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Literature Review on Data Envelopment Analysis: Energy Sector

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ABSTRACT

Energy sector play a key role in the provision of electricity services to the society. Assessment of performance of this sector is important to electricity providers, stake holders, etc. Performance can be assessed by the efficiency of decision-making units of this sector using some specific input and output variables. Efficiency can be evaluated through a nonparametric method of Data Envelopment Analysis (DEA). In the literature it can be found that, DEA emerging as a powerful tool in evaluating efficiency of decision-making units in various sectors. The current study stands out by significantly contributing to the literature review on the efficiency of energy. This research, will not only add depth to the current understanding but also address potential gaps in previous studies. The review findings become a valuable resource to new researchers, offer a foundation to fill those gaps and plan for future studies on the efficiency of energy sector.

Keywords: Energy sector, data envelopment analysis, efficiency, DEA review

1. INTRODUCTION

DEA is a nonparametric technique for assessing the efficiency of a decision-making unit (DMU). Charnes, Cooper, and Rhodes first presented the basic CCR model of DEA in their novel paper "Measuring the Efficiency of Decision-Making Units" published in the European Journal of Operational Research (EJOR) in 1978. Professor Charnes has published multiple papers on the theory and practical aspects of DEA as an author or co-author. Later, Banker, Charnes, and Cooper (1984) developed the BCC model from the extension of the CCR model. Applications have depended heavily on the stability of the CCR model of DEA, which was demonstrated by Charnes, Cooper, Sears, and Zlobec (1990).

The field of data envelope analysis has expanded rapidly and steadily since 1978. Several DEA models have been formulated and are frequently employed in a variety of contexts to evaluate the efficiency of DMUs, such as public organizations like government agencies, banks, and insurance companies to evaluate private entities like hospitals, insurance companies, and educational organizations, etc.

The efficiency and effectiveness of a public or private organization or unit determine its success in the utilization of its resources. By eliminating or reducing those shortcomings, the assessment of the efficiency of units will not only aid in identifying the unit's shortcomings but also aid in the unit's development and the development of a nation as a whole.

The first and foremost principle of efficiency is to attain the best outcome through the minimum utilization of resources. Efficiency measurement and efficiency enhancement are crucial and essential parts of every organization for its future development Kao (2019).

Therefore, in this review, we tried to study how scholars have used various models of data envelopment analysis to analyze and assess or evaluate the efficiencies of different DMUs. In these reviews, we concentrated mainly on the energy sector and hospital sector to see how the idea of efficiency was achieved.

2. REVIEW OF RELATED LITERATURES

Li et al. (2021) examined the links between energy efficiency, energy poverty, and social welfare in 14 countries using DEA. They found that inefficient energy policies contribute to energy poverty, with Indonesia having the highest energy poverty score. Key factors include electricity consumption, energy expenditure, and LPG use. The study suggests investing in renewable energy to break the cycle of energy poverty, advocating for distributed energy systems like rooftop solar and small generators to improve access, especially in remote areas.

Pérez and Tovar (2021) used a two-stage DEA to assess the technical efficiency of 15 Peruvian electricity distribution companies, comparing reformed and non-reformed firms. Their findings show that productivity and efficiency have improved, with a correlation between sector restructuring and efficiency gains. The study highlights the impact of public and private institutionalism on efficiency, noting that state institutionalism can restrict enterprise management. They suggest policy actions to address these constraints and support energy sector efficiency, especially amid global warming concerns.

Zhang and Fu (2021) analyzed the impact of technological advances on energy efficiency in Guangdong’s manufacturing sector (2000–2018) using a two-stage DEA model. They found that foreign direct investment (FDI) spillovers negatively affect energy efficiency through imitation, while competition has a positive rebound effect. Independent innovation also reduces energy efficiency. The study suggests policy efforts should focus on upgrading China's manufacturing sector from labor-intensive to technology-intensive industries.

Kannan et al. (2021) used a Three-Stage Virtual Frontier DEA with Variable Selection to measure and benchmark the efficiency of 21 electric utilities across six countries. They identified 13 key variables affecting efficiency and concluded that 3S-VF-DEA is the most effective method due to its high discriminatory power and ability to eliminate statistical noise. Their results showed that Utility 6 was the most efficient, while Utility 16 was the least efficient during the study period.

Susanty et al. (2022) assessed the efficiency of distribution units in the Perusahaan Listrik Negara (PLN) service area across seven districts in Semarang, Central Java, using an SSM-DEA approach. Their findings showed that four out of seven units (57%) were efficient, with an average efficiency score of 0.972. They recommended improving efficiency by optimizing network configuration, enhancing supervision with security agencies, and conducting promotional activities to attract new customers and encourage power upgrades.

Tengey et al. (2022) assessed productivity trends and performance factors of seven Ghanaian Electricity Distribution Companies (EDRs) using DEA. Their findings indicate overall productivity growth, mainly driven by technical competence rather than managerial efficiency. However, biannual productivity trends show a gradual slowdown. They recommend improving managerial skills among operations managers to maximize the benefits of technological innovations in the sector.

Aldieri et al. (2022) examined the impact of renewable energy innovation on energy sector efficiency in 148 developing countries using DEA and Tobit models. Their findings show that renewable energy innovations improve efficiency and resilience while reducing carbon emissions and particulates. The study highlights the role of energy transition in less developed nations and its implications for shaping energy policies with environmental benefits.

Xiao et al. (2022) analyzed the electricity generation efficiency of China's Yangtze River Economic Belt (YREB) under environmental regulations using the meta-frontier EBM model. Their findings show a widening efficiency gap between YREB and non-YREB regions, with YREB generating electricity at a consistently higher rate. Regional differences within YREB are smaller than in non-YREB areas. Additionally, clean energy power generation remains less efficient than thermal power generation.

Ramaiah and Jayasankar (2022) assessed the performance efficiency of 55 Indian electricity distribution utilities using DEA for 2018–2019. Their findings show that only 17 DMUs were efficient, while 38 were inefficient due to improper operating scales and low technical efficiency. They suggest cost-cutting measures, such as purchasing more economical power and reducing distribution costs, to improve efficiency.

Zeng et al. (2022) developed a DEA model to evaluate the energy mix adjustment efficiency of China's power industry across seven provinces, using 2 inputs and 3 outputs. By refining the DEA frontier, they proposed an improved benchmark for energy mix adjustment, surpassing the original efficiency measurement. Their findings offer management insights for cost reduction, improved electricity generation efficiency, and lower carbon emissions across Chinese provinces.

Xue et al. (2022) assessed the environmental performance of energy efficiency in Pakistan's six main industries using the Environmental Performance Index (EPI) and a slack-based DEA model with 1 input and 2 outputs. Their findings highlight poor environmental performance across all sectors, despite strong environmental regulations, due to a lack of proper execution. They recommend implementing a grading system, enhancing training, and improving environmental management capacity to encourage better compliance and sustainability.

Gouveia et al. (2023) examined eco-efficiency changes in the electricity and gas sector across 28 European nations using a value-based DEA productivity index. While most countries showed productivity gains, only nine maintained growth under stricter environmental criteria. The study identifies the catch-up effect as a key driver and calls for further research on eco-productivity impacts.

Duras et al. (2023) explored how machine learning techniques can improve variable selection in DEA models, analyzing 154 distribution system operators with three inputs. Their findings show that the LASSO method outperforms others in handling multicollinearity, while ALASSO is optimal for low to moderate correlation. This study is the first to apply these methods using real-world data from Swedish DSOs, demonstrating LASSO's accuracy in selecting production variables.

Okpala et al. (2023) analyzed energy consumption patterns in 10 Nigerian hotels using DEA with three inputs and one output. Their findings show that over 70% of electricity usage comes from HVAC systems. The study provides a framework for improving energy efficiency, reducing costs, and minimizing environmental impact, offering practical insights for hoteliers facing energy supply challenges in Nigeria.

Shimizu and Tiku (2023) analyzed Japan's manufacturing energy efficiency trends using DEA. They found a stable or declining Energy Efficiency Evolution (EEE) from the late 1990s to 2012, with improvements in some sectors but declines in "iron and steel." Tokyo, Aichi, and Okinawa were the most efficient regions. The study suggests Japan's manufacturing sector did not align with EEE improvements post-Kyoto Protocol and recommends environmentally friendly energy policies, considering the Paris Agreement in future research.

3. MATERIAL AND METHOD

In general, the DEA method assesses the efficiency of a production unit by comparing its position to the best-performing frontier.

This frontier is mathematically determined as the ratio of the weighted sum of outputs to the weighted sum of inputs. For a detailed explanation of the DEA technique, refer to Norman and Stoker (1991). The estimated best-performance frontier is also known as the efficient frontier or envelopment surface. This frontier represents the efficiency of production units and highlights inefficiencies based on observed performance levels. A production unit is considered 100% efficient only if it demonstrates no inefficiencies in utilizing inputs to produce outputs when compared to other relevant production units.

The initial DEA model, developed by Charnes, Cooper, and Rhodes (1978) and referred to as CCR, assumes constant returns to scale (CRS) and represents the production frontier as a piecewise linear envelopment surface.

First, we introduce the following measures:

$S = \{1, \dots, s\}$ is the set of outputs considered in the analysis

$M = \{1, \dots, m\}$ is the set of inputs considered in the analysis

$y_{rj} =$ known positive output level of production units $j, r \in S$

X_{ij} =known positive input level of production units $j, i \in M$

n =total number of production units evaluated.

The CCR model can be interpreted as estimating the proportional increase, θ, in all outputs necessary for DMU 'k' to attain efficiency is given by:

$$Min\ \mu_k \qquad (1)$$

Subject to

$$\sum_{j=1}^{n} \lambda_j y_{rj} \geq \frac{y_{rk}}{\mu_k}, \qquad r = 1,2, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j X_{ij} \leq X_{ik}, \quad i = 1,2, \dots, m$$

$$\lambda_j = j = 1,2, \dots, n$$

In the CCR model, the key variables are μ_k and λ_j. A Decision-Making Unit (DMU) 'k' is considered efficient if the optimal value of μ_k equals 1. Otherwise, it is deemed inefficient compared to other DMUs in the sample. The model's constraints ensure that the relative technical efficiency of DMU 'k', represented by μ_k, does not exceed 1. In the Constant Returns to Scale (CRS) model, the technical efficiency remains the same regardless of whether an input- or output-oriented approach is used. The optimal value of μ corresponds to Farrell's technical efficiency. Running a Data Envelopment Analysis (DEA) requires solving this model n times, once for each DMU being evaluated. The efficiency derived from solving model (1) is composed of two parts: pure technical efficiency and scale efficiency. In 1984, Banker, Charnes, and Cooper introduced a variable-returns-to-scale (VRS) version of model (1), which is referred to as the BCC model.

The BCC model is (1) together with the additional constraint

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad (2)$$

that captures returns to scale characteristics. Therefore, the efficiency estimates in the BCC model exclude the effects of scale economies, making them a measure of 'pure' technical efficiency, also known as managerial efficiency.

The model in (1) follows an output-oriented approach, as it determines the required proportional increase in output, while keeping input levels constant, for an inefficient unit to achieve DEA efficiency. Under the Constant Returns to Scale (CRS) specification, both input- and output-oriented approaches yield identical DEA efficiency estimates. Furthermore, the efficiency frontier remains the same for both orientations in DEA models. However, under the Variable Returns to Scale (VRS) specification, both orientations will identify the same set of efficient DMUs, but the efficiency scores for inefficient DMUs may vary depending on the chosen orientation.

A DEA analysis generates a relative efficiency score, μ, along with a set of $\lambda_j, j = 1,2, \dots, n$ values for each production unit. In DEA literature, these production units are referred to as Decision-Making Units (DMUs). The set of λ_j values for each unit define a point on the envelopment surface, which is formed by a convex combination of the efficient units. For an inefficient unit, this defined point serves as a benchmark, providing a reference for achieving efficiency. The group of efficient production units $\{j;\ \lambda_j > 0\}$ is known as the peer group of the given unit, 'k'.

The constraint in (2) is known as the convexity constraint and accounts for Variable Returns to Scale (VRS). The BCC model focuses solely on measuring technical efficiency, meaning the efficiency estimates it produces represent "pure" technical efficiency. If the convexity constraint is removed, the model transitions to a Constant Returns to Scale (CRS) framework. Under CRS, the efficiency score for a given unit reflects its overall technical efficiency and is always at least as high as the corresponding score under VRS. The efficiency score under VRS represents pure technical efficiency, and the difference between overall and pure technical efficiency is attributed to scale efficiency. Scale efficiency is calculated as the ratio of overall technical efficiency to pure technical efficiency.

4. Variable selection in DEA

Selecting the appropriate set of variables in DEA is an empirical challenge. Including too many variables is not practical, as it leads to an increasing number of production units appearing efficient. Conversely, omitting relevant variables results in an underestimation of efficiency, which has a more significant impact than incorporating irrelevant ones. The absence of a standardized approach for variable selection further complicates the process.

Several studies have assessed energy efficiency in the power industry by combining macroeconomic indicators, micro-level production efficiency, single-factor productivity, and total-factor productivity to determine suitable input and output indicators for the DEA method.

However, power generation not only produces electricity but also generates pollutants that harm the environment. In the past, attention was primarily given to positive outputs, such as power generation efficiency, while the negative environmental impacts of conversion efficiency were often overlooked. With the worsening pollution crisis in recent years, particularly the widespread haze caused by excessive PM2.5, the severe pollution resulting from low energy efficiency in production must also be addressed. Therefore, emissions from power plants should be considered in efficiency evaluations, with lower emissions being encouraged for improvement.

Building on previous research and considering the research objectives and problems to be addressed, multiple factors were selected. Based on the Cobb–Douglas production function, the number of employees (representing labor) and total installed capacity (representing capital) are used to measure production efficiency. The installed capacity of coal power and the total installed capacity of clean energy serve as input indicators, representing traditional and renewable power generation, respectively. Output variables include total power generation, sulfur dioxide emissions, nitrogen oxides emissions, and soot emissions, with pollutant emissions classified as undesirable outputs.

5. FINDINGS

A review of the literature on energy efficiency evaluation using the DEA method reveals that numerous studies have been conducted from both theoretical and applied perspectives, utilizing data from countries, regions, industries, and enterprises. Since 2011, research in this field has gained increasing attention, leading to a gradual rise in publications. From a methodological standpoint, DEA-based energy efficiency evaluation models have evolved to better reflect real-world conditions, expanding from single-output models to those that account for pollution emissions. Additionally, research has progressed from single-stage analyses to multi-stage energy conversion studies. Dynamic multi-year efficiency analysis has also become a key focus. In other words, DEA-based energy efficiency models have developed from simple static structures into complex dynamic network models, continuously improving the accuracy of efficiency evaluations. Building on the above analysis of related research on energy efficiency using DEA, this article examines the overall state of existing studies and identifies their limitations as follows:

(1) In terms of research subjects, numerous studies utilize data from countries, regions, industries, and companies, yielding significant findings. Given that China is a major consumer of energy and a leading source of carbon emissions, many studies have focused on its energy efficiency. To address the technical heterogeneity of energy efficiency and the competitive-cooperative dynamics among different entities, researchers have developed expanded models tailored to various scenarios, enhancing the accuracy of efficiency assessments. Notably, most existing energy efficiency analyses are conducted at the regional level. While corporate-level energy efficiency has gained scholarly interest, studies in this area remain relatively limited compared to those focusing on regional and industry sectors.

(2) From a methodological perspective, many scholars have enhanced the DEA model from various angles, leading to continuous improvements in energy efficiency assessment accuracy. As research expands, the alignment between DEA-based evaluation models and real-world conditions has strengthened. However, as a data-driven efficiency assessment method, DEA primarily relies on structured and well-defined data. There is still a lack of models capable of addressing energy efficiency issues in complex data environments, including heterogeneity, uncertainty, and big data. With the growing complexity of products and services, energy efficiency assessments—particularly at the microdata level, such as enterprise-level and production line data—often involve unstructured data, which affects the performance of DEA models. Variations in data structures can impact assessment accuracy, leading to increased errors. Therefore, as energy systems become more complex, developing DEA models that can operate effectively in complex data environments will allow for more precise energy efficiency evaluations.

Declaration by Authors

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