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Research Article

Performance Assessment of Malaysian Fossil Fuel Power Plants: A Data Envelopment Analysis (DEA) Approach

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Abstract. This paper investigated the performance of Malaysian power plants from the year 2015 to 2017 using Malmquist Total Factor Productivity (TFP) index, which is based on Data Envelopment Analysis (DEA). This approach offers substantial advantages as compared to other existing methods as it can measure productivity changes over time for a variety of inputs and outputs. Moreover, it comprises two primary components: the technical efficiency change and the technological change indexes that provide clearer insight into the factors that are responsible for shifts in total factor productivity. This study uses a single input, installed generation capacity (MW), and two outputs, average thermal efficiency (%) and average equivalent availability factor (%). These output-input data included ten main power plants: TNB Natural Gas, SESB Natural Gas, SESB Diesel, SEB Natural Gas, SEB Coal, SEB Diesel, IPP Semenanjung Natural Gas, IPP Semenanjung Coal, IPP Sabah Natural Gas, and IPP Sabah Diesel. The results have two significant implications for fossil fuel power plants in Malaysia. First, technological change was the primary factor in boosting the TFP performance of the fossil fuel power plants in Malaysia. Meanwhile, the decline in TFP performance in Malaysian fossil fuel power plants may be attributed, in part, to a lack of innovation in technical components as the results found that the average technical efficiency changes in 2015 – 2016 were at 146% and then dropped significantly to 2% in 2016 – 2017. Second, the average scale efficiency changes rose dramatically from -53% to 3% providing a significant contribution to the improvement of technical efficiency changes. The fossil fuel power plants become efficient as the power plants' size increases. This indicates that the size of a power plant positively impacts the performance of the TFP.

Keywords: energy, data envelopment analysis, efficiency, productivity, power plants, electricity

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1. Introduction

Electricity is generated by power plants using a variety of energy sources, including coal, natural gas, oil, hydropower, and nuclear energy (James, 2019; Hannah *et al*., 2020; Bahman and Patrick, 2021). A power plant, or electrical generating station, is an industrial facility that converts raw energy sources into electricity. The majority of power plants incorporate one or more generators into their operations to facilitate the transformation of mechanical energy into electrical energy. The electrical energy then is transmitted to the electrical grid and fulfills the needs of society. Examples of power plants include coal-fired plants, diesel-fired plants, wind farms, nuclear plants, solar panel farms, hydroelectric plants, and natural gas-fired plants (NS Energy Staff Writer, 2020; James, 2019).

According to U.S. Energy Information Administration, global energy consumption is expected to rise by twenty-eight percent between 2015 and 2040, as reported in International Energy Outlook 2017 (IEO2017) (Linda, 2017). The most recent report of International Energy Outlook 2021 (IEO2021) projected that both global energy demand and carbon emissions related to energy will continue to increase up until the year 2050 (U. S Energy Information Administration, 2021). The vast majority of the world's electricity supply originates from fossil fuels; this accounts for more than seventy-nine percent of the total energy mix in countries such as Australia, China, the United States, Russia, India, Indonesia, Singapore, Thailand, Philippines, and Malaysia. However, in recent years, countries such as Brazil, Canada, Norway, and Sweden have relied heavily on renewable energy sources to meet their electricity needs (IEA, 2019).

As of March 2022, Malaysia is currently among the top oil producer in Southeast Asia and also among the top three in the world in exporting liquefied natural gases. Although it is known for being one of the top oil producers in Southeast Asia, according to Petronas Annual Report (2019), Malaysia's oil reserves can last for only 28 years. The issue of the decreasing amount of fossil fuel reserves is currently being faced by most countries worldwide (Pritish and Francis, 2022).

In Malaysia, electricity is mainly generated via thermal and hydro-power plants. Thermal power plants convert coal, natural gas, biomass, and fuel oil into electricity, whereas hydro-power

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plants use water turbines (Samsudin *et al.* 2016; Abdul Latif *et al.*, 2021). Malaysia's electricity providers are Tenaga Nasional Berhad (TNB) in Peninsular Malaysia, Sabah Electricity Sdn. Bhd. (SESB) in Sabah, and Sarawak Energy Berhad (SEB) in Sarawak. and several Independent Power Producers (IPPs) such as IPP Semenanjung, IPP Sabah, and IPP Sarawak. These electricity providers are accountable for all aspects of electricity production, transmission, and distribution in Malaysia (Suruhanjaya Tenaga, 2021). As a result, they are responsible for ensuring that adequate electricity is delivered to customers on a regular and consistent basis.

As part of the United Nations' Sustainable Development Goals (SDGs) initiative, Malaysia has committed to meeting all 17 Sustainable Development Goal (SDG) indicators by the year 2030 (Azhar, 2021). In response, policymakers are constantly at work devising new development plans to realize the SDGs. As stated in Green Technology Master Plan Malaysia 2017 – 2030 report, several goals have the potential to change the direction of the energy agenda in SDG, namely Goal 7 (Affordable and Clean Energy), Goal 11 (Sustainable Cities and Communities), Goal 12 (Responsible Consumption and Production) and Goal 13 (Climate Action). These SDGs are among the important metrics for the government of Malaysia to monitor and work to improve. Demand for energy needs to be managed so that both energy security and supply can be sustained (Ministry of Energy, Green Technology and Water (KeTTHA), 2017).

The fossil fuel resources, such as oil, coal, diesel, and natural gas, have been playing a significant part in the transformation of the socioeconomic status in many countries especially Malaysia (Mushtaq *et al.* 2013). As reported by U.S. Energy Information Administration (2021), the vast majority of Malaysia's ever-increasing demand for electricity is satisfied by the combustion of fossil fuels, specifically natural gas and coal. Sharvini *et al.* (2018), Babatunde *et al.* (2018), and Abdul Latif *et al.* (2021) also emphasized that Malaysia's energy supply remains heavily dependent on conventional fossil fuels. They predicted the demand for conventional fossil fuels is likely to rise. It is anticipated that the production of power from conventional fossil fuels such as solid (coal), gas (natural gas), and liquid (crude oil, diesel) fossil fuels would see a significant increase over the next years, and eventually become the most significant source of energy. Hence, there is a pressing need to investigate the performance of Malaysian fossil fuel power plants in Malaysia.

In Malaysia, there are several types of fossil fuel power plants run by the main electricity providers and Independent Power Producers (IPPs). TNB, SESB, SEB, IPP in Semenanjung, and IPP in Sabah are responsible for the power generation of gas-fired power plants. Coal-fired power plants are run by SEB, and IPP in Semenanjung, whereas SESB, SEB, and IPP in Sabah are the companies responsible for the diesel-fired power plants (Suruhanjaya Tenaga, 2021).

The remainder of the paper is structured as follows: Section 2 discusses the literature survey on the performance of power plants. Section 3 presents the methodology and is followed by the results and discussion in Section 4. Section 5 is the concluding remarks.

2. Literature Survey

This section examines Data Envelopment Analysis-based past studies on fossil fuel power plant efficiency (DEA). The DEA is found to be an analytical tool for performance evaluation and ranking of similar entities or Decision-Making Units (DMUs) which transforms multiple inputs into multiple outputs (Cooper *et al.*, 2004). According to the relevant literature, there has been extensive use of DEA and its variations for assessing the efficiency of fossil fuel power plants.

Sarica and Or (2007) evaluated the efficiency of sixty-five Turkey's private and public thermal, hydro, and wind power plants in 2007 using DEA. Their study considered two efficiency metrics that represent operational and investment performance. They employed three DEA models namely constant-returns-to-scale (CRS), variable-returns-to-scale (VRS), and assurance region DEA models in their analysis. Besides, scale efficiency was examined. This study found that wind power systems had the highest efficiency values for operations and investments, showing their future potential. Coal-fired power stations were one of the main drivers of public investment inefficiency. Meanwhile, gas-fired natural plants had a better investment efficiency than coal gas plants, while natural gas public plants had slightly higher efficiency.

Next, Sözen *et al.* (2010) assessed the efficiency of Turkey's lignite, hard coal, and natural gas-powered thermal power plants in 2008 using DEA. These thermal power plants were owned by Turkey's state electricity production company, which was known as the Electricity Generation Cooperation Company (EUAS). Both operational performance and environmental performance were considered efficiency metrics. In this study, they employed CRS and VRS DEA models as Sarica and Or (2007). The results showed that the Somas AB power plant was discovered as the most efficient power plant in both models of all hard coal-fired facilities. The power plant at Hamitabat was the most efficient plant among all the natural gas-fired plants. They mentioned that the energy efficiency of electricity plants should be evaluated by analysis revealing the unit costs of production of power plants.

Munisamy and Arabi (2015) established a new slacks-based DEA measure to compute the Malmquiste-Luenberger productivity index. Throughout eight years of power sector reorganization, this technique was used to assess the productivity of forty-eight Iranian thermal power plants, including steam, gas, and mixed cycle. In addition, this technique analysed thermal power plant eco-efficiency changes operating under various technologies, as well as technological gap ratios, and investigated the degree to which power plants deviate from the meta-frontier. According to the findings, productivity grew faster in the latter years of the restructuring period, and all three kinds of thermal power plants increased their eco-efficiency over time.

In Iran, Mahmoudi *et al.* (2019) integrated DEA, multistage Principle Component Analysis (PCA), clustering, and game theory to assess the twenty-four Iranian thermal power plants (TPPs)'s performance in 2019. According to the findings, the majority of Iranian TPPs performed poorly. Since the energy industry is so important to local and national governments, poor TPP performance may cause economic, environmental, and social concerns. Therefore, raising TPP revenue was the most effective approach for improving their performance.

Later, Rezaee and Dadkhah (2019) proposed a new approach that combines DEA, Artificial Neural Network, and Inverse Problem to optimize the input parameters based on different output levels of a power plant. The Iranian thermal power plants were selected as a case study. First, a DEA model is used to determine efficient days. The efficient vectors obtained in the previous stage were then applied to an artificial neural network. The trained network's weights and biases were extracted and used in the inverse neural network model, which was known as a Gaussian nonlinear optimization problem.

Table 1
An overview of data and methodology used in past research to access the efficiency of fossil fuel power plants

Article	Type	Data	Period	Country	Methodology
Sarica and Or (2007)	Thermal, Hydro and Wind	11	2007	Turkey	CRS, VRS and assurance region type DEA models
Sözen *et al.* (2010)	Coal, Natural Gas	15	2008	Turkey	CRS, VRS DEA models
Munisamy and Arabi (2015)	Thermal	48	2003 – 2010	Iran	A new slacks-based DEA
Mustapa and Majid (2017)	Coal	48	2016	Malaysia	VRS and SBM-based DEA
Sahoo *et al.* (2018)	Coal	69	2009 – 2010	India	DEA and Tobit regression
Sun *et al.* (2018)	Fossil fuel	30	2005 – 2015	China	A new DEA approach - Intermediate approach
Li *et al.* (2018)	Fossil fuel	30	2004 – 2012	China	Static Unified Efficiency Indices (UEIs) and Meta-frontier Malmquist unified efficiency indices (MMUEI)
Sueyoshi *et al.* (2018)	Fossil fuel	30	2015	China	Radial, non-radial and intermediat DEA approaches
Tajbakhsh and Hassini (2018)	Fossil fuel	135	2012	United States	Two-stage DEA
Wu *et al.* (2018)	Coal	58	2015	China	PCA, super efficiency DEA, Kruskal-Wallis rank sum tests, Tobit regression
Mahmoudi *et al.* (2019)	Thermal	24	2019	Iran	Integrated DEA, multistage PCA, clustering and game theory
Rezaee and Dadkhah (2019)	Fossil fuel	8	March 2015 & November 2016	Iran	A novel hybrid approach - DEA, Artificial Neural Network and inverse problem
Sueyoshi *et al.* (2020a)	Fossil fuel	14	2007 – 2017	China	Intermediate approaches - Cross-sectional approach, window efficiency analysis and window index approach
Sueyoshi *et al.* (2020b)	Fossil fuel	30	2009 – 2015	China	Integrated DEA-Discriminant Analysis (DEA-DA), DEA environmental assessment and a rank sum test.
Du *et al.* (2021)	Fossil fuel	28	2005 – 2010	China	A new approach - Environmental DEA and restricted cost function
Zhang *et al.* (2022)	Fossil fuel	91	2005 – 2015	China	Meta-frontier hybrid DEA (MHDEA) model

In the context of market-based policies to mitigate the effects of climate change – Perform, Achieve, and Trade (PAT), Sahoo *et al.* (2018) explored the consequences of normalization on the energy consumption of the coal-based power industry in India. DEA and Tobit's regression were used in this cross-sectional analysis. A total of sixty-nine coal-fired thermal power facilities under PAT provided the sample data for this analysis. System demand, maintenance window, unplanned outages, fuel quality, and fuel mix were all shown to substantially impacted energy use. However, the quality of the coal used and the fuel mix had a larger role than any other variables. A steady certificate market may be maintained by the use of clean coal to maintain consistent energy demand.

Most studies on the efficiency of fossil fuel power plants were conducted in China. Wu *et al.* (2018) evaluated the ecological and economic efficiency of sixteen different coal-fired power plants located in China using a two-stage analysis model. In the first step, Principal Component Analysis (PCA) was used to minimize the number of dimensions and differentiate between the components that were prioritized. In the second step, a super-efficiency DEA was used to evaluate eco-efficiency with an overall ranking. In the third stage, Kruskal-Wallis rank sum tests were utilized to identify macro-environmental factors. Last but not least, after taking into account chain interactions and the influence of time, they employed Tobit regression to identify direct external factors. The findings showed that over sixty percent of coal-fired power plants were operating at an appropriate level of productivity, even though some of them were still dealing with challenges resulting from poor investment. A stable operation may be expected from plants that have a large installed capacity. The performance of local plants may be significantly influenced by macro-environmental factors such as policy preference and economic circumstances, whereas resource distribution has limited effects due to excellent transit conditions.

The next study is a new DEA method presented by Sun *et al.* (2018), which involves a combination of an intermediate method and heterogeneity of a group in a time horizon. This technique was used to assess the unified efficiency of thirty fossil fuel power plants located in coastal and inland provinces of China between 2005 and 2015. The findings showed that coastal provinces outperformed inland provinces, indicating significant group heterogeneity. Besides, there was substantial variation in the unified efficiency measures between provinces.

Table 2
A brief summary of the methodology and variables integrated into the data envelopment analysis efficiency assessment of fossil fuel power plants

Article(s)	**Input**	**Intermediate**	**Output**
Sarica and Or (2007)	**Model 1** 1. Fuel cost 2. Production 3. Availability **Model 2** 1. Investment cost 2. Construction time	None	*Desirable:* 1. Thermal efficiency 2. Environmental cost 3. Carbon monoxide (CO) *Desirable:* 1. Installed power capacity 2. Average utilization
Sözen *et al.* (2010)	**Model 1** Production **Model 2** Production	None	*Desirable:* Fuel cost per production *Desirable:* Gas emissions
Munisamy and Arabi (2015)	1. Installed generation capacity 2. Fuel consumption	None	*Undesirable*: 1. SO_2, emissions 2. NO_2, emissions 3. CO_2 emissions 4. Operational availability/ deviation from generation plan *Desirable:* Electricity generation
Mustapa and Majid (2017)	1. Coal consumption 2. Energy consumption 3. Sulphur dioxide emissions 4. CO_2 emissions	None	*Desirable:* 1. Ratio of resource output 2. Total output value per power generation unit
Sahoo *et al.* (2018)	*Controllable:* 1. Capacity 2. Coal consumption 3. Auxiliary power consumption 4. Plant load factor *Uncontrollable (Normalization):* 1. Unscheduled outage 2. Forced outage 3. Planned maintenance 4. Fuel supply reliability 5. Gross calorific value 6. Specific secondary fuel consumption	None	*Desirable:* Electricity generation

Table 2 (cont.)
A brief summary of the methodology and variables integrated into the data envelopment analysis efficiency assessment of fossil fuel power plants

Article(s)	Input	Intermediate	Output
Tajbakhsh and Hassini (2018)	1. Annual fuel consumed 2. Book value of plant and land 3. Annual production expenses 4. Plant nameplate capacity 5. Annual number of employees	1. Annual electricity net generation 2. Availability factor	*Desirable:* 1. Number of deaths per year 2. Number of heart attacks per year 3. Number of asthma attacks per year 4. Number of hospital admissions per year 5. Number of chronic bronchitis per year 6. Number of asthma ER visits per year 7. CO_2 emission 8. N_2O emission 9. CH_4 emission 10. SO_2 emission 11. NO emission 12. Annual revenue
Wu *et al.* (2018)	1. Installed capacity 2. Labor 3. Coal consumption 4. Auxiliary power consumption 5. Oil consumption 6. Water consumption	None	*Undesirable:* 1. SO_2, emissions 2. NO_2 emissions 3. CO_2 emissions 4. Dust emissions *Desirable:* 5. Electricity generation 6. Equivalent available coefficient
Sun *et al.* (2018)	1. Installed generation capacity 2. Labor 3. Energy consumption	None	*Undesirable:* CO_2 emissions *Desirable:* Electricity generation
Li *et al.* (2018)	1. Capital 2. Labor 3. Energy consumption	None	*Undesirable:* CO_2 emissions *Desirable:* Electricity generation
Sueyoshi *et al.* (2018)	1. Installed generation capacity 2. Labor 3. Energy consumption	None	*Undesirable:* CO_2 emissions *Desirable:* Electricity generation
Mahmoudi *et al.* (2019)	1. Installed generation capacity 2. Total hours of operation per period 3. Internal consuming 4. Fuel consumption 5. Number of non-operational employees 6. Number of operational employees 7. Generated power cost per kWh 8. Total cost of training	None	*Desirable:* 1. Electricity generation 2. CO_2 emissions 3. Total revenue

Table 2 (cont.)
A brief summary of the methodology and variables integrated into the data envelopment analysis efficiency assessment of fossil fuel power plants

Article(s)	Input	Intermediate	Output
Rezaee and Dadkhah (2019)	1. Energy consumption 2. Water consumption 3. Internal electricity consumption	None	*Desirable:* Power or output load
Sueyoshi *et al.* (2020a)	1. Installed generation capacity 2. Labor 3. Energy consumption	None	*Undesirable*: CO_2 emissions *Desirable:* Electricity generation
Sueyoshi *et al.* (2020b)	1. Installed generation capacity 2. Labor 3. Energy consumption	None	*Undesirable:* *CO_2 emissions* *Desirable:* Electricity generation
Du *et al.* (2021)	4. Installed generation capacity 5. Labor 6. Energy consumption	None	*Undesirable:* *SO_2 emissions* *Desirable:* Electricity generation
Zhang *et al.* (2022)	1. Labor 2. Capital 3. Energy consumption	None	*Desirable:* 1. Electricity generation 2. Sales *Undesirable:* CO_2 emissions

Li et al. (2018) further investigated a similar case study as Sun *et al.* (2018), however using data from 2004 – 2012. Besides, they used several approaches, static unified efficiency indices (UEIs) and dynamic unified efficiency indices – Meta-frontier Malmquist unified efficiency indices (MMUEI). The results found that MMUEIs provided more useful information compared to UEIs. For both coastal and inland areas, the MMUEI time paths followed an M-shaped curve. Besides, each UEI measured unified efficiency from various angles, and as a result, their time paths differed. Finally, there are significant variations either in MMUEI or UEI across China provinces.

Sueyoshi *et al.* (2018) compared three different approaches namely radial, non-radial, and intermediate methods while taking into account the heterogeneity of the groups. Similar to Sun *et al.* (2018), these approaches were used to examine the sustainability of the thirty fossil fuel power plant industry in China's coastal and inland provinces but the data used in this study was only considered in 2015. Under the government's catching-up policy, Chinese provinces focused on operational efficiencies. Coastal provinces were found to be more efficient than inland ones, indicating there was a regional imbalance between these two groups.

Furthermore, using data from 2007–2017, Sueyoshi *et al.* (2020a) compared the performances of fourteen Chinese fossil fuel power plants using three different types of intermediate approaches namely cross-sectional, window efficiency analysis, and window index. The findings of this study found that these three approaches differed significantly, indicating a methodological bias. China's capital, Beijing outperformed other provinces in terms of air pollution measures because the regulations exercised by the government of Beijing focused on air pollution caused by fossil fuel power plants.

A new method that incorporated Data Envelopment Analysis-Discriminant Analysis (DEA-DA), an evaluation of the DEA's environmental impact, and a rank sum test was proposed by Sueyoshi *et al.* (2020b). This study also used the same case study in China provinces as Sun *et al.* (2018), Li *et al.* (2018), Sueyoshi *et al.* (2018), and Sueyoshi *et al.* (2020). However, the data were collected from 2009 – 2015. This study indicated that the unified efficiency measurement showed that there was diversity between two groups of Chinese provinces. On top of that, there were significant differences in the level of unified efficiency between provinces. Besides, provinces that performed poorly in both natural and managerial disposability should receive special attention. Lastly, the DEA and DEA-DA models differentiated between the two types of disposability-natural and managerial.

In 2021, Du *et al.* proposed a regulatory stringency index using DEA's non-parametric distance function. The proposed model was integrated with the restricted cost function to measure the impact of environmental regulation, productivity, and substitution elasticities on power plants. The impact of environmental regulation on productivity growth appeared to be approximately U-shaped, according to the findings. Besides, the advancement of technology was the primary factor in rising productivity.

In a recent article, Zhang *et al.* (2022) introduced a meta-frontier hybrid data envelopment analysis (MHDEA) model that combines group heterogeneity, undesirable outputs, and hybrid metrics. This method was utilized to examine the total factor carbon performance index of twenty-eight of China's fossil fuel power plants between 2005 and 2015. This model accounted for group heterogeneity, undesirable outputs, and hybrid metrics. The efficiency change, best-practice gap, and technology gap change (TGC) were examined as drivers of productivity growth using the Malmquist-Luenberger (ML) index.

U.S. researchers Tajbakhsh and Hassini (2018) built on prior work on centralized DEA models for two-stage systems to introduce a nonlinear DEA model. They introduced an accurate and efficient algorithm to tackle the problem and then applied it to a case study of fossil fuel power plants in the United States. When compared to other models, this algorithm yielded more stable computational results.

To the best of our knowledge, there is a lack of studies on the performance of fossil fuel power plants in Malaysia. Mustapa and Majid (2017) were the only researchers that evaluated the efficiency of coal-fired power plants in Malaysia using DEA. The sample of data consisted of four individual plants, with each plant's data covering a period of the year 2016. The simulation results suggested that the Banker, Charnes, and Cooper (BCC) or VRS and Slack-Based Measure (SBM) based DEA models can be used to identify inefficient units of coal-fired power plants for improvements. Several unit plants were identified as circular economy benchmarks to improve Malaysia's electricity generation. For a better understanding, Table 1 provides an overview of the data and methodology used in past research to evaluate the efficiency of fossil fuel power plants.

Several studies investigated the performance of renewable power plants such as solar (Wang *et al.*, 2017; Wang *et al.* 2018; Wang *et al.*, 2021; Mariano *et al.*, 2021; Wang *et al.*, 2022), hydro-electric (Sarica and Or, 2007; Seyma *et al.*, 2019), wind (Sarica and Or, 2007; Khanjarpanah and Jabbarzadeh, 2019), biomass (Nattanin *et al.*, 2015; Rentizelas *et al.*, 2019) and hybrid wind-photovoltaic (Khanjarpanah *et al.*, 2022).

In contrast to the methods that were utilized in earlier studies, the purpose of this paper is to investigate the performance the Malaysian fossil fuel power plants using the DEA-based Malmquist Total Factor Productivity (TFP) Index.

3. Data and Methodology

This paper employed a DEA-based output-oriented Malmquist Total Factor Productivity (TFP) Index to maximize outputs while keeping inputs constant and to compare efficiency over two different periods. Data Envelopment Analysis (DEA) and the Malmquist index techniques, which are both linear programming methods, are two of the most common methods that are used to evaluate the relative efficiency and productivity of multiple DMUs or similar entities. Both of these approaches are linear programming methods. The DEA was first developed by Charnes *et al.* (1978) to assess the efficiency of portfolios. On the other hand, the Malmquist index was introduced by Fare *et al.* (1989) to measure the growth of productivity in Swedish hospitals.

The Malmquist index is a tool for comparing the total change in a Decision-Making Unit's (DMU) productivity factor over time. It can be divided into technical efficiency and technological changes. To be specific, this Malmquist index calculates the ratio of the distance function over two different periods to determine the change in TFP between two data points:

$$E(y_s, y_t, x_s, x_t) = \frac{W^t(y^t, x^t)}{W^s(y^s, x^s)} \qquad (1)$$

which the function $E(.)$ is denoted as the technical efficiency change index, with the subscript s and t referring to the time period. The numerator in this Equation (1) represents the data period, while the denominator represents the technology period.

This Malmquist TFP productivity index employs a distance function approach. When a set of input requirements describes the production technology, the distance function is said to be meaningful. Fare *et al.* (1994) calculated the productivity technical change component as a mixed index that measures time period data s versus time period technology t, $(W^t(y^s,x^s))$ and another mixed index that measures time period t versus time period technology s, $(W^s(y^t,x^t))$ as follows:

$$T(y_s, y_t, x_s, x_t) = \sqrt{\frac{W^s(y^t, x^t)}{W^t(y^t, x^t)} \times \frac{W^s(y^s, x^s)}{W^t(y^s, x^s)}} \qquad (2)$$

where, $T(.)$ is a non-negative input vector that denotes the technological change index, $x = (x_1, x_2, \ldots, x_n)$ and y is a non-negative output vector, $y = (y_1, y_2, \ldots, y_n)$. The overall change in output-oriented Malmquist TFP index productivity factor across time periods s and t, according to Fare *et al.* (1994), is:

$$\begin{aligned} & M_i(y_s, y_t, x_s, x_t) \\ & = E_i(y_s, y_t, x_s, x_t) \times T_i(y_s, y_t, x_s, x_t) \\ & = \underbrace{\frac{W^t(y^t, x^t)}{W^s(y^s, x^s)}}_{\text{Technical Efficiency Change}} \times \underbrace{\sqrt{\frac{W^s(y^t, x^t)}{W^t(y^t, x^t)} \times \frac{W^s(y^s, x^s)}{W^t(y^s, x^s)}}}_{\text{Technological Change}} \end{aligned} \qquad (3)$$

The Malmquist productivity index in Equation (3) has two components: technical efficiency change and technological change. If the function $M > 1$ is employed, TFP increases from the time s to time t. If $M < 1$, on the other hand, it shows that TFP drops from the time s to time t.

This paper uses an enhanced decomposition of the Malmquist index (Fare *et al.* 1994). The enhanced decomposition separates the technical efficiency change component of the Malmquist index, which is calculated relative to CRS technology, into two distinct components namely a pure efficiency component, and a scale efficiency change component as:

$$\text{Technical Efficiency change} = \text{Pure Efficiency change} \times \text{Scale Efficiency change} \qquad (4)$$

Changes in pure efficiency analyze a company's ability to effectively transform inputs into outputs, while scale efficiency examines how well a company can exploit returns to scale by changing its size to the appropriate scale

3.1 Selection of Input and Output

This paper focuses on fossil fuel power plants, and the models are applied to three types of fossil fuel power plants: gas-fired, coal-fired, and diesel-fired power plants. Table 2 presents an overview of prior research that provides researchers with a roadmap for identifying the most relevant input-output variables as well as intermediate variables for data envelopment analysis efficiency assessment of fossil fuel power plants.

Table 3
Input-output variables definitions

Variables	Definition
Input: Installed generation capacity (MW)	The plant's maximum potential capacity is often known as its nameplate rating. It is the amount of power that the plant is capable of producing. Performance tests are often used to estimate a plant's capacity, which in turn allows utilities to predict the maximum load that a plant can safely handle. Megawatts and kilowatts are the usual units of capacity measurement.
Output 1: Average thermal efficiency (%)	Thermal efficiency is defined as a ratio of the amount of electrical energy generated to the amount of energy released by the fuel that was used. It can be expressed in a percentage which must be between 0% and 100%
Output 2: Average equivalent availability factor (%)	The percentage of a particular operational time when a generator is available without outages or equipment deratings.

Sources: Resource Adequacy Planning (2020); Suruhanjaya Tenaga Malaysia (2021); James (2022)

The input and output variables considered in this study were selected based on prior research and data availability. The input-output variables used for measuring the efficiency of Malaysian fossil fuel power plants are listed in Table 3, and they were determined based on the availability and access to data in the non-public domain.

This paper considers three variables: one input and two outputs. Installed generation capacity (MW) (Munisamy and Arabi 2015; Sahoo *et al.* 2018; Wu *et al.* 2018; Sun *et al.*, 2018; Sueyoshi *et al.*, 2018; Mahmoudi *et al.* 2019; Sueyoshi *et al.* (2020a); Sueyoshi *et al.*, 2020b; Du *et al.*, 2021) was selected as input. Most previous studies utilized installed capacity, represented as capital input in MW, which is the total of all operating turbine capacity.

As stated in Table 3, the outputs used in this study were the average thermal efficiency (%) (Sarica and Or 2007) and average equivalent availability factor (%) (Sarica and Or 2007; Wu *et al.* 2018). The first output, the average thermal efficiency measures how much the heat is transformed into electrical energy. Maximizing thermal efficiency provides environmental and economic benefits since it reduces emissions and energy use. The second output, the average equivalent availability factor measures the amount of time that the power plant can provide electricity without interruption. An increase in availability is a significant positive indicator.

3.2 Data Sources

For this study, a total of ten fossil fuel power plants, categorized by producer were collected from 2015 to 2017. The input-output data used in this study was limited to three (3) years and also did not consider environmental factors due to data availability.

Table 4
List of fossil fuel power plants by producer

Producer	Source of energy
Tenaga Nasional Berhad (TNB)	Natural gas
Sabah Electricity Sdn. Bhd. (SESB)	Natural gas and diesel
Sarawak Energy Berhad (SEB)	Natural gas, coal and diesel
IPP Semenanjung	Natural gas and coal
IPP Sabah	Natural gas and diesel

Sources: Suruhanjaya Tenaga Malaysia (2020); Suruhanjaya Tenaga Malaysia (2021)

The primary source of data was the Performance & Statistical Information on the Malaysian Electricity Supply Industry 2018, obtained from Suruhanjaya Tenaga Malaysia (2020).

Electricity in Peninsular Malaysia is generated by three different types of fossil fuel power plants:

i. Peninsular of Malaysia – TNB Natural Gas, IPP Semenanjung Natural Gas, and IPP Semenanjung Coal.
ii. Sabah – SESB Natural Gas, SESB Diesel, and IPP Sabah Natural Gas.
iii. Sarawak – IPP Sarawak Diesel, SESB Natural Gas, and SESB Diesel.

Table 4 presents a list of fossil fuel power plants by the producer. These data and selected models were analyzed using DEAP software Version 2.1, and Microsoft Excel.

4. Results and Discussion

4.1 Descriptive Statistics

Table 5 presents descriptive statistics for the input-output of ten fossil fuel power plants in Malaysia between 2015 and 2017. Fossil fuel power plants had an average installed generation capacity (MW), average thermal efficiency (%), and average equivalent availability factor (%) of 2,330.97 MW, 32.46%, and 86.59% in 2015 – 2017, respectively. To determine whether a standard deviation number is large or low, the coefficient of variation (CV) of each variable was calculated.

The greater the coefficient of variation, the more spread out the data is around the mean. When the coefficient of variation value is greater than one means that the standard deviation is greater than the mean.

Table 5
Descriptive statistics of inputs-outputs Malaysian fossil fuel power plants between 2015 and 2017

Description	Input	Output	
	Installed Generation Capacity (MW)	Average Thermal Efficiency (%)	Average Equivalent Availability Factor (%)
Mean	2,330.97	32.46	86.59
Median	537.50	33.27	87.65
Standard deviation	3,280.65	4.16	6.63
Minimum	36.00	24.35	71.70
Maximum	10,066.00	39.22	98.05

Table 6
Efficiency of Malaysian fossil fuel power plants, 2015 – 2017

No.	Power plants (DMUs)	CCR model (Constant-return-scale,CRS)			BCC model (Variable-return-scale,VRS)		
		2015	2016	2017	2015	2016	2017
1	TNB Natural Gas	0.0270	0.0100	0.0190	0.9400	0.9420	0.9740
2	SESB Natural Gas	0.8710	0.3260	0.3470	**1.0000**	0.7320	0.8470
3	SESB Diesel	0.5520	0.2330	0.2400	0.8760	0.8480	0.9600
4	SEB Natural Gas	0.1670	0.0650	0.0730	0.8550	0.8490	0.8170
5	SEB Coal	0.2490	0.0930	0.0950	0.9500	0.8450	0.9120
6	SEB Diesel	**1.0000**	**1.0000**	0.4040	**1.0000**	**1.0000**	**1.0000**
7	IPP Semenanjung Natural Gas	0.0200	0.0070	0.0060	0.9800	0.9530	0.9370
8	IPP Semenanjung Coal	0.0160	0.0060	0.0050	**1.0000**	0.9610	0.8850
9	IPP Sabah Natural Gas	0.1340	0.0550	0.0670	**1.0000**	**1.0000**	**1.0000**
10	IPP Sabah Diesel	0.6700	0.5100	**1.0000**	**1.0000**	**1.0000**	**1.0000**
	Average	0.3710	0.2300	0.2260	0.9600	0.9130	0.9330

Table 7
Malaysian fossil fuel power plants relative Malmquist TFP, technological and technical efficiency changes, 2015 – 2017

No.	Power plants (DMUs)	Malmquist TFP productivity change		Technological change		Technical efficiency change	
		2015-2016	2016-2017	2015-2016	2016-2017	2015-2016	2016-2017
1	TNB Natural Gas	0.9020	1.9110	**2.4840**	0.9710	0.3630	**1.9690**
2	SESB Natural Gas	0.9120	1.0330	2.4370	0.9720	0.3740	1.0640
3	SESB Diesel	1.0090	1.1020	2.3880	**1.0740**	0.4230	1.0260
4	SEB Natural Gas	0.9510	1.0910	2.4590	0.9590	0.3870	1.1370
5	SEB Coal	0.9270	0.9810	**2.4840**	0.9590	0.3730	1.0230
6	SEB Diesel	**2.4360**	0.3990	2.4360	0.9870	**1.0000**	0.4040
7	IPP Semenanjung Natural Gas	0.8770	0.7890	**2.4840**	0.9590	0.3530	0.8220
8	IPP Semenanjung Coal	0.9040	0.8580	**2.4840**	0.9590	0.3640	0.8950
9	IPP Sabah Natural Gas	1.0180	1.1630	**2.4840**	0.9590	0.4100	1.2130
10	IPP Sabah Diesel	1.8910	**2.0340**	**2.4840**	1.0380	0.7610	1.9600
	Geomean	1.1053	1.0405	2.4622	0.9830	0.4489	1.0586

The lower the coefficient of variation value, the more precise the estimate. In this study, the coefficient of variation of installed generation capacity was recorded at 1.4. This implies the installed generating capacity's standard deviation was above the mean. Meanwhile, the CV for both outputs was less than 1, indicating that the spread of data values is low relative to the mean.

Specifically, IPP Sabah Diesel produced the least amount of inputs in the year 2017, while IPP Semenanjung Coal produced the highest amount of inputs in the same year. In regards to the outputs, IPP Sabah Diesel gained the least thermal efficiency in 2017 and SESB Natural Gas obtained the least equivalent availability factor in 2016. In 2016, IPP Sabah Natural Gas had the best thermal efficiency and SEB Diesel had the best equivalent availability factor.

4.2 Relative Efficiency

The fundamental component of the Malmquist productivity index is associated with efficiency measures. If the values are equal to or greater than one suggests that the power plant is operating at the industrial frontier, while values that are less than one indicate the power plant is inefficient. In other words, the farther values are from one, the less efficient they are. Table 6 depicts the change in efficiency for the ten fossil fuel power plants from 2015 to 2017 for both constant-returns-to-scale (CRS) or known as Charnes, Cooper, and Rhodes (CCR), and variable returns-to-scale (VRS) or known as Banker, Charnes, and Cooper (BCC) indices. The best performance among all DMUs is indicated in boldface.

As reported in Table 6, SEB Diesel was the sole efficient power plant for both CRS and VRS in 2015 and 2016. In 2017, only IPP Sabah Diesel maintained the performance that was deemed to represent the industry's frontier under both CRS and VRS models. In addition, SEB Diesel, IPP Sabah Natural Gas, and IPP Sabah Diesel were consistently efficient for three consecutive years, 2015 – 2017 in terms of VRS. SESB Natural Gas and IPP Semenanjung Coal were also efficient in 2015 under the VRS model. On average, in 2015, fossil fuel power plants generated the highest potential output level about 37.1% under CRS. and 96% under VRS.

According to CRS or VRS, the efficiency of five power plants was found to be above average for all of the years of the study (9.9% for CRS), whereas according to VRS, the efficiency of six power plants was found to be above the average of 93.26%. SEB Diesel had the highest CRS (73.93%) and VRS (100%) scores, making it the most efficient power plant. Besides, IPP Sabah Natural Gas and IPP Sabah Diesel also obtained 100% efficiency under the VRS model. The power plants with the lowest efficiency ratings were IPP Semenanjung Coal (0.78%) under the CRS and SEB Natural Gas (84.02%) under the VRS.

As observed in Table 6, the overall industrial efficiency under CRS declined from 37.1% to 23% between 2015 and 2016 and further decreased to 22.6% in 2020. In regards to VRS, the average efficiency in 2015 diminished to 91.3% from 96%. The efficiency improved slightly to 93.3% in the following year. On average, the efficiency of Malaysian fossil fuel power plants for CRS model demonstrated a downward trend over a three-year period of study. However, the VRS model showed an inconsistent trend. These findings suggest that some power plants require a strategic action plan in order to enhance their levels of efficiency.

4.3 Productivity Performance

Table 7 presents the performance of fossil fuel power plants from 2015 to 2017 in terms of the change in total factor productivity (TFP) as well as the TFP change's two subcomponents, namely the change in technical efficiency and the change in technology. TFP productivity indices and their components that have a value that is less than one imply a loss of productivity or deterioration in productivity. On the other hand, values that are more than one suggest that there has been an increase in production in the relevant area. Given the relevant time period and relevant performance metric, the average yearly growth or decline is determined by subtracting one from the value shown in the table. Also, note that these measures are based on best-practice decision-making unit performance (DMU).

According to Table 7, SEB Diesel and IPP Sabah Diesel had the greatest average TFP growth at an annual average rate of 143.6% and 103.4% for the period of 2015 – 2016 and 2016 – 2017, respectively. On the contrary, IPP Semenanjung Natural Gas had the greatest decline in TFP for 2015 – 2016, at an annual average rate of –12.3%, while SEB Diesel had the slowest growth for 2016 – 2017 at –60.1%. On average, however, TFP changes both improved at an annual rate of 10.53% and 4.05%, between 2015 – 2016 and 2016 – 2017, respectively.

In regards to the technological changes, the average growth in technological change for all power plants over the years 2015 – 2016 was positive, with yearly growth rates of 146.22%. On the other hand, the growth rate in technological change was slightly negative from 2016 to 2017 (–1.7%). Specifically, TNB Natural Gas, SEB Coal, and all IPPs such as IPP Semenanjung Natural Gas and Coal, and IPP Sabah Natural Gas and Coal had the greatest technological growth in 2015 – 2016 at 148.4% and SESB Diesel in 2016 – 2017 with the annual growth of 7.4%. SESB Diesel had a minimum annual growth of 138.8% in 2015 – 2016. Several power plants had the largest technological regress of 1.7%, on average for 2016 – 2017, with the lowest technological growth at 4.1%. They were SEB Natural Gas, SEB Coal, IPP Semenanjung Natural Gas, IPP Semenanjung Coal and IPP Sabah Natural Gas.

Lastly, the average of technical efficiency change for the whole industry was positive only in 2016 – 2017, with an annual rate of 5.86%, however, it was technically inefficient throughout 2015 – 2016, at –55.11%. There was no improvement in SEB Diesel's efficiency between 2015 and 2016 while others were technically inefficient. Nonetheless, from 2016 – 2017, TNB Natural Gas was technically efficient, recorded at 96.9% of annual growth.

Table 8
Changes in efficiency components of Malaysian fossil fuel power plants, 2015 – 2017

No.	Power plants (DMUs)	Pure efficiency change		Scale efficiency change	
		2015-2016	2016-2017	2015-2016	2016-2017
1	TNB Natural Gas	**1.0020**	1.0340	0.3620	1.9050
2	SESB Natural Gas	0.7320	1.1570	0.5110	0.9190
3	SESB Diesel	0.9680	**1.1320**	0.4370	0.9060
4	SEB Natural Gas	0.9930	0.9620	0.3890	1.1820
5	SEB Coal	0.8890	1.0790	0.4200	0.9480
6	SEB Diesel	1.0000	1.0000	**1.0000**	0.4040
7	IPP Semenanjung Natural Gas	0.9730	0.9830	0.3630	0.8360
8	IPP Semenanjung Coal	0.9610	0.9220	0.3790	0.9710
9	IPP Sabah Natural Gas	1.0000	1.0000	0.4100	1.2130
10	IPP Sabah Diesel	1.0000	1.0000	0.7610	**1.9600**
	Geomean	**0.9480**	**1.0245**	**0.4735**	**1.0332**

Table 9
Mean summary of Malmquist TFP index of Malaysian fossil fuel power plants, 2015 – 2017

No.	Power plants (DMUs)	Total of Malmquist TFP productivity change	Technological change	Technical efficiency change	Pure efficiency change	Scale efficiency change
1	TNB Natural Gas	1.3130	1.5530	0.8460	1.0180	0.8310
2	SESB Natural Gas	0.9710	1.5390	0.6310	0.9200	0.6850
3	SESB Diesel	1.0550	1.6010	0.6590	**1.0470**	0.6290
4	SEB Natural Gas	1.0180	1.5360	0.6630	0.9780	0.6780
5	SEB Coal	0.9540	1.5440	0.6180	0.9800	0.6310
6	SEB Diesel	0.9860	1.5510	0.6360	1.0000	0.6360
7	IPP Semenanjung Natural Gas	0.8310	1.5440	0.5390	0.9780	0.5510
8	IPP Semenanjung Coal	0.8810	1.5440	0.5710	0.9410	0.6060
9	IPP Sabah Natural Gas	1.0880	1.5440	0.7050	1.0000	0.7050
10	IPP Sabah Diesel	**1.9610**	**1.6060**	**1.2210**	1.0000	**1.2210**
	Geomean	**1.0724**	**1.5560**	**0.6895**	**0.9856**	**0.6994**

To sum up, the majority of the changes in TFP that occurred over 2015 – 2016 were caused by changes in technological change rather than efficiency change. As a result of improvements in technological change efficiency, the growth rates of TFP were positive in 2015 – 2016. Conversely, in 2016 – 2017, most of the shift in TFP was due to changes in efficiency change rather than technological change. Furthermore, the TFP change, on average, produced positive growth rates, with 10.53% between 2015 and 2016, and deteriorated to 4.05% between 2016 and 2017. This demonstrates a gradual decline during the years 2015 and 2017.

Next, Table 8 presents the efficiency change components of Malaysian fossil fuel power plants between 2015 – 2017. The efficiency change can be decomposed into two subcomponents namely the pure efficiency change and the scale efficiency change. Based on Table 8, pure efficiency and scale efficiency were the essential sources for the growth and reduction in efficiency change. TNB Natural Gas had the highest advancement in pure efficiency in 2015 – 2016, with an annual growth rate of only 0.2%. This was followed by SEB Diesel, IPP Sabah Natural Gas, and IPP Sabah Diesel, however without any improvements. Conversely, SESB Natural Gas showed the highest decline in pure efficiency in 2015 – 2016 with a decline of 26.8% as compared to IPP Semenanjung Coal in 2016 – 2017 with merely a 7.8% decline.

With an average decline rate of 52.65% in 2015 – 2016, SEB Diesel was the only power plant that had positive scale efficiency, despite the fact that it did not improve. In addition, in 2016 – 2017, IPP Sabah Diesel achieved the highest progress in scale efficiency with 96%. On the other hand, IPP Sabah Diesel showed the largest degradation in scale efficiency, with – 59.6% in 2016 – 2017.

Generally, the negative average rates of pure efficiency (–5.2%) and scale efficiency (–52.65%) were recorded between 2015 and 2016. On the other hand, between 2016 and 2017, the average rates of pure efficiency (2.4%) and scale efficiency (3.32%) were slightly improved.

4.4 Industry Productivity

The performance of the Malmquist TFP index of the fossil fuel power plants in Malaysia between 2015 and 2017 is summarised in Table 9. On average, about 50% (5 out of 10) of fossil fuel power plants recorded improvements in their TFP performance. The highest improvement was made by IPP Sabah Diesel at 96.1%, while IPP Semenanjung Natural Gas experienced the largest decline in TFP, with annual rates of –16.9%. In addition, about 30% of power plants had TFP performances above the industry average of 7.24%.

In regard to technological change, the annual average growth rates of each fossil fuel power plant were completely optimized. IPP Sabah Diesel had the largest growth, at 60.6%, followed by SESB Diesel (60.1%) and TNB Natural Gas (55.3%). SEB Natural Gas had the lowest growth rate in efficiency, with an annual rate of 53.6%. Approximately 20% of fossil fuel power plants improved their efficiency over the industry average of 55.6%.

With an average rate of –31.05%, the fossil fuel power plants in Malaysia were deemed to be technically inefficient. IPP Semenanjung Natural Gas experienced the highest deterioration in technical efficiency (–46.1%), followed by IPP Semenanjung Coal (–42.9%) and SEB Coal (–38.2%).

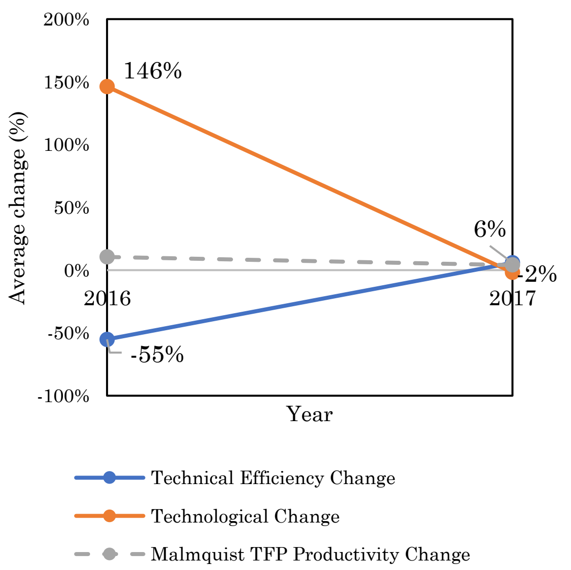

Fig. 1 Average changes in TFP, technical efficiency and technological, 2015 –2017

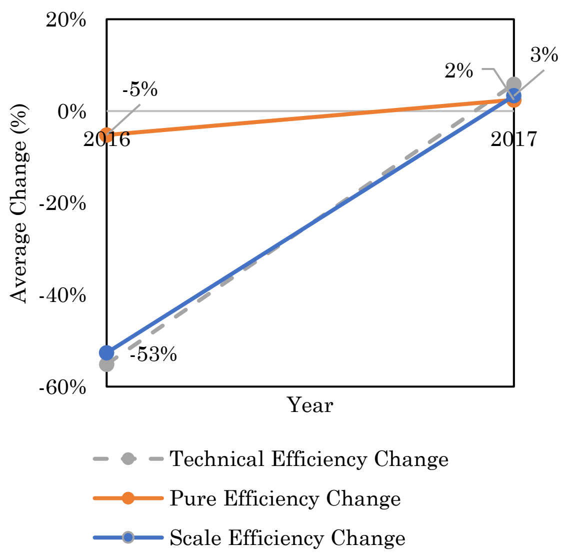

Fig. 2 Average changes in technical efficiency, pure efficiency and scale efficiency, 2015 –2017

About 70% of fossil fuel power plants demonstrated average declines in technical efficiency that were lower than the industry average of –31.05%. Overall, the average industry TFP had slightly improved (7.24%) mainly due to technological change (55.6%). Also, the decline in technical efficiency change was mostly due to scale efficiency (–30.06%) rather than pure efficiency (–1.44%).

Figure 1 demonstrates the average changes in total factor productivity (TFP) with technical efficiency and technology. Meanwhile. Figure 2 depicts the average changes in technical efficiency with pure efficiency and scale efficiency. As mentioned earlier, the increment of TFP change was due to the technological change where its average change in 2015 – 2016 at 146% while dropped drastically to 2% in 2016 – 2017. However, technical efficiency also somewhat contributed to the TFP. According to Figure 2, the changes in technical efficiency on average were negative from 2015-2017 but improved from 2016-2017 due to an increase in scale efficiency.

5. Concluding Remarks

Conventional fossil fuels continue to provide a significant portion of Malaysia's total energy supply. It is predicted that there would be an increase in the demand for conventional fossil fuels. As a result, fossil fuel power plants will be subjected to performance evaluations to guarantee their efficiency and productivity. In this paper, the performance of Malaysian fossil fuel-based power plants was examined for the years 2015 through 2017. The input-output data of fossil fuel power plants were evaluated using the DEA-Malmquist Total Factor Productivity (TFP) Index technique. This approach can measure the efficiency and productivity of DMUs with multiple inputs and outputs either over a single-period, multi-period, or cross-period changes. Besides, the two main components of Malmquist TFP: technical efficiency changes and technological changes provide better understanding about the factors that affect the total factor productivity. In general, several power plants such as TNB Natural Gas, IPP Sabah Natural Gas, and Diesel experienced improvements in efficiency as TFP performances were above the industrial average. Based on our findings, only IPP Sabah Diesel was technically efficient and contributed substantially to the increment of TFP. The positive technological change in all power plants impacted TFP performances as a whole. In addition, the decline in the average change in technical efficiency was mostly impacted by scale efficiency as opposed to pure efficiency. This demonstrated that there is a positive relationship between the size of the power plants and the TFP performance of the power plants. In addition, the reduction in TFP in Malaysian fossil fuel power plants was shown to be associated with a lack of technical efficiency. These insights should assist power plant owners to optimize the production of output from a given set of inputs.

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