Energy Efficiency

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The importance and urgency of energy efficiency in sustainable development are increasing. Patterson [3] first proposed the concept of energy efficiency, considering that it means using fewer resources at the same output, and gave four indicators of energy efficiency measurement. According to this definition, the indicators that measure energy efficiency can be divided into economic energy efficiency and physical energy efficiency. In order to measure energy efficiency more accurately, many scholars have studied the measurement of energy efficiency. Among them, Hu and Wang [4] proposed the concept of total factor energy efficiency (TFEE), which was widely recognized.The TFEE index incorporates energy, labor, and capital into the input system to generate economic output. Energy efficiency is defined as the ratio of target energy input to actual energy input. As a total factor efficiency assessment method, DEA method can better deal with the efficiency evaluation of decision-making units under the complicated situation of multiple inputs–outputs, it has been widely used to study energy efficiency.

energy efficiency DEA

1.Definition and evaluation of energy efficiency

Energy efficiency is a major global issue that plays an essential role in achieving sustainable development. Although the use of clean energy is gradually increasing, about 80% of global energy consumption is still fossil fuels, such as oil and natural gas, and about 50% of power generation depends on coal resources [1]. As a result, the public, researchers and governments are paying more attention to this issue. It is of considerable significance to evaluate the energy efficiency of different regions and sectors, not only can help identify differences in energy efficiency, but also to provide a quantitative basis for improving efficiency [2].

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As the energy efficiency measured by different definitions and indicators varies widely, many scholars have studied the measurement of energy efficiency to measure energy efficiency more accurately. Among them, Hu and Wang [4] proposed the concept of total factor energy efficiency (TFEE), which was widely recognized. TFEE believes that a single energy input cannot produce any output, which means that energy must be combined with other factors (such as labor and capital) to produce output. Based on the TFEE framework, energy efficiency is defined as the ratio of the target energy input to the actual input required at a particular output level. The proposal of TFEE effectively makes up for the shortcomings of traditional single-factor energy efficiency evaluation and has significant enlightening effects on subsequent research.

As the importance and urgency of energy efficiency in sustainable development is increasing, accurate assessment of energy efficiency is of great significance and necessity. The Non-parametric Data Envelopment Analysis (DEA) method can better deal with the efficiency evaluation of decision-making units under the complicated situation of multiple inputs–outputs and has been widely used to evaluate the TFEE. DEA was first proposed in 1978 as a mathematical programming method for determining the relative effectiveness of homogeneous decision-making units (DMUs) [5]. Zhu, et al. [6] pointed out that DEA is a data-oriented method for evaluating the efficiency of a set of homogeneous DMUs. Compared with previous efficiency evaluation methods, DEA does not need to build a production function, which means that it can better deal with the efficiency of DMUs.

2. Application of DEA Model in Energy Efficiency Evaluation

As DEA has become an important and commonly used analysis tool and method in the field of energy efficiency assessment, a large amount of the literature evaluates energy efficiency based on data from countries, regions, industries and companies. This section will introduce the application of DEA in energy efficiency evaluation.

2.1. Energy Efficiency Evaluation of Regions

After Hu and Wang [4] first proposed the total factor energy efficiency framework and evaluated the energy efficiency of various regions in China, the DEA method was widely used in national and regional energy efficiency evaluation. This section reviews the studies that have evaluated energy efficiency in different regions using DEA from 2015 to 2019 and the results are shown in Table 1.

Jebali, et al. [7] analyzed the energy efficiency and influencing factors of Mediterranean countries during 2009–2012. The results of the study indicate that the energy efficiency levels in Mediterranean countries are high and decline over time. Gross national income per capita, population density and the use of renewable energy can affect energy efficiency. Zhao, et al. [8] measured the energy efficiency of 35 Belt and Road countries in 2015 based on a three-stage DEA model. The results show that South Korea, Singapore, Israel, and Turkey have a TFEE of 1. Uzbekistan, Ukraine, South Africa and Bulgaria are less efficient. He, et al. [9] established an DEA-based energy efficiency evaluation model for measuring the energy efficiency of 32 OECD countries from 1995 to 2016. Additionally, the effects of environmental factors on energy efficiency assessment were compared through efficiency analysis and predicted value analysis. Wang, et al. [10] use the DEA-Malmquist method to measure the energy efficiency of 25 countries; the results of this study show that by using the same inputs as developing countries, the developed countries’ balance between GDP growth and carbon dioxide emissions is more balanced. In addition, India and China increased their energy intensity during 2010–2017.

Table 1. Energy efficiency evaluation of regions.

Author	Subject of Evaluation	Model
He, Sun, Shen, Jian and Yu [9]	32 OECD countries	CCR DEA
Bampatsou, et al. [11]	15 EU countries	CCR-DEA
Zhang, et al. [12]	23 developing countries	BCC DEA
Zhang and Choi [13]	30 provinces in China	SBM DEA
Guo, et al. [14]	Western of China	SBM DEA
Apergis, et al. [15]	20 OECD countries	SBM-Undesirable DEA
Zhao, Zhang, Zeng, Li, Liu, Qin and Yuan [8]	35 Belt and Road countries	Network DEA
Jebali, Essid and Khraief [7]	24 Mediterranean countries	Network DEA
Wu, et al. [16]	30 provinces in China	Network DEA
Wu, et al. [17]	30 provinces in China	Dynamic DEA
Wang, et al. [18]	29 provinces in China	Dynamic DEA
Guo, et al. [19]	27 countries	Dynamic DEA
Wang, Le and Nguyen [10]	25 countries	Dynamic DEA
Amowine, et al. [20]	25 African countries	Dynamic DEA

Wang, et al. [21]	Guangdong province	Meta-Frontier DEA
Zhang, et al. [22]	16 CDM countries	Meta-Frontier DEA
Li and Lin [23]	30 provinces in China	Meta-Frontier DEA
Yu, et al. [24]	30 provinces in China	Meta-Frontier DEA
Sun, et al. [25]	211 cities in China	Meta-Frontier DEA
Yu, et al. [26]	277 cities in China	Meta-Frontier SBM
Yang and Wei [27]	26 cities in China	Game Cross-Efficiency DEA

In addition to evaluating a country's energy efficiency, the energy efficiency of provinces and cities has also attracted the attention of many researchers, especially in China's provinces and cities. Wang, Yu and Zhang [18], Li and Lin [23], and Wu, Zhu, Yin and Song [17] adopt the DEA method to evaluate the energy efficiency of 30 provinces in China, and research shows that most provinces are less energy efficient. Eastern China has the highest energy efficiency, while western China has the worst energy efficiency. Efficiency has improved in most regions during 2006–2010. Yu, You, Zhang and Ma [26] proposed an energy efficiency evaluation model that takes into account regional technological heterogeneity and carbon emissions. By evaluating the energy efficiency of 277 cities in China between 2007 and 2014, the study found that there are large differences in the energy efficiency of Chinese cities. Sun, Wang and Li [25] considered the heterogeneity and technology gap of energy management in different regions and measured the energy efficiency of 211 cities in the country. The results show that the overall efficiency of Chinese cities is low, while that of central China is the lowest, and there is a huge technological gap between regions. Yang and Wei [27] used the game cross-efficiency DEA method to analyze the urban total factor energy efficiency of 26 prefecture-level cities in China from 2005 to 2015. The results show that the energy efficiency of cities considering competition is lower than traditionally calculated energy efficiency. During the study period, the study concluded that urban energy efficiency did not improve. There are also studies evaluating regional energy efficiency in other countries. For example, Honma and Hu [28] used the DEA method to analyze total factor energy efficiency based on data from 47 cities and counties in Japan.

2.2. Energy Efficiency Evaluation of Industries and Companies

DEA is also widely used in assessing industry energy efficiency. Through a search of the related literature, it can be found that research on industry energy efficiency is mainly concentrated in high energy consuming industries such as electricity, construction, and transportation. Table 2 shows the energy efficiency evaluation of industries.

Makridou, et al. [29] used the DEA method to assess the energy efficiency of five energy-intensive industries (building, power, manufacturing, mining, and transportation sectors) in 23 EU countries between 2000 and 2009. The study found that overall efficiency has improved across all sectors during this period. Lee and Choi [30] evaluated the energy and environmental efficiency of seven manufacturing sectors in South Korea from 2011 to 2017, and the results showed that energy efficiency improved by an average of 0.3% during the study period. Zhou, et al. [31] conducted an empirical study on the energy efficiency of China's industrial sector from 2010 to 2014, and the results showed that most sectors of Chinese industry performed poorly, especially those related to energy extraction. Lei, et al. [32] evaluated the energy efficiency of 30 provincial transport departments in China. The results show that the energy efficiency of the provincial transport departments in China varies widely; efficiency is better than in the midwest of China. Djordjevic and Krmac [33] uses a non-radial DEA to evaluate the energy efficiency of the transportation industry (road, railway and aviation sectors) in Europe. Studies indicate that the energy efficiency of the road sector is improving, while the energy efficiency of the railway transport sector in many assessed countries is low.

Table 2. Energy efficiency evaluation of industries.

Author & Year	Subject of Evaluation	Model
Zhou, Xu, Wang and Wu [31]	38 Chinese industrial sectors	BCC DEA
Wang, et al. [34]	30 Chinese provincial industrial sectors	BCC DEA
Lei, Li, Zhang, Dai and Fu [32]	30 Chinese interprovincial transport sectors	SBM-DEA
Liu and Wang [35]	30 Chinese provincial industrial sectors	Network DEA
Wu, et al. [36]	30 Chinese provincial industrial sectors	Network DEA

Makridou, Andriosopoulos, Doumpos and Zopounidis [29]	23 Energy-intensive industries in EU countries	Dynamic DEA
Lee and Choi [30]	7 Korean manufacturing sectors	Dynamic DEA
Perez, et al. [37]	20 Chilean manufacturing industry	Dynamic DEA
Fei and Lin [38]	30 Chinese provincial agricultural sectors	Meta-Frontier Malmquist DEA
Feng and Wang [39]	30 Chinese provincial industrial sectors	Meta-Frontier Malmquist DEA
Han, et al. [40]	42 Chinese industrial sectors	Game Cross-Efficiency DEA
Xie, et al. [41]	30 Chinese provincial generation sectors	Game Cross-Efficiency DEA

Compared to the regional and industry levels, energy efficiency at the enterprise level is relatively low. In the existing research, Cui and Li [42] used DEA to analyze the energy efficiency of 11 airlines from 2008 to 2012. The results show that capital efficiency is an important factor to promote energy efficiency. The US financial crisis had a significant impact on energy efficiency. Zhang and Choi [13] carried out an empirical analysis of the energy efficiency of fossil fuel power generation in Korea by using the DEA method. The results show that coal-fired power plants have higher total energy efficiency than oil-fired power plants, and the technology gap of coal-fired power plants is smaller than that of oil-fired power plants. Studies show that the Korean government should promote technological innovation to reduce the technology gap in coal-fired power plants. Bi, et al. [43] analyzed the energy efficiency of Chinese fossil fuel power generation enterprises. They pointed out that the energy and environmental efficiency of the enterprises are low, and there are large differences between provinces. In addition to power generation companies, Zhang, et al.[44] also analyzed the energy efficiency of 62 power generation equipment.

3. Findings and Future Research Discussions

3.1. Main Findings

By analyzing the literature on energy efficiency evaluation using the DEA method, it can be found that a large number of studies are conducted from the perspective of theory and application based on the data of countries, regions, industries and enterprises. The research has attracted more researchers' attention and the number of publications has gradually increased since 2011. From a methodological perspective, the DEA-based energy efficiency evaluation models are more consistent with the actual situation, such as extending from a single output model to an evaluation model that considers pollution emissions. The analysis of the research stage also ranges from a single stage to a multi-stage energy conversion issue. In addition, a dynamic analysis of multi-year efficiency is also the focus of one study. In other words, the construction of the energy efficiency evaluation model based on DEA has evolved from a static structure of a simple structure to a dynamic model of a complex network structure, and the accuracy of the efficiency evaluation has also been continuously improved.

Based on the above analysis of the related research on energy efficiency using DEA, this article discusses the overall situation of existing research and existing research deficiencies as follows:

(1) From the perspective of research objects, a large number of documents use data from countries, regions, industries and companies. Many research results have been obtained. Especially as China is a large country of energy consumption and carbon emissions, a large number of studies have been conducted on energy efficiency in China. Aiming at the technical heterogeneity of energy efficiency and competitive cooperation between different research objects, existing research proposes corresponding expansion models for different scenarios to improve the accuracy of efficiency assessment. It is not difficult to find that most of the existing energy efficiency is analyzed at the regional level. Although the energy efficiency at the company level has also attracted the attention of many scholars, compared with the regional and industry sectors, the energy efficiency analysis for enterprises is relatively small.

(2) From a method point of view, a large number of scholars have improved the model from different perspectives, and the accuracy of energy efficiency assessment has also continuously improved. With the expansion of research, the level of agreement between the construction of the DEA-based energy efficiency evaluation model and the actual situation continues to increase. However, as a data-oriented efficiency assessment method, DEA is mainly based on analysis with structured and clear data. Model studies that can deal with energy efficiency issues in complex data environments such as heterogeneity, uncertainty, or big data are still lacking. As the complexity of products and services continues to increase, the depth of energy efficiency assessment objects, especially at the microdata level, such as enterprise-level data and production line data, is often unstructured, and different data structures affect DEA. The accuracy of the assessment will also have an impact, resulting in increased errors in the efficiency assessment. Therefore, with the increasing complexity of the energy system, building a DEA model in a complex data environment will enable a more effective evaluation of energy efficiency.

3.2. Future Research Discussions

In order to inspire subsequent research on energy efficiency assessment using DEA, this paper proposes possible future studies from the perspective of application areas and models.

3.2.1. Further Research on Energy Efficiency Issues in Enterprises

This paper believes that research on the energy efficiency of enterprises will help to further improve energy efficiency if data are available. Specifically, the analysis of corporate data helps reveal the state of corporate energy-saving technologies. Besides, with the continuous improvement of carbon trading markets and policies, analyzing the energy efficiency level of enterprises will help companies to manage carbon emission quotas and improve their competitiveness.

3.2.2. Further Research on Energy Efficiency Based on Complex Data Environment

For energy efficiency assessment models based on complex data environment, as the complexity of energy systems continues to increase, it is particularly important to build evaluation models that can analyze complex data. In this article, complex data may include inaccurate or ambiguous observations of input and output data, large datasets for analysis, and heterogeneous data due to differences in input or output structure.

(1)The DEA energy efficiency evaluation model in the heterogeneous data environment.

Despite the continuous development of current information technology and the continuous improvement of data retrieval and analysis capabilities, there will still be data heterogeneity in the evaluation. Unlike the problem of data loss caused by data retrieval and data storage, the data heterogeneity discussed here is due to differences in the input or output variables caused by the complexity of the production system. For instance, Cook, et al. [45] pointed out that steel plants will produce different types of steel even if they invest the same resource structure. When the traditional DEA method is used for evaluation, the efficiency will be biased. In fact, researchers have begun to consider the heterogeneity of output indicators. Wu, et al. [46] have started to discuss the use of improved DEA analysis to evaluate the efficiency of DMUs with different input and output indicators. It is not difficult to find that under different energy consumption scenarios, especially at the microdata level, it is particularly important to expand the efficiency assessment method in the case of heterogeneous input–output variables.

(2) The DEA energy efficiency evaluation model in the uncertain data environment.

In the reality of energy efficiency assessments, the observations of input and output data may be inaccurate or ambiguous [47]. The efficiency evaluation in the uncertain environment has attracted the attention of many researchers. Among them, the fuzzy set theory proposed by Zadeh, et al. [48] and others has been widely adopted. Based on fuzzy theory, some researchers have suggested the Fuzzy DEA model [49][50]. In the field of energy efficiency assessment, the expansion and application of the Fuzzy DEA model will help to improve the accuracy of energy efficiency assessment.

(3) The DEA energy efficiency evaluation model in the big data environment.

In the big data environment, the dataset used for analysis is usually very large, which causes the traditional DEA calculation process to take a long time. Therefore, analyzing big data makes researchers face many difficulties [51].

Recently, scholars have begun to evaluate energy efficiency based on a large number of data environments. For example, Zhu, et al. [52] proposed a DEA-based method for the allocation and utilization of natural resources in China, using big data technology to characterize the production technology in each region. Li, et al. [53] uses big data theory to analyze and evaluate the efficiency of China's forest resources, taking into account many evaluation indicators and large amounts of data in the big data environment. With the continuous improvement of information and information technology and data retrieval capabilities in the future, how to make full use of the big data environment in the energy field and expand DEA models and algorithms will help further enhance the application space of DEA.

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