportion of which will be imported from Laos or Myanmar. Up to two nuclear plants are also in the plans. Critics charge that power needs are overstated. Thailand plans for a reserve margin—the amount of energy available over that used at peak demand—of 15%. However, the plan identifies reserve margins as high as 39% in some years. The root cause for this is that Thailand regularly overestimates its economic growth, assuming that it will be over 4% when it is historically around 3%. The role of imported hydro is also at issue. In 2015, hydro accounted for approximately 7% of Thailand's power output. Under the plan, it will increase to 15% to 20% by 2036, and additional hydro will be imported from the Xayaburi Dam on the Mekong River and from the Hat Gyi and Mong Ton dams in Myanmar. While these sources may look clean on Thailand's balance sheets, the devastating environmental impacts to locals are

simply outsourced. Many have asked why Thailand pursues large coal power plants when it could be adopting safer, possibly more affordable routes, such as biomass reactors, like the 40 MWe plant operated by Double-A in Prachinburi using wood and offcuts. The answer may lie in the fact that large, centralized mega-projects benefit the centralized system of project approval. With a public sector corruption rate of 25%, according to the Thai Chamber of Commerce, they can be beneficial for unscrupulous officials.

There is a strong relationship between energy consumption and economic growth. Ferguson et al. (2000) showed that "economic development occurred 'hand in hand' with energy consumption and, in particular, with an increase in the proportion of energy used in the form of energy". This can thus be seen in the important roles of the organizations whose objectives are relative to energy production and generation, which may directly affect the economy of one nation. Therefore, new discoveries in Thailand, energy efficiency or electricity consumption, are needed. In addition, performance evaluation is important for companies and authorities to propose appropriate policies for their operators, and it is also an ideal channel for corporate stakeholders.

Even though there are a lot of companies in this industrial segment, some are listed on the stock markets or they have a lot of different small business sectors. Therefore, we can skip those unlisted companies for our study consideration. The final selected companies for this research were examined based on the type of industry or business they are involved in and their stock exchange index. The subsequent ordering of the 12 companies (decision-making unit (DMU)) were named as DMU1 to DMU12, respectively. The authors follow this naming scheme for these companies throughout this study. The authors follow the same naming scheme even when applying the Grey systems theory methods, just for the sake of convenience.

This study will provide results for performance evaluation through the periods in the past; further, this study will provide a good reference to decision-makers and entrepreneurs in the power sector in Southeast Asia. They need to adjust and revise their development strategies and plans if they can see future outcomes. Expected sectorial efficiency will be maximized by indicating the source of defects. In addition, this study could be used as a further study of new measurements to achieve higher-performance contributions. Finally, the information in this study can be used as a tool for evaluating investment opportunities.

2. Literature Review

2.1. Data Envelopment Analysis (DEA) Model

Model Data Envelopment Analysis (DEA) was first described in a 1978 paper by Charles, Copper, and Rhodes [4]. In that work, the authors described a "data-oriented" approach for evaluating the performance of a set of peer entities called Decision Making Units (DMUs) which convert multiple inputs into multiple outputs. DMUs can be banks, managers, shipping companies, or—as we will evaluate in this paper—areas within the EMS industry. Recent years have seen a great variety of applications of DEA in both the public and private sectors of various countries.

In this section, the researchers collected some authors who have already performed research that is especially important with respect to their inputs and outputs utilizing the DEA model.

W. Chandraprakaikul and A. Suebpongsakorn (2012) used data envelopment analysis to explore the operation performances of 55 Thai logistics companies from 2007 to 2010 [5]. The results point out the reasons for the inefficient Decision-Making Units and provide directions for the improvement of inefficient companies accordingly.

Chia-Nan Wang, Kun-Zhong Li, Cheng-Ter Ho, K.-L.Yang, Chih-Hong Wang (2007) applied data envelopment analysis (DEA) and the heuristic technique approach to help department stores in finding out the most appropriate partner for a strategic alliances [6]. The results indicate that candidate selection for strategic alliance can be an effective strategy for enterprises to find the right partners of cooperation.

Chia-Nan Wang, Kun-Zhong Li, Wen-Po Tseng, Ke Yi Li, Ming-Yen Kan, Kun-Tsung Tsai, Pan-Hsin Tsai (2006) explored whether alliance strategies in Taiwan radio frequency identification companies had resulted in an increase in productive efficiency [7]. Based on the methodology of data envelopment analysis (DEA) and the heuristic technique, the authors proposed a new systematic approach to resolving the issues of strategic alliances.

2.2. Literature Related to Grey Systems Theory

The Grey System Theory was first proposed by Julong Deng (1989) [8]. In his paper, he stated that Grey System theory had been successfully applied in many fields. Grey system theory forecasts an explanation for something that has not yet been previously observed or is unknown. The main task of Grey system theory is to extract realistic governing laws for a system using available data. This process is known as the generation of a Grey sequence (Liu and Lin, 1998). In recent years, many methods have been proposed for forecasting, especially forecasting in business, such as fuzzy theory, neural networks, and Grey prediction. It is necessary to present a review of Grey system theory to form the basis for forecasting the performance of energy companies in the next few years.

Grey system theory, developed originally in the early 1980s by Deng (1982), is an interdisciplinary scientific area. This theory has become a very popular method to deal with uncertainty problems under discrete data and incomplete information. As for superiority to conventional statistical models, Grey models require only a limited amount of data to estimate the behavior of unknown systems (Deng, 1989). In the past, many studies have applied the Grey system. For example, in 2017, Chia-Nan Wang and Han-Khanh Nguyen used the Grey and DEA model to study enhancing urban development quality based on the results of appraising efficient performance of investors in Vietnam [9]. In 2018, Chia-Nan Wang, Tien-Muoi Le, and Han-Khanh Nguyen used the Grey theory model to select contractors to develop strategies and policies for the development of transport infrastructure [10]. Forecasting is a broad topic, and there are now many methods in which the predicted GM (1,1) can achieve the optimal predictive value. Therefore, in this study, GM (1,1) would be used to predict the business performance of the DMUs for the period 2018–2020.

Mean absolute percent error (MAPE) is a measurement that relates the forecast error to the level of demand and is useful for putting forecast performance in the proper perspective. When the MAPE is small, the forecast value is typically close to the actual value.

$$MAPE = \frac{1}{n}\left[\sum_{i=1}^{n}\left|\frac{A_i - F_i}{A_i}\right| \times 100\right] \tag{1}$$

Lewis (1982) divided the MAPE into four ranks, as shown in Table 1 [11]:

Table 1. Classes of reliability for Mean absolute percent error (MAPE).

MAPE	<10%	10–20%	20–50%	>50%
Grade	Good	Qualified	Just	Unqualified

Source: [9].

3. Materials and Methodology

3.1. Materials

3.1.1. DMU Collection

The data for this study were collected from the Stock Exchange of Thailand's (SET) website and companies' yearly financial reports audited by a reliable independent institution during the five-year period from 2013 to 2017 [12]. The companies were running a business within the energy

industrial sector. This study does not include data from unlisted companies. The final 12 companies selected for this study are treated as decision-making units (DMU), from DMU1 to DMU12, accordingly. The Electricity Generating Authority of Thailand (EGAT) was chosen, despite being a state-owned enterprise, because its capacity remains in the dominant position in the market, at 38.32% (EGAT, Sep 2017).

This study selected 12 companies that were running their business in the field of energy in Thailand. These companies represent the energy industry of the country. First, according to the Ministry of Energy Thailand, energy in Thailand refers to its energy and electricity production, consumption, imports, and exports.

Thus, this study selected these 12 companies to evaluate performance, which can be considered representative of the Thai energy industry. As mentioned, these are companies that have clear annual finance data and information related to their transactions in the stock market. Table 2 shows their name and their DMU designation for this study.

Table 2. Research sample.

DMUs	1	2	3	4	5	6	7	8	9	10	11	12
symbol	EGAT	GLOW	BANPU	RATCH	EGCO	SPCG	CKP	EARTH	EA	TSE	IFEC	GUNKUL

Source: [11].

3.1.2. Inputs/Outputs Collection

DEA is a sensitive tool that can select the inputs and outputs that affect the results. The correct number of variables can be ignored based on inadequate benefit analysis. However, there is no unified method of selecting variables. In Table 3, the study lists the selection of input and output variables in some of the literature related to the DEA model.

The above studies, with the measurement of firm performance and application of DEA, vary in terms of models employed and also differ in the selection of input and output variables. The table indicates that what appears to be common among the above studies is that, generally, employees, assets, and cost (expenses) are selected as input variables. Likewise, most studies choose revenues and income as outputs. Therefore, presenting a review of related research on the DEA model is necessary to form the basis for our selection of input and output variables in the next chapter.

We decided to choose three key financial indicators that are considered to directly contribute to the performance of the sector, including fixed assets, total expenses, and equity. We chose net income and gross profit as the output factors, because they are important indicators for measuring current and future performance.

In addition, the studies of Ittner and Larcker, Baier et al. and Simpson and Kohers indicate seven factors, i.e., staff cost, energy purchase, total expenses, equity capital, net income, net profit, and Earnings per share (EPS), to be the key factors contributing to the performance of firms.

Table 3. Input and output variable selection using Data Envelopment Analysis (DEA).

The Authors	Research Theme	Variables	
		Input Factors	Output Factors
W. Chandraprakaikul And A. Suebpongsakorn (2012) [5].	Evaluation of Logistics Companies Using Data Envelopment Analysis	✔ Fixed assets ✔ Operating expenses ✔ Cost of sale ✔ Current liabilities ✔ Shareholder funds	✔ Profit ✔ Revenue
Chia-Nan Wang, Kun-Zhong Li, Cheng-Ter Ho, K.-L.Yang, Chih-Hong Wang (2007) [6].	A Model for Candidate Selection of Strategic Alliances: Case on Industry of Department Store	✔ Capital ✔ Number of employees	✔ Revenues ✔ Equity
Chia-Nan Wang, Kun-Zhong Li, Wen-Po Tseng, Ke Yi Li, Ming-Yen Kan, Kun-Tsung Tsai, Pan-Hsin Tsai (2006) [7].	A Strategic Alliance Approach for the Industry of Radio Frequency Identification in Taiwan.	✔ Capital ✔ Expenditures	✔ Revenue ✔ Gross Profits
Yang and Chang (2009) [12].	Using DEA window analysis to measure the efficiencies of Taiwan's integrated telecommunication firms	✔ Assets ✔ Operating costs ✔ Operating expenses	✔ Operating revenues ✔ Mobile phone subscribers ✔ Mobile phone calls
Chia-Nan Wang, Ting-Chia Wu (2008) [13].	A Decision Making Approach on Strategic Alliance of Photovoltaic Industry Based on DEA and GM	✔ R&D Expenses ✔ Operating Exp	✔ Operating Income ✔ Retained earnings
Diskaya, Emir, and Orhan (2011) [14].	Measuring the Technical Efficiency of Telecommunication A sector within Global Crisis: Comparison of G8 Countries and Turkey	✔ Capital Expenditure ✔ Total Debt ✔ Total access lines ✔ Employees units	✔ Revenue ✔ Net income ✔ Mobile Subscribers

3.2. Methodology

This study uses GM (1,1) and the DEA model as the foundation of a set of models for forecasting and selecting alliance partners. The research development in this paper is implemented in the EMS industry and also refers to all related documentation. Then, after confirming the subject and proceeding with the industrial analysis, the resulting research process of this study is shown schematically in Figure 1.

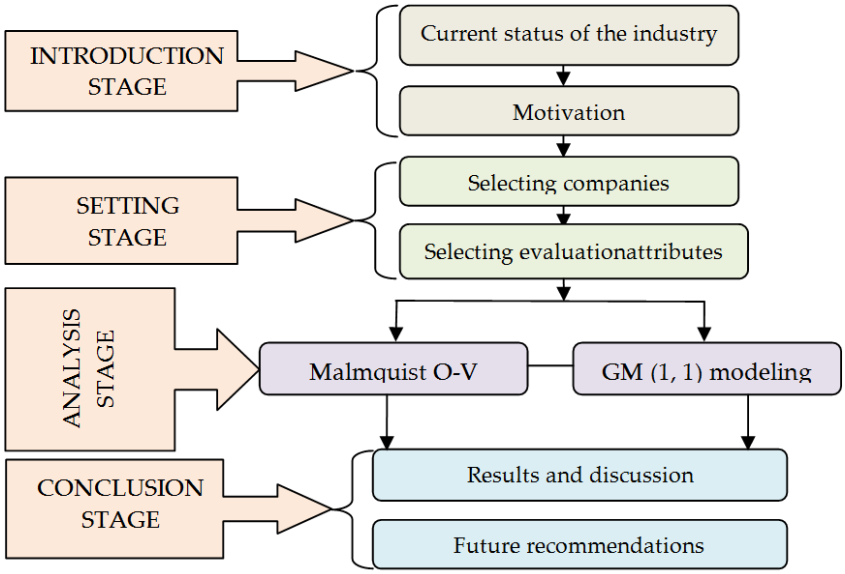

Figure 1. Research process.

The research process in this study was divided into seven steps, as follows:

Step 1: Collect the data from companies in the industry

By referring to the domestic and foreign literature related to DEA, Grey theory, the authors determined the subject and approach that the paper will use.

The authors investigated the related enterprises to find all potential candidates to be on the DMUs list. Ten Vietnamese agro-forestry companies, which listed their financial performance in the stock market during the period 2011 to 2014, were selected.

Step 2: Choose input/output variables

DEA is tool for the estimation of production correspondences. Therefore, before using it, a deep analysis of the selection of input and output parameters is needed for the correct utilization of DEA, since such parameters and the correlation between them determine the correctness of the final efficiency results. It is better to have a wider range of input and output variables to analyze, but too many variables will dilute the variation among DMUs, leading to insensitivity of benefit analysis. Therefore, this paper considers the following critical factors in selecting input and output items: related literature discussions and necessary variables were selected using the factor analysis method, and the Pearson correlation coefficient was used for testing the correlation and significance level between inputs and outputs. Furthermore, input/output items must correspond to the units to be evaluated; the data are trusted by the public, and each variable can be quantified for analysis.

Step 3: Grey prediction

Grey prediction, based on the Grey model (GM) (1,1), is used to predict data values in 2015 and 2016. However, error always exists in the forecast. Therefore, in this study, the mean absolute percent error (MAPE) is applied to measure the forecasting error.

Step 4: Forecasting accuracy

It is difficult to expect that forecasts will effectively be correct most of the time. Therefore, the MAPE is employed to measure the prediction accuracy. If the forecasting error is too high, the study has to reselect the inputs and outputs.

Step 5: Choose the DEA model

In this paper, DEA-Solver software is employed to calculate the Malmquist O-V model. The measurement of efficiency by ranking DMUs' performance is then performed.

Step 6: Pearson correlation

The formulation of DEA is used to measure the efficiency of each decision-making unit by constructing a relative efficiency score via the transformation of the multiple inputs and outputs into a ratio of a single virtual output to a single virtual input. Therefore, to test whether the data will match the basic assumptions of the DEA methodology, the correlation analysis of variables is used to verify a positive relationship between the selected inputs and outputs. If the variables with negative coefficients need to be removed, then we go back to Step 2 of the selection process and redo the variable selection until it can satisfy our conditions. In this study, we employ the Pearson correlation coefficient test.

Step 7: Analyzing company performance

In this step, the researcher has to use a deep analysis of the industry. The three factors of performance and the forecasting results are carefully analyzed.

3.2.1. Data Envelopment Analysis—Malmquist Models (DEA–MI)

DEA has been successfully applied for various types of entities in a wide range of industries, such as manufacturing, environmental and operations management, and data-center operation. In this work, we employ Data Envelopment Analysis—Malmquist Models (DEA–MI) to evaluate the business performance of a set of DMUs which represent companies in the energy industry. DEA–MI was first used to measure the changes in DMU yield over two time periods under multiple inputs and outputs. The change in efficiency is based on change in product technology (transitive effect) and change in efficiency (effect catch up) [15–18]. The change in efficiency is a two-stage performance measurement of 1 and 2 changes. Technological change measures changes in the boundaries between the two phases. In this study, the variable yield model is applied to the input orientation assumptions.

DMU_0 at periods 1 and 2 is denoted by (x_0^1, y_0^1) and (x_0^2, y_0^2). The efficiency score of DMU $(x_0, y_0)^{t_1}$is measured by the technological frontier t_2: $d^{t_2}((x_0, y_0)^{t_1})$ $(t_1 = 1, 2$ and $t_2 = 1, 2)$.

The efficiency change (catch-up effect) denoted by C is calculated by using the following formula:

$$C = \frac{d^2((x_0, y_0)^2)}{d^1((x_0, y_0)^1)} \tag{2}$$

The technological change (frontier-shift effect) denoted by F is calculated as below

$$F = \left[\frac{d^1((x_0, y_0)^1)}{d^2((x_0, y_0)^1)} \times \frac{d^1((x_0, y_0)^2)}{d^2((x_0, y_0)^2)}\right]^{1/2} \tag{3}$$

Malmquist Productivity Index (MPI) is generated by obtaining the product of C and F, that is, MPI = (catch-up) × (frontier-shift) or

$$MI = \left[\frac{d^1((x_0, y_0)^2)}{d^1((x_0, y_0)^1)} \times \frac{d^2((x_0, y_0)^2)}{d^2((x_0, y_0)^1)}\right]^{1/2} \tag{4}$$

The productivity of a DMU is deemed to be progressing when MI is larger than one. Productivity remains unchanged when MI equals one and exhibits regress when MI is less than one.

3.2.2. GM (1,1) Model: Forecasting Process

The Grey model is suitable for forecasting the competitive environment in which decision-makers can refer only to limited historical data.

Although various existing types of Grey model can be applied for forecasting, the most frequently used Grey forecasting model is GM (1,1), due to its computational efficiency. In this study, GM (1,1) was used to get prediction results. This model is a time series forecasting model, encompassing a group of differential equations adapted for parameter variance, rather than a first-order differential equation. Its differential equations have structures that vary with time, rather than being general differential equations. Although it is not necessary to employ all the data from the original series to construct the GM (1,1), the potency of the series must be more than four. In addition, the data must be taken at equal intervals and in consecutive order without bypassing any data [12]. The GM (1,1) model construction process is described as follows:

Denote the variable primitive series $X^{(0)}$ as a formula:

$$X^{(0)} = (X^{(0)}(1), X^{(0)}(2), ..., X^{(0)}(n)),\ n \geq 4 \tag{5}$$

where: a non-negative sequence.

n: the number of data observed.

Accumulating Generation Operator (AGO) is one of the most important characteristics of Grey theory, with the aim of eliminating the uncertainty of the primitive data and smoothing the randomness. The accumulated generating operation (AGO) formation of $X^{(0)}$, defined as:

$$X^{(1)} = (X^{(1)}(1), X^{(1)}(2), ..., X^{(1)}(n)),\ n \geq 4 \tag{6}$$

where:

$$X^{(1)}(1) = X^{(0)}(1) \tag{7}$$

$$X^{(1)}(k) = \sum_{i=1}^{k} X^{(0)}(i),\ k = 1, 2, 3, ..., n \tag{8}$$

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

$$Z^{(1)} = (Z^{(1)}(1), Z^{(1)}(2), ..., Z^{(1)}(n)) \tag{9}$$

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

$$Z^{(1)}(k) = \frac{1}{2}\left(X^{(1)}(k) + X^{(1)}(k-1)\right),\ k = 2, 3, ...n \tag{10}$$

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

$$\frac{dX^1(k)}{dk} + aX^{(1)}(k) = b \tag{11}$$

where parameters a and b are called the developing coefficient and Grey input, respectively.

In practice, parameters a and b are not calculated directly from Equation (11). Hence, the solution of the above equation can be obtained using the least square method. That is:

$$\hat{X}^{(1)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right]e^{-ak} + \frac{b}{a} \tag{12}$$

where $X^{(1)}$ $(k+1)$ denotes the prediction X at time point $k+1$ and the coefficients $[a,b]^T$ can be obtained by the Ordinary Least Squares (OLS) method:

$$[a,b]^T = (B^T B)^{-1} B^T Y \tag{13}$$

And

$$Y = \begin{bmatrix} x^{(0)}(2) \\ x^{(0)}(3) \\ \cdots\cdots\cdots \\ \cdots\cdots\cdots \\ x^{(0)}(n) \end{bmatrix} \tag{14}$$

$$B = \begin{bmatrix} -z^{(1)}(2) & 1 \\ -z^{(1)}(3) & 1 \\ \cdots\cdots\cdots\cdots & \vdots \\ \cdots\cdots\cdots\cdots & \vdots \\ -z^{(1)}(n) & 1 \end{bmatrix} \tag{15}$$

where Y is called a data series, B is called a data matrix, and $[a,b]^T$ is called a parameter series.

We obtained $\hat{X}^{(1)}$ from Equation (12). Let $\hat{X}^{(0)}$ be the fitted and predicted series

$$\hat{X}^{(0)} = X^{(0)}(1), \hat{X}^{(0)}(2), \ldots\ldots\ldots\ldots, \hat{X}^{(0)}(n) \qquad Where \qquad \hat{X}^{(0)}(1) = X^{(0)}(1) \tag{16}$$

Apply the inverse accumulated generation operation (IAGO); namely:

$$X^{(0)}(k+1) = \left[X^{(0)}(1) - \frac{b}{a}\right] e^{-ak}(1-e^{a}) \tag{17}$$

The Grey model prediction is a local curve fitting extrapolation scheme. At least four data sets are required by the predictor to obtain a reasonably accurate prediction (Huang and Huang, 1996 and Deng, 2002).

3.2.3. Pearson Correlation

To apply the DEA model, the authors have to make sure the relationship between input and output factors is isotonic, which means that if the input quantity increases, the output quantity could not decrease under the same condition. In this study, firstly, the authors conducted a simple correlation test—Pearson correlation—to measure the degree of association between two variables. Higher correlation coefficients mean a closer relationship between two variables, while a lower correlation coefficient means that they are less correlated.

The interpretation of the correlation coefficient is explained in more detail as follows:

The correlation coefficient is always between −1 and +1. The closer the correlation is to +/−1, the closer to a perfect linear relationship. Its general meaning is shown in Table 4.

Table 4. Pearson correlation coefficient.

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

4. Results

4.1. Pearson Correlation

The results shown in Table 5 indicate a remarkably high degree of correlation between input and output variables for both the original data set (2013 to 2017) and the forecasted data set (2018 and 2020). The fact that all coefficients are larger than 0.9 shows a strong positive linear relationship, and the coefficient is in compliance with the condition of the DEA model. In addition, these positive correlations justify calculating the correlation coefficients with other DEA–Malmquist coefficients using DEA Solver, and then converting them into an Excel file. The correlation is significant in the analysis of the effect on the performance.

Table 5. Correlation coefficients in 2013-2020.

		FA (Fixed Assets)	TE (Total Expenses)	SE (Shareholders' Equity)	TR (Total Revenues)	NP (Net Profit)
2013	FA	0.958335	1	0.980749	0.999834	0.976248
	TE	0.959368	0.980749	1	0.983084	0.983366
	SE	0.961252	0.999834	0.983084	1	0.979788
	TR	0.976915	0.976248	0.983366	0.979788	1
	NP	0.958335	1	0.980749	0.999834	0.976248
2014	FA	1	0.956109	0.96586	0.960901	0.980179
	TE	0.956109	1	0.980849	0.999791	0.966051
	SE	0.96586	0.980849	1	0.983651	0.983083
	TR	0.960901	0.999791	0.983651	1	0.969605
	NP	0.980179	0.966051	0.983083	0.969605	1
2015	FA	1	0.946332	0.964999	0.953216	0.966939
	TE	0.946332	1	0.981605	0.999728	0.944446
	SE	0.964999	0.981605	1	0.984241	0.946083
	TR	0.953216	0.999728	0.984241	1	0.950598
	NP	0.966939	0.944446	0.946083	0.950598	1
2016	FA	1	0.956872	0.965461	0.963031	0.980048
	TE	0.956872	1	0.984121	0.999688	0.965219
	SE	0.965461	0.984121	1	0.986725	0.97345
	TR	0.963031	0.999688	0.986725	1	0.971021
	NP	0.980048	0.965219	0.97345	0.971021	1
2017	FA	1	0.951778	0.961649	0.959425	0.981849
	TE	0.951778	1	0.985626	0.999523	0.967796
	SE	0.961649	0.985626	1	0.987583	0.96779
	TR	0.959425	0.999523	0.987583	1	0.97472
	NP	0.981849	0.967796	0.96779	0.97472	1
2018	FA	1	0.945206	0.95368	0.954362	0.979776
	TE	0.945206	1	0.987538	0.999345	0.966027
	SE	0.95368	0.987538	1	0.988673	0.961688
	TR	0.954362	0.999345	0.988673	1	0.974323
	NP	0.979776	0.966027	0.961688	0.974323	1
2019	FA	1	0.93032	0.93853	0.942044	0.975655
	TE	0.93032	1	0.989456	0.999121	0.962104
	SE	0.93853	0.989456	1	0.989589	0.954319
	TR	0.942044	0.999121	0.989589	1	0.972251
	NP	0.975655	0.962104	0.954319	0.972251	1
2020	FA	1	0.90053	0.911802	0.916793	0.967507
	TE	0.90053	1	0.991024	0.998814	0.954265
	SE	0.911802	0.991024	1	0.990185	0.945085
	TR	0.916793	0.998814	0.990185	1	0.967278
	NP	0.967507	0.954265	0.945085	0.967278	1

4.2. Data Used for Performance Analysis

The financial results of energy companies from 2013 to 2017 are demonstrated in the following tables. The authors chose three input factors, which were Fixed Assets, Total Expenses, and Shareholders' Equity, which are significant for this industry. On the other hand, we selected Total Revenues and Net Profits as the output variables. In addition, Fixed Assets (land, equipment, property,...), Total Expenses (the sum of money spent on generating revenue for a business), Shareholders' Equity (a firm's total assets minus its total liabilities), Total Revenues (the income resulting from the sale of goods or services before deducting any costs or expenses), Net Profits (the amount of money that the firm has gained or lost in a period of time, measured by deducting its total expenses from total revenues) play significant roles in evaluating the performance of companies. The practical data from 2013 to 2017 collected from the Stock Exchange of Thailand in Millions of Baht (Thai currency unit) are illustrated in Table 6:

Table 6. The financial results of energy companies in 2013.

	Inputs (Million Baht)			Outputs (Million Baht)	
DMUs	**FA**	**TE**	**SE**	**TR**	**NP**
			2013		
DMU1	261,012.92	495,049.34	315,928.05	584,655.35	40,181.8
DMU2	97,300.77	57,464.7	40,576.3	69,771.53	7214.44
DMU3	47,769.34	95,904.59	73,556.63	108,338.55	3151
DMU4	41,845.68	45,089.15	54,700.98	54,197.91	6186.85
DMU5	48,991.66	14,924.9	69,269.22	26,057.32	6913.74
DMU6	18,937	1191.02	2639.46	2523.3	499.32
DMU7	5933.2	3704.36	11,589.78	5649.16	218.88
DMU8	242.44	11,866.09	4328.98	13,522.15	1110.6
DMU9	8092.56	3653.82	4359.54	3998.99	267.92
DMU10	4682.61	787.54	932.73	607.35	−15.62
DMU11	452.40	564.89	1540.29	629.97	28.01
DMU12	657.66	1916.23	2848.68	3005.73	882.89
			2014		
DMU1	260,073.84	497,550.06	338,417.63	546,303.3	38,427.27
DMU2	87,192.56	58,096.98	52,571	73,323.7	9138.89
DMU3	43,883.06	94,072.17	67,774.46	106,461.15	2679.63
DMU4	14,480.21	50,120.33	60,781.67	59,048.31	6279.03
DMU5	55,275.08	13,265.81	73,264.01	24,659.17	7666.98
DMU6	18,779.09	1551.51	5786.08	4410.72	1655.61
DMU7	5830.29	4960.67	12,048.13	7062.04	471.82
DMU8	800.99	13,356.99	5295.81	14,917.29	1042.03
DMU9	16,184.17	5643.56	5893.4	7601.27	1608.46
DMU10	4742.18	612.03	3487.34	1348.69	581.26
DMU11	1469.68	480.07	4200.69	638.07	72.70
DMU12	913.20	2648.59	3357.12	3330.83	545.27
			2015		
DMU1	273,251.44	486,335.44	346,993.49	549,880.28	31,384.28
DMU2	84,024.27	51,357.62	48,537.68	65,369.33	8355.42
DMU3	42,588.13	80,992.98	63,206.93	88,168.04	−1534.25
DMU4	13,479.05	53,517.62	60,189.52	59,326.29	3187.87
DMU5	72,527.3	13,134.48	77,242.16	24,833.57	4319.18
DMU6	18,314.47	1766.61	7170.61	5057.64	2190.16
DMU7	5610.91	4989.85	17,754.45	6886.44	411.88
DMU8	1419.13	15323	10,708.04	17,168.08	1026.88
DMU9	27,414.88	5849.83	8504.94	9212.17	2686.92
DMU10	1977.47	207.51	4040.33	765.62	526.59
DMU11	8161.19	704.22	5366.94	704.22	332.20
DMU12	7646.25	3946.27	8063.38	4870.70	685.14

Table 6. *Cont.*

	Inputs (Million Baht)			Outputs (Million Baht)	
DMUs	**FA**	**TE**	**SE**	**TR**	**NP**
			2016		
DMU1	276,496.24	417,562.87	366,240.24	496,883	43,691.94
DMU2	80,741.76	39,448.68	48,971.28	53,092.13	8953.13
DMU3	46,000.91	74,627.89	78,875	85,092.29	1677.12
DMU4	13,806.68	43,099.32	62,321.47	51,437.55	6165.72
DMU5	62,416.99	17,891.09	81,972.78	30,921.9	8320.8
DMU6	17,743.67	2172.16	8294.62	5544.3	2314.21
DMU7	5374.18	5038.2	17,743.74	6386.55	55.05
DMU8	1899.38	16,612.8	11,106.58	18,502.56	871.9
DMU9	33,485.32	6197.38	11,383.45	10,439.25	3251.51
DMU10	2850.49	306.06	4562.58	1013.13	617.63
DMU11	9003.79	3444.53	3226.64	1924.53	−1886.07
DMU12	13,604.87	2652.10	9107.96	3638.65	537.72
			2017		
DMU1	277,496.24	418,562.87	376,240.24	497,883.00	44,691.94
DMU2	81,741.76	394,548.68	49,971.28	54,092.13	9953.13
DMU3	47,000.91	74,627.89	79,875.00	86,092.29	1777.12
DMU4	14,806.68	44,099.32	63,321.47	52,437.55	6265.72
DMU5	63,416.99	18,891.09	82,972.78	31,921.90	8420.80
DMU6	18,743.67	2272.16	8394.62	5644.30	2414.21
DMU7	5474.18	5138.20	18,743.74	6486.55	65.05
DMU8	1999.38	17,612.80	12,106.58	19,502.56	871.90
DMU9	34,485.32	6297.38	12,383.45	11,439.25	3351.51
DMU10	2950.49	316.06	4662.58	1113.13	627.63
DMU11	9103.79	3544.53	3326.64	1934.53	−1786.07
DMU12	13,704.87	2752.10	9207.96	3738.65	637.72

4.3. DEA−Malmquist Results Analysis for Original Data

The original DEA used past data to evaluate the past performance of DMUs from 2013 to 2016. This study uses the GM model to forecast future data and then uses the future data as input for the DEA to evaluate future performance. The trend of each DMU can be considered much better than the original DEA. The analysis of technical change, efficiency change, and Malmquist Productivity Index is conducted for the future results in the next section of this study.

The original dataset of the period 2013-2017 collected from the Stock Exchange of Thailand is used as input for DEA−Malmquist. We employed DEA Solver Pro Version 8.0 (SAITECH, Holmdel, NJ, USA), which was developed by SAITECH to calculate the past efficiency of DMUs. The results are divided into 3 components, which are depicted in a line graph. Table 7 shows the efficiency change or catch-up effect of DMUs of the Thailand energy industry from 2013 to 2017.

Table 7 shows the "efficiency change" of the industries over each time interval. This reveals that the efficiency changes are not so consistent due to the nature of their financial management, which is not really steadily improving or not steadily outperforming over the frame. Based on Table 7, we observe that there are no big changes in efficiency, since all the scores are very close to 1. DMU3, DMU4, and DMU9 show some slight changes in efficiency, while the other 9 DMUs score an average of 1, which means that the level of efficiency remains the same from 2013 to 2019, as demonstrated by the straight overlapping horizontal lines. The maximum score in efficiency change is 1.3, scored by DMU9 in the period from 2013 to 2014. The minimum score is 0.82, and this number belongs to DMU12 in the 2015-2016 period.

Table 7. Efficiency (catch-up) change over the period from 2013 to 2017.

Catch-up	2013–2014	2014–2015	2015–2016	2016–2017	Average
DMU1	1	1	1	1	1
DMU2	1	1	1	1	1
DMU3	1.0463759	0.958746	0.990417	1.0126895	1.0020571
DMU4	1.0468585	1	1	1	1.0117146
DMU5	1	1	1	1	1
DMU6	1	1	1	1	1
DMU7	1.0559803	1	0.9363077	0.9917374	0.9960063
DMU8	1	1	1	1	1
DMU9	1.3476479	1	1	1	1.086912
DMU 10	1.000006	1	1	1	1.0000015
DMU 11	1.0000012	0.7528126	1.3283467	1	1.0202901
DMU 12	1	0.838181	0.8293193	1.0053743	0.9182186
Average	1.0414058	0.9624783	1.0070326	1.0008168	1.0029334
Max	1.3476479	1	1.3283467	1.0126895	1.086912
Min	1	0.7528126	0.8293193	0.9917374	0.9182186
SD	0.0989793	0.080957	0.1130159	0.004769	0.0365659

Table 8 demonstrates the technical changes (frontier-shift effect) in Thailand's energy industry. Overall, there are some differences in the technical changes level among the DMUs. The most fluctuating lines belong to DMU4, DMU5 and DMU10. For instance, the technical changes level of DMU4 starts with the highest score of 1.541495218 among the DMUs. However, 2014–2015 witnessed a sharp decrease to 0.611828901, a drop of more than 50%. However, this trend did not last long, as the level reached 1.47101766 in the following period, and then dropped to 0.9. The rest of the DMUs exhibited no such changes, just a slight increase and decrease. However, despite the major differences at the starting point, most of the lines end at around a score of 1.

Table 8. Technical (frontier-shift) change over the period from 2013 to 2017.

Frontier	2013–2014	2014–2015	2015–2016	2016–2017	Average
DMU1	0.9790729	1	1	0.9876207	0.9916734
DMU2	1.0487983	0.9378505	1.2051994	0.9206112	1.0281148
DMU3	0.966799	0.9761934	1.0032806	0.9967318	0.9857512
DMU4	1.5355181	0.6118289	1.4710177	0.9713138	1.1474196
DMU5	1.3780611	0.5499431	1.6288571	0.9837443	1.1351514
DMU6	1.297602	1.1933256	1.013224	1.0313677	1.1338798
DMU7	0.9431184	0.9639311	0.9882904	1.0049394	0.9750698
DMU8	0.521143	0.7226094	0.8177173	1.0249509	0.7716052
DMU9	1.0795808	1.1005271	1.156919	1.0176316	1.0886646
DMU 10	0.7898609	1.5290509	0.8256459	1.030268	1.0437064
DMU 11	0.6993688	0.8795847	1.1273874	0.9742969	0.9201594
DMU 12	0.5542341	0.7085061	0.9851769	0.9933388	0.810314
Average	0.9827631	0.9311126	1.101893	0.9947346	1.0026258
Max	1.5355181	1.5290509	1.6288571	1.0313677	1.1474196
Min	0.521143	0.5499431	0.8177173	0.9206112	0.7716052
SD	0.3148954	0.2706561	0.2411826	0.0313106	0.1220339

The product of the efficiency changes level and the technical changes level is the Malmquist productivity index (MPI); the results are shown in Table 9.

Table 9. Productivity index (Malmquist-MPI) change over the period from 2013 to 2017.

Malmquist	2013–2014	2014–2015	2015–2016	2016–2017	Average
DMU1	0.9790729	1	1	0.9876207	0.9916734
DMU2	1.0487983	0.9378505	1.2051994	0.9206112	1.0281148
DMU3	1.0116352	0.9359215	0.9936662	1.0093798	0.9876507
DMU4	1.6074703	0.6118289	1.4710177	0.9713138	1.1654077
DMU5	1.3780611	0.5499431	1.6288571	0.9837443	1.1351514
DMU6	1.297602	1.1933256	1.013224	1.0313677	1.1338798
DMU7	0.9959144	0.9639311	0.9253439	0.9966359	0.9704563
DMU8	0.521143	0.7226094	0.8177173	1.0249509	0.7716052
DMU9	1.4548947	1.1005271	1.156919	1.0176316	1.1824931
DMU 10	0.7898656	1.5290509	0.8256459	1.030268	1.0437076
DMU 11	0.6993696	0.6621624	1.4975613	0.9742969	0.9583476
DMU 12	0.5542341	0.5938563	0.8170262	0.9986773	0.7409485
Average	1.0281718	0.9000839	1.1126815	0.9955415	1.0091197
Max	1.6074703	1.5290509	1.6288571	1.0313677	1.1824931
Min	0.521143	0.5499431	0.8170262	0.9206112	0.7409485
SD	0.3520641	0.2901577	0.2831873	0.0314782	0.1416325

DMU9 was the only company that showed an improvement in productivity during the period, although these indicators only rose slightly. DMU4 and DMU5 again share the same model, and this model is almost identical to the technology change or "boundary" effect level model. In addition, it is clear that some DMUs have the same data in the MPI as the "boundary" effect. The same result occurs because many DMUs (except DMU3 and DMU4) score 1 at variable efficiency levels.

During 2013–2014, the productivity of DMU4 and DMU5 increased, but the index of the next period dropped significantly, to 0.611829 and 0.549943, respectively. This decline may have been caused by the political crisis in 2014, which had some negative effects on the industry. From 2015 to 2016, the yields of DMU4 and DMU5 increased, and they would be the first and second highest rate of return changes when both indices were greater than one. The yield of the first stage of DMU1 will decrease slightly, as MPI < 1 and does not change for two stages (MPI = 1).

4.4. Forecasting Results

In the previous section, GM (1,1) was used to predict future DMU data and was used as input for the DEA–Malmquist evaluation of future performance. In addition, the accuracy prediction problem needs to be carefully examined to ensure the results of future data and further analysis to solve the problem. This is the absolute percentage error used to test the GM prediction accuracy (1,1) between the two sets of data. The results are shown in Table 10.

Table 10. Average MAPE of DMUs.

DMUs	Average MAPE (%)
DMU1	1.27
DMU2	1.34
DMU3	2.61
DMU4	2.38
DMU5	4.06
DMU6	0.82
DMU7	1.88
DMU8	4.63
DMU9	2.08
DMU10	2.34
DMU11	2.36
DMU12	2.35
Average MAPE of all DMUs	2.34

As can be seen from the table that there is no more than 10% MAPE, showing very good accuracy. In addition, the average MAPE for all decision-making units is 2.34%, which is lower than 10%, meaning that the GM model (1.1) can predict accurate data in the future.

This calculation was repeated to collect forecast data for all decision units from 2018 to 2020. The results are shown in the Table 11 below.

Table 11. The forecasted data of all DMUs from 2018–2020.

	Inputs (Million Baht)			Outputs (Million Baht)	
DMUs	**FA**	**TE**	**SE**	**TR**	**NP**
			2018		
DMU1	295,453.942	362,270.6972	394,836.411	462,589.2968	47,372.09337
DMU2	74,804.2165	28,201.71149	44,810.73065	39,639.23454	8533.914877
DMU3	47,500.3224	58,039.65429	89,514.64674	65,137.4924	1204.26549
DMU4	12,929.09148	39,758.09	63,465.03	46,411.06951	5006.04615
DMU5	74,138.66448	23,924.6039	91,619.47	38,287.53623	8049.287123
DMU6	16,786.0319	3026.493857	11,835.86127	6976.279113	3235.777525
DMU7	4958.092508	5113.845726	26,022.7727	5838.515646	54.34849074
DMU8	4132.09581	20,706.84748	21,047.29483	23,015.9885	758.1822928
DMU9	64,874.1178	6786.254222	21,341.98722	14,306.03967	6184.860955
DMU10	1977.97	169.35	5270.73	935.00	649,32
DMU11	13,746.7531	7311.995185	3026.95469	3061.224981	−9635.41
DMU12	24,724.2034	2779.701837	12,594.94271	3892.712479	634.1842812
			2019		
DMU1	30,4522.0518	333,139.4719	410,901.0968	441,920.4663	51,106.29004
DMU2	71,986.87024	23,459.54179	43,203.95998	33,908.77134	8442.108612
DMU3	48,674.13935	51,566.2411	97,287.30786	57,908.30835	977.6958152
DMU4	12,615.19779	37,126.58	64,275.87	43,463.52017	4939.732338
DMU5	78,132.069	28,224.97934	96,922.40	43,216.36798	8533.092523
DMU6	16,317.75614	3594.959464	14,106.84855	7807.277463	3777.676161
DMU7	4760.538637	5153.702915	30,811.72365	5556.978961	31.22071474
DMU8	6092.340144	23,043.56693	28,168.29224	25,570.58502	696.6098365
DMU9	89,583.79584	7113.802331	29,342.30171	16,701.16935	8458.252886
DMU10	1662.75	128.36	5792.54	889.91	675.80
DMU11	18,200.52781	12,356.89728	2707.86243	4442.020603	−20,392.2845
DMU12	37,209.49827	2696.861963	15,687,03064	3891.914797	647.8478821
			2020		
DMU1	313,868.4811	306,350.7719	427,619.4054	422,175.1345	55,134.842
DMU2	69,275.6335	19,514.77666	41,654.80302	29,006.73505	8351.28998
DMU3	49,876.96339	45,814.83562	105,734.8782	51,481.44413	793.752802
DMU4	12,308.92483	34,669.24	65,097.06	40,703.16857	4874.29697
DMU5	82,340.57422	33,298.33429	102,532.27	48,779.69818	9045.97723
DMU6	15,862.54377	4270.199829	16,813.57795	8737.26243	4410.32706
DMU7	4570.856247	5193.870751	36,481.98157	5289.018142	17.9348684
DMU8	8,982.513991	25,643.97972	37,698.5591	28,408.72198	640.037718
DMU9	123,705.0576	7457.160011	40,341.63551	19,497.29373	11,567.2838
DMU10	1397.76	97.29	6366.01	847.00	703.36
DMU11	24,097,26938	20,882,52339	2422.407896	6445.637666	−43,158.02
DMU12	55,999.65098	2616.490858	19,538.23341	3891.117278	661.8058675

4.5. Future Performance Analysis

The future productivity index and its components are calculated using the DEA-Solver software developed by SAITECH. The results include three levels of change efficiency (catch-up), technology change level (border change), and Malmquist productivity index.

Table 12 shows the extent of changes in effectiveness between 2018 and 2020. It can be seen that DMU4, DMU5, DMU6, DMU9, DMU10, DMU11, and DMU12 maintain stable effectiveness. Because

they all point to 1, as shown, there are multiple horizontal lines. DMU9 also has the same model, but the performance difference is close to 1 during this time. It is noteworthy that DMU3 dropped sharply and DMU7 grew significantly during this period. The rest of the DMUs barely changed during this time.

Table 12. The efficiency (catch-up) changes level over the period from 2018 to 2020.

Catch-Up	2018=>2019	2019=>2020	Average
DMU1	0.2938568	1.7845282	1.0391925
DMU2	0.7231496	1.3828397	1.0529947
DMU3	2.3824091	1	1.1912046
DMU4	1	1	1
DMU5	1	1	1
DMU6	1	0.5161274	0.7580637
DMU7	0.2772715	3.6065733	1.9419224
DMU8	0.4889787	0.9440158	0.7164973
DMU9	0.5794734	1.2212955	0.9003845
DMU10	1	1	1
DMU11	1	1	1
DMU12	1	1	1
Average	2.4787616	1.2879483	1.883355
Max	2.382409	3.6065733	1.191205
Min	0.2772715	0.5161274	0.7164973
SD	5.9599983	0.7889892	2.9470671

Table 13 shows the second component of the Malmquist Productivity Index, which is the change in technology (frontier-shift). Overall, Thailand's overall energy industry grew by an average of 27%. Most DMUs are affected by the decline in the boundary index. In particular, the level of technical change in DMU5 was still significantly higher than 1 in this period, suggesting that they were working to improve the technology applicable to this business.

Table 13. The technical (frontier-shift) changes level over the period from 2018 to 2020.

Frontier	2018=>2019	2019=>2020	Average
DMU1	1.4605304	0.3943567	0.9274435
DMU2	1.2550978	0.6358301	0.9454639
DMU3	0.846048	0.5559984	0.7010232
DMU4	1	1.0015505	1.0007753
DMU5	0.3129909	4.9772362	3.1451136
DMU6	0.3647972	0.3820797	0.3734385
DMU7	0.6850652	0.2700326	0.4775489
DMU8	1.0363715	0.2947928	0.6655821
DMU9	2.8330902	0.3265762	1.5798332
DMU10	1	1	1
DMU11	1	1	1
DMU12	1	1	1
Average	1.0661659	4.4032044	2.7346852
Max	2.8330902	4.977236	3.145114
Min	0.3129909	0.2700326	0.3734385
SD	0.6455808	13.095913	6.4350437

Table 14 shows the Malmquist productivity index, which is the most important figure in this paper. This indicator is used to evaluate the future performance of 12 energy companies that can represent the industry in a reliable way. In general, productivity indexes are similar to technical change indexes, because most DMUs have a variable level of efficiency. In addition, the Malmquist productivity index is the result of the change in a multiplier effect with technology change. Therefore, the same result will be generated. The DMU1 productivity index remains at level 1, meaning its productivity over the next

four years will remain unchanged. DMU8 is in line with the level of technology change. The DMU9 productivity index stands in first place, prominent in the industry, with a significant index and a 33.5% average increase over the next three years. DMU5 and DMU7 also show increased productivity.

Table 14. The Malmquist productivity index changes level over the period from 2018 to 2020.

Malmquist	2018=>2019	2019=>2020	Average
DMU1	0.4291867	0.7037407	0.5664637
DMU2	0.9076235	0.8792511	0.8934373
DMU3	2.0156325	0.5559984	0.835062
DMU4	1	1.0015505	1.0007753
DMU5	0.3129909	4.9772362	3.1451136
DMU6	0.3647972	0.1972018	0.2809995
DMU7	0.1899491	0.9738922	0.5819206
DMU8	0.5067636	0.278289	0.3925263
DMU9	1.6417005	0.398846	1.0202732
DMU10	1	1	1
DMU11	1	1	1
DMU12	1	1	1
Average	2.2036297	4.4971672	3.3503984
Max	1.090545	4.977236	3.145114
Min	0.1899491	0.1972018	0.2809995
SD	5.0201694	13.066322	6.7058382

5. Conclusions and Future work

This study uses the DEA model and the Malmquist productivity index to assess the efficiency of Thailand's power sector by analyzing the future performance of 12 listed companies (DMUs). The DEA–Malmquist index was executed twice in the process of calculating the model when the direction input, or IV, was too short to calculate the VRS once, in order to produce the data for the period of five years from 2013 to 2017, calculate 2018 once, and calculate the year-to-2020 forecast data for the three-year period. The data for the first analysis were taken from the Thai Stock Exchange website, and the financial statements were audited by a trusted third party. The future analysis data and prediction accuracy generated using the GM prediction model (1,1) were tested using MAPE. The average MAPE of all DUMs was 2.34% and rated as excellent. This study uses three inputs (total cost, equity, fixed assets) and two outputs (gross income, net profit). Pearson correlation tests show that these variables are highly correlated with DEA conditions.

In assessing past performance, industry productivity has increased by 2.4%; especially in the cases of DMU4 and EGCO (DMU5), productivity indexes have changed significantly over the years. The political crisis in 2014 had a significant negative impact on the economy, so it is no surprise that productivity has declined. However, the two companies increased sharply in the last quarter from 2015 to 2017, and their productivity increased by 47% and 62.8%, respectively. Others follow a consistent trend and make small changes, either progressing or exhibiting a decrease in productivity. With the exception of DMU8, all of DMUs' performances increased from 90% to over 100% during this time.

In terms of future performance, most decision-making units will exhibit stable changes with respect to the productivity index. It is worth noting that DMU9 (Energy Absolute) maintains ultrasustainable development in the four years from 2017 to 2020, with an average growth rate of 73.6% (2019 to 96.5% in 2020). Despite its dominant position in the power generation and distribution market, EGAT (DMU1) has almost no future changes.

The limitations of this study are that it does not yet engage with internal parameters. In the future, the authors will undertake more research regarding internal parameters to provide corrective measures. In addition to that, due to the specific nature of the Energy Industry, it is under strict management by legislative provisions. Therefore, future research should incorporate the analysis of

regulations and policies by which the state manages the Energy Industry in order to produce more accurate assessments and decisions.

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