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Research Article

Assessing the energy efficiency of fossil fuel in ASEAN

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Abstract. The world's industries, transportation systems, and households rely heavily on fossil fuels despite their limited availability and high carbon content. Therefore, it is of the utmost importance to improve fossil fuel energy efficiency in order to facilitate the shift towards a sustainable energy system with reduced greenhouse gas emissions. This paper employs a slacks-based measure network data envelopment analysis model with undesirable outputs to assess the efficiencies of fossil fuel energy in the Association of Southeast Asian Nations (ASEAN) countries during a span of seven years, specifically from 2015 to 2021. The inclusion of undesirable outputs in this study is important because it allows for a more realistic assessment of efficiency by considering factors like CO_2 emissions, which are undesirable outcomes associated with fossil fuel use. The datasets utilised in this study are sourced from the U.S. Energy Information Administration and the open data website of Our World in Data. Based on the findings, it can be observed that Singapore and the Philippines have demonstrated outstanding performance in maximising the utilisation of fossil fuels. In contrast, Myanmar exhibits the lowest level of efficiency in this analysis. By identifying top-performing countries in terms of fossil fuel efficiency, it is possible to implement measures to boost efficiency in under-performing countries. This can be achieved through the promotion and adoption of cleaner energy alternatives, specifically renewable energy sources that exhibit a low or negligible carbon footprint. These findings offer significant contributions to policymakers exploring sustainable energy usage, environmental stewardship, and the formulation and execution of comprehensive strategies that aim to mitigate carbon dioxide emissions arising from the consumption of fossil fuels in the ASEAN region.

Keywords: energy efficiency, fuel fossil, ASEAN, Data Envelopment Analysis (DEA), ranking

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1. Introduction

According to the Environmental and Energy Study Institute (2021), about 80% of the world's energy needs are met by fossil fuels like coal, oil and natural gas, which have been fuelling economies for over 150 years. Fossil fuels are non-renewable resources, which cannot be replaced once they are used up. Converting these forms of energy into electricity in power stations results in the release of carbon dioxide (CO2) into the atmosphere. This release of carbon dioxide can have negative consequences such as an increase in the greenhouse effect and increased levels of air pollution.

Linda Doman (2017) as cited in Abdul Rahman *et al.* (2023) mentioned that the U.S. Energy Information Administration's International Energy Outlook 2017 (IEO2017) predicts a 28% increase in global energy consumption between 2015 and 2040. Besides, it is anticipated that there will be a surge in energy demand and carbon emissions until the year 2050 as reported by International Energy Outlook 2021 (IEO2021) (U.S. Energy Information Administration, 2021).

In addition, World Nuclear Association (2022) stated that the combustion of fossil fuels worldwide leads to an annual release of approximately 34 billion tonnes (Gt) of carbon dioxide (CO_2) into our atmosphere. Approximately 45% of the energy generation is derived from coal, while around 35% is sourced from oil, and the remaining 20% is obtained from natural gas.

By reducing greenhouse gas emissions, lowering energy consumption and lowering energy costs, improving energy efficiency can help mitigate climate change and foster sustainable development. Energy efficiency is defined as the inverse of energy intensity and refers to the process of increasing economic output per unit of energy consumed. Dogan & Tugcu (2015) indicated that energy efficiency has been a study focus due to causes including global warming, rising energy prices, a less secure energy supply, and the idea of sustainable development. Therefore, making significant improvements in energy efficiency is crucial.

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Improving energy efficiency is an important issue for the member states of the Association of Southeast Asian Nations (ASEAN). The ASEAN region is comprised of ten countries of Southeast Asia namely Brunei Darussalam, Burma, Cambodia, Indonesia, Laos, Malaysia, Philippines, Singapore, Thailand, and Vietnam (The ASEAN Secretariat, 2020). As reported by Liu & Noor (2020) in ADBI Working Paper 1196, the ASEAN region primarily relies on fossil fuels (75%). Oil accounts for 34% of all fossil fuel consumption, while natural gas and coal each account for 22% and 17% respectively.

ASEAN Centre for Energy (ACE) is an intergovernmental organization that plays a key role in promoting energy efficiency and the field of energy in the region. The ACE works with member countries to implement energy efficiency policies and provides technical assistance and capacity building to support these efforts (ASEAN Centre for Energy, 2022). The establishment of this centre in 1999 has resulted in significant progress in enhancing energy efficiency in ASEAN nations in recent years. Despite the growing body of research on these efforts, further improvements are still possible. This paper examines the energy efficiency of fossil fuels in ASEAN countries.

The remaining sections of the paper are organised in the following manner: In Section 2, an extensive literature survey is conducted to explore the topic of fossil fuel energy efficiency. Section 3 of this study offers a comprehensive outline of the methodology implemented, while Section 4 presents the results and discussion. Lastly, Section 5 serves as the concluding remarks.

2. Literature Survey

The Data Envelopment Analysis (DEA) is a non-parametric approach employed for the evaluation and prioritisation of comparable entities, commonly referred to as Decision-Making Units (DMUs) (Cooper, W.W., Seiford, L.M., Zhu, 2004). Unlike parametric models, the DEA method does not require any assumptions about the distribution of the data.

2.1 Fundamental of Data Envelopment Analysis (DEA)

DEA involves the conversion of multiple inputs into multiple outputs, enabling a comprehensive assessment of the DMUs. To be specific, the DMU's efficiency is calculated as the ratio of its outputs to its inputs. The goal of the DEA is to find the most efficient DMUs in the set and to identify the factors that contribute to their efficiency.

It is applicable in a wide range of contexts, including the allocation of resources, the evaluation of performance, and the establishment of benchmarks. It is especially helpful in situations in which it is difficult to compare the performance of various organisations or units utilising traditional methods, such as financial ratios. In these kinds of situations, this method can be very useful.

DEA is commonly used to analyse the efficiency of organizations. Variants of DEA models have been utilised in multiple sectors such as agriculture (Geng *et al.*, 2019; Hesampour *et al.*, 2022; Pan *et al.*, 2022; Sun & Sui, 2023), healthcare (Afonso *et al.*, 2023; Kumar *et al.*, 2020; Onder *et al.*, 2022), financial (Amin & Ibn Boamah, 2023; Boubaker *et al.*, 2023; Muhammad Adib *et al.*, 2023; Ullah *et al.*, 2023), education (Abankina *et al.*, 2016; Ghasemi *et al.*, 2020; Mammadov & Aypay, 2020) and many more.

According to a survey paper by J. S. Liu *et al.* (2013), there are a few different DEA methods that can be used in energy efficiency research. These methods include the traditional DEA model, the slack-based model (SBM), the derived DEA model, the two-stage DEA, and the network DEA model.

2.2 Fossil Fuel Energy Efficiency Measurement

This section presents a review of previous studies that have utilised Data Envelopment Analysis (DEA) as a methodological approach for the assessment of fossil fuel energy efficiency. Several studies have been undertaken to assess the energy efficiency of fossil fuel power plants. Noteworthy contributions in this area include the works of (Abdul Rahman *et al.*, 2023; Du *et al.*, 2021; Jahangoshai Rezaee & Dadkhah, 2019; Mahmoudi *et al.*, 2019; Sueyoshi, Liu, *et al.*, 2020; Sueyoshi, Qu, *et al.*, 2020; Zhang *et al.*, 2022).

Meanwhile, several studies investigated energy efficiency of fossil fuels across a variety of industries and regions. There are a few DEA models employed namely basic DEA models (Charnes, Cooper and Rhodes (CCR), Banker, Charnes and Cooper (BCC) and scale efficiency models), extended versions of the DEA model (slacks-based measure (SBM) model, cross-efficiency DEA model, super efficiency DEA model), multistage and multilevel models (network DEA model) and hybrid model in which DEA is integrated with other techniques.

Wang *et al.* (2012) examined the energy efficiency of industrial sectors of 30 provinces and municipalities in China's eastern, central, and western regions from 2005 to 2009. They evaluated their efficiency using the CCR model. Results showed that China can improve energy efficiency, especially in western provinces with high energy inputs. Low technological investment and manufacturing scale make energy efficiency in China difficult.

Dogan & Tugcu (2015) employed an input-oriented CCR model of DEA to compute the technical and super-efficiency scores of G-20 nations concerning their electricity generation during five different years. According to the findings, China and Russia were the most energy-efficient countries. Meanwhile, France and the EU were inefficient in four of the five time periods studied. Additionally, recent U.S. electricity production was also inefficient.

Several studies considered both energy efficiency and environmental impacts. Chen *et al.* (2017) used a cross-efficiency model to assess the efficiency of 30 China's provincial power industries. The assessment was conducted over a period spanning from 2005 to 2014, taking into account environmental constraints. Based on electric energy efficiency values, clustering, and regional similarity analysis were performed. The findings demonstrated that provincial electric energy efficiency in China had not changed in the past decade and was volatile, specifically in western China. The efficiency of China's electric energy in the east was significantly higher than in the west and central regions. Besides, clustering data revealed that China's electric energy efficiency was not polarised. Moreover, the electric energy efficiency of western China demonstrated an improvement in recent years, accompanied by significant fluctuations.

Iftikhar *et al.* (2018) employed a network DEA model to assess the energy and CO_2 emissions efficiency of major economies. The model assumed free disposability for all undesirable outputs in both divisions of economies. The findings discovered that overall, 85% of energy use and 89% of CO_2 emissions were solely attributable to both economic inefficiencies. Some economies were efficient in one division but not both. The US was the largest consumer of excess energy due to its economic inefficiency, while China was the largest consumer of excess energy due to their distributive inefficiency.

Yang *et al.* (2018) compared the energy efficiency of 30 China's western, central, and eastern regions using the super efficiency SBM model with undesirable outputs in 2013 and 2014. The results were then used to present the pertinent policy implications. The results were then used to draw policy conclusions. The energy efficiency of China experienced a decline when taking into account undesirable outputs. Furthermore, east China displayed the highest levels of energy efficiency, while west China showed relatively lower levels. There exists a significant disparity in energy efficiency levels across the various provinces of China. To achieve improvements in China's overall energy efficiency, therefore, targeted policies that take into account the specific conditions of the various regions need to be developed.

About 26 prefecture-level cities in China were analysed by Z. Yang & Wei (2019) for their total factor energy efficiency using game cross-efficiency. The analysis spanned from 2005 to 2015 and incorporated environmental constraints. Ten potential influences were then analysed using a Tobit regression model. Considering competitive relationships, urban energy efficiency was lower than traditional efficiency. Urban energy efficiency did not improve either. Regression analysis shows that economic development, city scale, government expenditure, industrial structures, energy prices, foreign investments, research investments and production endowment all reduce urban energy efficiency.

In contrast to other studies, Robaina & Arshad (2020) studied the impact of energy efficiency improvements on CO_2 emissions from 1990 to 2014 through an ASEAN committee using a parametric approach. First, stochastic frontier analysis (SFA) was used to determine energy efficiency, and then the two-stage Generalised Methods of Moments (GMM) approach was utilised to identify energy's short- and long-term elasticities. The dataset used in this study was incomplete, so only Indonesia, Malaysia, Philippines, Thailand, and Vietnam datasets were available. The findings concluded that fossil fuels, which produce the most energy, degrade the environment. It implies that energy efficiency preserves environmental quality.

Motivated by Robaina & Arshad's (2020) and Dogan & Tugcu's (2015) studies, this study employs a non-parametric approach, specifically a modified version of the slack-based measure (SBM) DEA model, to assess the performance of fossil-fired power generation, across ASEAN member states. The inclusion of CO_2 emissions in the analysis adds an important dimension to the assessment. The findings of this study have major implications for ASEAN policy and research, particularly in the areas of sustainable energy, preservation of the environment, and fossil fuel carbon dioxide reduction. Table 1 provides a summary of the reviewed articles on the topic of energy efficiency of fossil fuels in various industries and countries.

3. Research Methodology

In traditional DEA, only desirable outputs are considered, while undesirable outputs like pollution (gas emission etc.), waste and energy consumption are ignored. Therefore, an SBM model with an undesirable output model, a variant of the DEA model that addresses the issue of undesirable outputs is considered in this study.

3.1 SBM with Undesirable Output Model

There are two variants of the undesirable outputs model: the undesirable outputs model and the non-separable model. The slacks-based measure (SBM) model, initially proposed by Tone (2001), was modified by Cooper *et al.* (2007) to account for undesirable output factors.

The SBM model can be classified as a non-radial and non-oriented approach, which employs input and output slacks to determine efficiency. Then, undesirable outputs are embedded into the SBM framework. This study utilises the BadOutput model, specifically the BadOutput-C variant, as it aligns with the general principle of the model.

Assume there might be n DMUs, each of which has three components: desirable input, desirable output and undesirable (bad) output. These three components are represented by three vectors:

$$x \in R^p \text{ where } X = [x_1, x_2, \cdots, x_n] \in R^{pxn}, x > 0 \tag{1}$$

$$y^g \in R^q \text{ where } Y^g = [y_1^g, y_2^g, \cdots, y_n^g] \in R^{qxn},\ y^g > 0 \tag{2}$$

$$y^b \in R^r \text{ where } Y^b = [y_1^b, y_2^b, \cdots, y_n^b] \in R^{rxn}, y^b > 0 \tag{3}$$

Table 1
Overview of the reviewed articles in various industries and countries

Article	Number of samples	Period of study	Location	Methodology
Wang *et al.* (2012)	30	2005 to 2009	China	CCR DEA model
Dogan & Tugcu (2015)	17	1990, 1995, 2000, 2005 and 2011	G-20	CCR DEA model
Chen *et al.* (2017)	30	2005 to 2014	China	Cross-efficiency DEA model
Iftikhar *et al.* (2018)	19	2011	Major economies of the world	Network DEA model
Yang *et al.* (2018)	30	2013 and 2014	China	Super efficiency slack-based measure (SBM) model with undesirable outputs
Z. Yang & Wei (2019)	26	2005 to 2015	China	Game cross-efficiency DEA, Tobit regression model
Robaina & Arshad (2020)	5	1990 to 2014	ASEAN	Stochastic frontier analysis (SFA), two-stage Generalised Methods of Moments (GMM)

$$P = \{(x, y^g, y^b) | x \geq X\lambda, y^g \leq Y^g\lambda, y^b \geq Y^b\lambda, L \leq e\lambda \leq U, \lambda \geq 0\} \quad (4)$$

where $\boldsymbol{\lambda}$ is the intensity vector, L is the lower bounds of $\boldsymbol{\lambda}$ and U is the upper bounds of $\boldsymbol{\lambda}$. Equations (1) – (2) are the desirable input and output variables, respectively. Equation (3) denotes an undesirable (bad) output variable. Lastly, Equation (4) represents a production possibility set.

In this frame, the efficiency of DMU is defined. When bad outputs are present, a DMU (x, y^g, y^b) is efficient if there is no vector $(x, y^g, y^b) \in F$ such that $x_o \geq x,\ y_0^g \leq y^g, y_0^b \geq y^b$ with at least one inequality (Cooper *et al.*, 2007).

Based on the SBM developed by Tone (2001), the undesirable model's objective is then modified as follows:

$$\rho^* = min \frac{1 - \frac{1}{p}\sum_{t=1}^{p} \frac{s_t^-}{x_{to}}}{1 + \frac{1}{q+r}\left(\sum_{t=1}^{q} \frac{s_t^g}{y_{t0}^g} + \sum_{t=1}^{r} \frac{s_t^b}{y_{t0}^b})\right)} \quad (5)$$

subject to

$$x_o = X\lambda + s^- \quad (6)$$

$$y_0^g = Y^g\lambda - s^g \quad (7)$$

$$y_0^b = Y^b\lambda + s^b \quad (8)$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \lambda \geq 0 \quad (9)$$

The vector $s^- \in R^p$ refers to input excess and $s^b \in R^r$ denotes as bad outputs excesses, meanwhile, the vector, $s^g \in R^q$ represents good outputs shortages. The objective value (5) must equal to $0 < \rho^* \leq 0$ at the same time its function is lowered concerning $s_t^-(\forall t), s_t^g(\forall t),\ s_t^b(\forall t)$ and let the optimal solution be $(\lambda^*, s^{-*}, s^{g*}, s^{b*})$.

Cooper *et al.* (2007) stated that the DMUo demonstrates efficiency when undesirable outputs are present only if the conditions $\rho^* = 1, s^{-*} = 0, s^{g*} = 0, s^{b*} = 0$ are met. If the *DMUo* is not equal to 1, $\rho^* < 1$, eliminating input excesses (Equation 10) and bad outputs (Equation 12) and increasing good output deficiencies (Equation 11) can improve efficiency.

$$X_0 \leftarrow x_0 - s^{-*} \quad (10)$$

$$Y_0^g \leftarrow y_0^g + s^{g*} \quad (11)$$

$$Y_0^b \leftarrow y_0^b - s^{b*} \quad (12)$$

By employing the transformation proposed by Charnes and Cooper in 1962, equivalent linear programming involving the variables t, γ, s^-, s^g and s^b is established.

$$\rho^* = \min t - \frac{1}{p}\sum_{t=1}^{p} \frac{s_t^-}{x_{to}} \quad (13)$$

subject to

$$t = 1 + \frac{1}{q+r}\left(\sum_{t=1}^{q} \frac{s_t^g}{y_{t0}^g} + \sum_{t=1}^{r} \frac{s_t^b}{y_{t0}^b})\right) \quad (14)$$

$$x_o t = X\gamma + s^- \quad (15)$$

$$y_0^g t = Y^g\gamma - s^g \quad (16)$$

$$y_0^b t = Y^b\gamma + s^b \quad (17)$$

$$s^- \geq 0, s^g \geq 0, s^b \geq 0, \gamma \geq 0, t > 0 \quad (18)$$

Let the optimal solution of this model be $(t^*, \gamma^*, s^{-*}, s^{g*}, s^{b*})$ where $\rho^* = \tau^*, \lambda^* = \gamma^*/t^*, s^{-*} = S^{-*}/t^*, s^{g*} = S^{g*}/t^*, S^{b*} = s^{b*}/t^*$. This is only satisfied if $t^* > 0$. Next, the dual program of this model is presented as:

$$\varepsilon^* = \max \varepsilon \quad (19)$$

subject to

$$\varepsilon + vx_0 - u^g y_0^g + u^b y_0^b = 1 \quad (20)$$

$$-vX + u^g Y^g - u^b Y^b \leq 0 \quad (21)$$

$$v \geq \frac{1}{p\left[\frac{1}{x_0}\right]} \quad (22)$$

$$u^g \geq \frac{\varepsilon}{(q+r)\left[\frac{1}{y_0^g}\right]} \quad (23)$$

$$u^b \geq \frac{\varepsilon}{(q+r)\left[\frac{1}{y_0^b}\right]} \quad (24)$$

The dual variable vectors, $v \in R^p, u^g \in R^q$ and $u^b \in R^r$ correspond to the constraints (15) – (16), respectively. Therefore, by removing ε, this dual model of the case of constant return to scale $(L = 0, U = \infty)$ is equivalent to the following:

$$\max u^g y_0^g - vx_0 - u^b y_0^b \quad (25)$$

subject to

$$u^g Y^g - vX - u^b Y^b \leq 0 \quad (26)$$

$$v \geq \frac{1}{p\left[\frac{1}{x_0}\right]} \quad (27)$$

$$u^g \geq \frac{1 + u^g y_0^g - vx_0 - u^b y_0^b}{(q+r)\left[\frac{1}{y_0^g}\right]} \quad (28)$$

$$u^b \geq \frac{1 + u^g y_0^g - vx_0 - u^b y_0^b}{(q+r)\left[\frac{1}{y_0^b}\right]} \quad (29)$$

The dual variables v and u^b represent the virtual costs (prices) of inputs and undesirable outputs, respectively while the dual price of desirable outputs is represented by u^g. This dual program determines the optimal virtual costs and prices for the DMU such that the inequality $u^g Y^g - vX - u^b Y^b \leq 0$ holds true for all DMUs and also maximises the objective function (profit), $u^g y_0^g - vx_0 - u^b y_0^b$ for the DMU that is being considered. The DMU can be considered efficient if the optimal profit is at best zero.

When there is a need to prioritise input/output items, weights on inputs and/or outputs can be assigned to the objective function in Equation (5) (Cooper *et al.*, 2007).

$$\rho^* = min \frac{1 - \frac{1}{p}\sum_{t=1}^{p} \frac{w_t^- s_t^-}{x_{to}}}{1 + \frac{1}{q+r}\left(\sum_{t=1}^{q} \frac{w_t^g s_t^g}{y_{t0}^g} + \sum_{t=1}^{r} \frac{w_t^b s_t^b}{y_{t0}^b})\right)} \quad (30)$$

Table 2
Input-output data used in selected studies

Article	Variables: Input	Variables: Output	Variables: Intermediate (i.e. Network DEA)
Wang *et al.* (2012)	· Annual average balance of fixed capital and working capital of industrial enterprises (Capital) · Annual average number of employees of industrial enterprises (Labor) · Energy consumption of industrial enterprises (Energy)	Desirable: Gross product value of industrial enterprises	-
Dogan & Tugcu (2015)	· Coal sources · Hydroelectric sources · Natural gas sources · Oil sources · Renewable energy sources	Desirable: Electricity generated	-
Chen *et al.* (2017)	· Fixed capital investment (Capital) · Employed population (Labor) · Power consumption (Energy)	Desirable: GRDP (Gross Regional Product) Undesirable: · SO_2 emission · COD emission · Ammonia emission	-
Iftikhar *et al.* (2018)	Division 1: · Gross capital formation (Capital) · Total labor force (Labor) · Primary energy consumption (Energy) Division 2: Total population	Division 1 (Undesirable): CO_2 emissions from consumption of primary energy Division 2 (Desirable): · Middle-income class population Division 2 (Undesirable): · High-income class population · Low-income class population	GDP (Gross Domestic Product)
Yang *et al.* (2018)	· Fixed capital investment (Capital) · Employed population (Labor) · Energy consumption (Energy)	Desirable: GDP Undesirable: · SO_2 emission · NO_x emission · Soot emission	-
Z. Yang & Wei (2019)	· Variable depreciation rate (Capital) · The amount · of labor force (Labor) · The total electric consumption in urban districts (Energy)	Desirable: GDP (Gross Domestic Product) Undesirable: · Wastewater (WW) · SO_2 emission · Smoke and dust (SD)	-

where weights for the input t, the desirable output t and the undesirable output t are denoted by w_t, w_t^g and w_t^b, respectively and $\sum_{t=1}^{p} w_t^- = p, w_t^- \geq 0\ (\forall t), \sum_{t=1}^{q} w_t^g + \sum_{t=1}^{r} w_t^b = q + r$, $w_t^g \geq 0\ (\forall t), w_t^b \geq 0\ (\forall t)$.

As for the bad-output model, the weights are imposed on good and bad outputs. Based on Cooper *et al.* (2007), the default values are provided where both the total weight of good outputs, $\sum_{t=1}^{q} w_t^g = 1$ and the total weight of undesirable (bad) outputs, $\sum_{t=1}^{r} w_t^b = 1$.

4. Variables and Data

The amount of primary energy required to produce a given amount of electricity can vary significantly depending on a variety of factors, including the type of energy source used, the efficiency of the power plant, and the electricity demand. This paper investigates the energy efficiency of power generation derived from fossil fuels.

The data utilised in this study are obtained from reputable databases such as the U.S. Energy Information Administration (EIA) (U.S. Energy Information Administration, 2023) and Our

Table 3
Descriptive statistics of the research data

Variable	Unit	Minimum	Maximum	Mean	Standard deviation
Primary energy consumption (Desirable input)	Quadrillion British thermal units (Btu)	1.02	49.04	17.04	15.5
Electricity generation (Desirable output)	Billions of kilowatt-hours (kWh)	24.6	1548	547.55	507.5
CO_2 emission (Undesirable output)	Million metric tons (MMtonnes) or megatonnes	64.74	3951.15	1070.57	1182.02

World in Data (Ritchie *et al.*, 2023). These databases hold a vast amount of energy data regarding primary energy consumption, measured in quad Btu, which acts as an input variable for our analysis. Additionally, this study considers data on electricity production, measured in billion kWh, as a desirable output and the emission of carbon dioxide (CO_2), measured in MMtonnes, as an undesirable output.

These data pertain specifically to the 10 member countries of the Association of Southeast Asian Nations (ASEAN). These countries are Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand and Vietnam. The data covers the period from 2015 to 2021. Table 2 presents an overview of the input and output data used in this study. The DEA Pro Solver software, version 5.0, as well as Microsoft Excel, are utilized in the analysis of these data and selected models.

4.1 Input Variables

Primary energy consumption: Primary energy consumption is defined as the total energy consumed by an economy in its original form, without undergoing any transformation after extraction (Institut national de la statistique et des etudes economiques, 2020; Laloui & Rotta Loria, 2020). In other words, it measures a nation's total energy demand encompassing the energy sector's consumption, losses incurred during the conversion and distribution processes (e.g., converting oil or gas into electricity), and final consumption by end users (Eurostat Statistics Explained, 2018). It is measured in quadrillion British thermal units (Btu), which is a unit of energy used to express the heat content of fuels and other energy sources. All energy sources considered in this study namely crude oil, natural gas and coal. The efficiency of a fossil fuel-fired power plant refers to the percentage of the primary energy input that is converted into usable electricity.

4.2 Output Variables

i) Electricity generation: Electricity generation in this study, refers to the process of producing electrical energy through the combustion of fossil fuels. It comprises the electricity generated in combined heat and power facilities, typically measured in billions of kilowatt-hours (kWh). Understanding both primary energy consumption and electricity generation can provide valuable insights into a country or region's energy use and production patterns.

ii) CO_2 emission: Carbon dioxide (CO_2), a gas produced by burning carbon and in the respiration of living things, is colourless, odourless, and non-poisonous (Eurostat Statistics Explained, 2023). It is also regarded as a greenhouse gas. Carbon dioxide (CO_2) emissions arise as a direct result of the combustion of fossil fuels. It can be measured in million metric tons (MMtonnes) or megatonnes. This unit is used to express the mass of CO_2 emissions and is commonly used to quantify the greenhouse gas emissions of countries, regions or individual facilities.

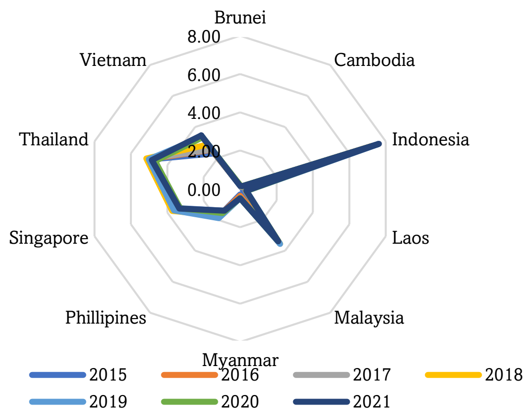

Fig 1 Primary energy consumption of 10 ASEAN countries in 2015 – 2021

The descriptive statistics for this dataset are shown in Table 3. The average value of ASEAN's primary energy consumption in 2015-2021 was 17.04 quad Btu. According to Figure 1, Indonesia had the highest primary energy consumption during the observed period of 2015 to 2021. Meanwhile, Cambodia's primary energy was the lowest, especially in 2015.

From 2015 to 2021, there was a clear indication of an upward trend in all input and output variables of the majority of countries, as seen in Figures 1 through 3. However, it is noteworthy that Brunei, the Philippines and Thailand experienced minimal declines of 6%, 1%, and 2% in their primary energy consumption during this period, respectively. Among the 10 countries, Laos, Cambodia, Myanmar and Vietnam demonstrated the most significant growth in terms of the percentage of primary energy consumption.

According to Figures 2 and 3, there were a consistent pattern that can be observed across all of the output variables. Throughout three years of study, Indonesia's electricity production was higher than that of any other country, leading to higher levels of carbon dioxide emissions. In contrast, Brunei and Cambodia emitted the fewest carbon dioxide and generated the least amount of electricity.

The variation between the highest and lowest values of all variables was very large, as shown in Table 3. The variations in geographical regions, limited availability of fossil fuel-based energy sources, reliance on imported energy from other nations and the scale of the population could potentially account for the significant disparities observed.

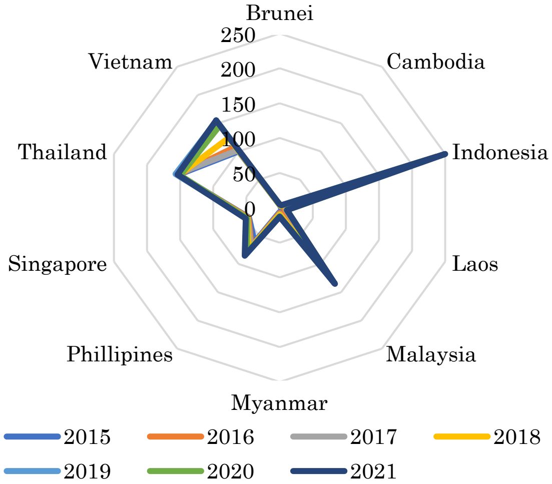

Fig 2 Electricity generation of 10 ASEAN countries in 2015 – 2021

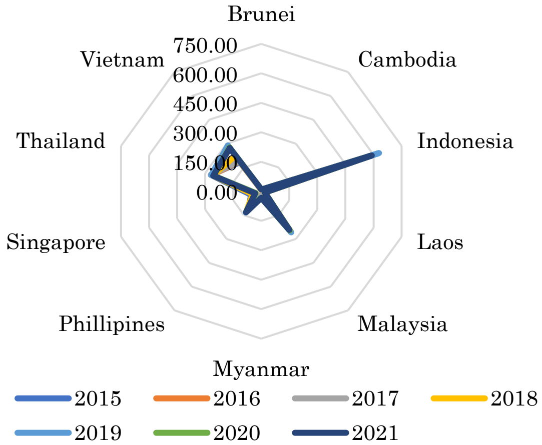

Fig 3 CO_2 emissions of 10 ASEAN countries in 2015 – 2021

Next, the size of the standard deviations for primary energy consumption and electricity production was observed to be 91% and 93% of their respective means, indicating a low coefficient of variation (CV). A lower CV signifies a smaller degree of variability in the dataset about its mean value. This suggests that there was a slight variation across different geographical areas in the amount of primary energy consumed and the generation of electricity. Meanwhile, the coefficient of variation for CO_2 emissions was larger than 100% (CV = 110%), indicating greater volatility and a wider range in the data.

4.3 Correlation Analysis

Establishing a positive correlation between the input and output variables is a crucial step for conducting a DEA analysis. This suggests that as the input variable increases, the output variable also increases, assuming all other conditions remain constant. The most common method to investigate the strength of a linear relationship between two variables is the Pearson correlation.

Table 4
The Pearson correlation scores

Variable	Primary energy consumption	Electricity generation	CO_2 emission
Primary energy consumption	1	0.939	0.903
Electricity generation	0.939	1	0.967
CO_2 emission	0.903	0.967	1

A correlation coefficient that is close to +1 implies a strong positive linear relationship, while a value close to -1 indicates a strong negative linear relationship. On the other hand, a correlation coefficient of 0 suggests the absence of a linear relationship between the variables (Bewick *et al*., 2003). Table 4 shows the Pearson correlation analysis of all variables.

The findings of the study revealed a statistically significant positive correlation between the input and output variables, with a significance level of at least 5%. There was a very strong correlation between primary energy consumption, the generation of electricity, and the emissions of CO_2. The Pearson correlation coefficients about the variables of primary energy consumption, electricity generation and CO_2 emissions were observed to be 0.939 and 0.903, respectively.

Furthermore, it is worth noting that a significant correlation was also observed between the emissions of CO_2 and the generation of electricity. These results met DEA model preconditions and showed consistent input-output variable selection. This means those data can be used for DEA calculations and analysis.

5. Results and Discussion

5.1 Relative Efficiency

This study employs the undesirable output model, specifically the BadOutput-C model to evaluate the relative performances and ranks 10 ASEAN countries. Table 5 presents the overall energy efficiency scores and rankings for the 10 ASEAN countries that were analysed using the DEA undesirable output model.

According to Table 5, there were 2 efficient DMUs, specifically Singapore and the Philippines, which operated at a

Table 5
Energy efficiency scores and rankings from 2015-201

Rank	DMU	Efficiency scores
1	Singapore	1
1	Philippines	1
3	Vietnam	0.8745
4	Malaysia	0.7720
5	Thailand	0.6374
6	Laos	0.6052
7	Indonesia	0.5640
8	Brunei	0.4503
9	Cambodia	0.4093
10	Myanmar	0.4053

Table 6
Input-output factors projections

DMU	Efficiency score	(I)Primary energy consumption		(O)Electricity generation		(Obad) CO_2 emissions	
		Projection	Change (%)	Projection	Change (%)	Projection	Change (%)
Brunei	0.4503	0.6213	-49.28	29.5	0.00	48.3710	-25.29
Cambodia	0.4093	0.5181	-49.16	24.6	0.00	40.3365	-48.47
Indonesia	0.5640	32.6022	-33.52	1548	0.00	2538.246	-35.76
Laos	0.6052	1.3395	-36.70	63.6	0.00	104.2845	-9.18
Malaysia	0.7720	19.1864	-18.05	911	0.00	1439.761	-12.31
Myanmar	0.4053	1.4911	-51.35	70.8	0.00	116.0903	-40.07
Philippines	1	11.078	0.00	526	0.00	862.4788	0.00
Singapore	1	24.381	0.00	338	0.00	267.6297	0.00
Thailand	0.6374	22.6404	-34.83	1075	0.00	1762.671	-4.51
Vietnam	0.8745	18.7231	-8.09	889	0.00	1457.688	-10.21

relative efficiency level of 1. The remaining 8 DMUs, namely Vietnam, Malaysia, Thailand, Laos, Indonesia, Brunei, Cambodia and Myanmar achieved low-efficiency scores, with percentages less than 1. To be specific, Myanmar was in the last position among ASEAN countries with an efficiency score of 0.4053, followed closely by Cambodia and Brunei with scores of 0.4093 and 0.4503, respectively.

5.2 Performance Improvement

The projection of each DMU onto the model's efficient frontier is conducted for the purpose of variance analysis. The inefficient DMU has the potential to be improved and become efficient by removing input and bad output excesses while addressing the shortfalls in desirable output through the proposed projection, as shown in Table 6.

Table 6 presents the efficiency scores, projection values, and percentage changes for each input and output of the DMUs. Note that the positive or negative changes were indicated in boldface. For instance, Brunei could reduce 49.28%, almost half of its primary energy consumption from 1.225 quad Btu to 0.6213 quad Btu. Besides, carbon dioxide emissions in Brunei can be reduced by 25.29% from 64.7412 MMtonnes to 48.371 MMtonnes.

Based on the data presented in Table 5, it can be observed that Myanmar had the lowest efficiency score compared to the other ASEAN countries. To improve its efficiency, primary energy consumption should be reduced by approximately 51.35% or approximately double its total. Furthermore, to enhance the environmental performance of its nation, carbon dioxide emissions must be reduced by about 40.07%. The increase in the consumption of fossil fuels in Myanmar has resulted in a corresponding increase in CO_2 emissions. Specifically, the annual growth rate of Myanmar's fossil fuel emissions is 18.0%, which is more than seven times higher than the average global rate. Between 2010 and 2019, these emissions experienced a growth rate of 6.3% per year (Cui *et al.*, 2023).

In contrast, Singapore and the Philippines were energy-efficient. National Climate Change Secretariat (NCCS), (2016) stated that Singapore implemented strategic policy decisions in the early stages that effectively decreased greenhouse gas (GHG) emissions. One notable measure was the transition from fuel oil to natural gas, which is widely recognised as the most environmentally friendly type of fossil fuel, for power generation. Currently, approximately 95% of its electricity production relies on the utilisation of natural gas.

Carbon content is higher in coal than in oil or gas. During the combustion process, the higher concentration of carbon present in coal undergoes chemical reactions, resulting in the production of carbon dioxide (MIT Climate Portal Writing Team, 2022). In Singapore, coal accounts for less than 2% of its current electricity production and has always been a minor contributor to the country's energy mix (National Climate Change Secretariat (NCCS), 2021). Besides, as a part of the Long-Term Environmental Development Strategy (LEDS), Singapore announced in October 2022 that it will increase its national climate target to achieve net zero emissions by the year 2050 (National Climate Change Secretariat (NCCS), 2022).

Yuichi Shiga (2022) mentioned that approximately 60% of the Philippines' electricity is derived from coal. Yet, the coal capacity (in megawatts (MW)) of the Philippines was comparatively lower than that of the top three largest coal producers, specifically Indonesia, Vietnam and Malaysia, according to Vinay Trivedi's report in 2021 (Vinay Trivedi, 2021). Consequently, it was anticipated that the carbon dioxide emissions would be marginally lower compared to those of other nations.

Observe that, there is no need for the electricity generation to change for all countries. The efficiency of all countries can be substantially upgraded if all the affected inputs or outputs as listed in Table 6 improved. In practice, energy efficiency is influenced by various complex factors. Hence, the utilisation of this empirical analysis for improvement purposes, such as primary energy consumption and CO_2 emissions, poses significant challenges. As the primary energy consumption derived from fossil fuel energy is directly proportional to CO_2 emissions, therefore limiting those emissions will be challenging. To promote the establishment of sustainable growth in the energy sector, all nations must contemplate a transition to a low-carbon economy, towards safer renewable energy sources.

6. Concluding Remarks

The energy supply of the Association of Southeast Asian Nations (ASEAN) continues to demonstrate a significant dependence on fossil fuels, which continue to play a substantial role in meeting the countries' energy needs. Based on current projections, the use of fossil fuels is expected to increase significantly. To ensure optimal efficiency and productivity, performance evaluations of fossil fuel energy should be investigated. In this paper, ASEAN fossil fuel energy performance is examined for the years 2015 through 2021 using an undesirable output model, modified from the Slack-Based Measure (SBM) model. Note that the limitation of this study relates to the accessibility of data. The analysis of energy efficiency often relies on data pertaining to energy consumption and production, which may not consistently be readily available. This study assesses the fossil fuel energy efficiency of ASEAN countries and provides a projection value of inputs/outputs to improve inefficient countries. Based on the results of our analysis, Singapore and the Philippines were efficient in their utilisation of fossil fuel energy, therefore served as benchmarks for other countries. Conversely, Myanmar emerged as the country with the lowest level of efficiency in this regard. These valuable findings will aid the policymakers in formulating a comprehensive strategy to explore alternative solutions that can effectively mitigate the emissions of CO_2 stemming from the combustion of fossil fuels. One potential solution involves transitioning towards the establishment and expansion of renewable energy infrastructure.

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