Energy Efficiency Analysis of China Based on DEA Methods Under Dual Carbon Target

Jingqi Wang
College of Science, North China University of Technology, Beijing, 100043, China

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Abstract: With the increasingly serious environmental problems, the realization of low-carbon energy transformation in China's energy system has been promoted to the national strategic height. It has certain practical significance and necessity to investigate its production efficiency scientifically and accurately and analysis its improvement path. In this paper, the Data envelopment analysis (DEA) method is utilized to measure the energy of 30 provinces and municipalities in China from 2010 to 2020 using deep2.1 software, from a temporal and spatial perspective. According to the data analysis, this paper makes suggestions: pay attention to the important role of technological innovation in improving energy efficiency, strengthen the scientific research investment of new energy enterprises, cultivate internationally competitive energy talents; strengthen regional energy cooperation, promote clean energy to replace traditional energy, increase the research on clean coal utilization technology, improve coal utilization efficiency and reduce carbon emissions, and further improve environmental protection policies, and increase the punishment of polluting enterprises. At the same time, encourages enterprises to trade carbon emission rights, increase carbon emission costs, promote enterprises to improve energy efficiency. In the production process, Chinese companies should try their best to energy conservation and emission reduction, and reduce energy consumption. In energy consumption, popularize energy-saving products and improve energy efficiency; strengthen regional energy cooperation and promote the rational allocation of energy resources. Through regional coordination, the improvement of energy efficiency can be realized, reduction of national energy consumption level can be promoted.

1 INTRODUCTION

Energy plays a crucial role in supporting human survival and facilitating social development. With the increasing energy demand, environmental problems caused by energy shortage and excessive energy consumption have gradually attracted people's attention. How to effectively improve energy efficiency is crucial for the sustainable development of China's economy. Therefore, it is of great theoretical and practical significance to scientifically evaluate the energy efficiency situation and the major influencing factors in China to provide reliable suggestions and empirical data reference for improving energy efficiency.

Through theoretical induction, the Data envelopment analysis (DEA) model is widely used in energy efficiency measurement. Yao et al. proposed a methodology that decomposes total factor productivity change into two distinct elements, technological progress and changed in technical efficiency (Yao et al, 2023). Guo et al. investigated how entry and innovation affect total factor productivity growth (Guo et al, 2023). Yang et al. observed Significant effects that persist over time (Yang et al, 2023). Jin et al. developed a framework to evaluate China's agricultural research investment trends and its impact on total factor productivity (Jin et al, 2002). Chen examined heterogeneous total factor productivity (TFP) (Chen & Moore, 2009). Asche analyzed total factor productivity change (Liang & Wang, 2023).

With the gradual improvement of DEA models and the increasingly prominent problem of the product of environment, domestic scholars also began to study green total factor productivity. Li utilized the Malmquist index and a spatial Durbin model to analyze the impact of the effect on green total factor productivity (Asche, 2013, Li & Wu, et al, 2017). Li used the Super-SBM model to calculate China's agricultural green total factor productivity according to carbon emissions (Li & Lin, 2017). The carbon

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emissions are usually used to calculate green total factor production efficiency (Liu et al, 2021).

The main body of this paper is energy efficiency. Through the literature research, the author understands the variety of testing methods for energy efficiency, combined with the knowledge that has been learned.

2 METHODOLOGY

2.1 Data Source and Description

For the construction of energy efficiency index system, most scholars choose to consider energy, labor, technology, capital input, economic output interaction and alternative relationship of the total factor energy efficiency index. This paper refers to the actual research, and chooses capital input, labor input, technology input three indexes as input elements, with local fiscal revenue to measure capital input, with the end of employment to measure labor input. Research and experimental development personnel collaborated to measure the impact of technology, using per capita GDP as the desired output and the carbon dioxide emissions as the undesired output. The specific input-output index system is shown in the following table.

$$EC = \sum_{n=i}^{6} EC_I = \sum_{i=1}^{6} E_i \times CF_i \times CC_i \times COF_i \times 3.6 \tag{1}$$

Among them, represents the estimated total carbon dioxide emissions of various energy consumption; i represents energy consumption, including coal, coke, gasoline, kerosene, fuel oil and natural gas. 6 is the total energy consumption of each province: represents the heat value of energy: represents the carbon content: represents the oxidation factor of energy in i. It's called carbon dioxide emission.

2.2 Index Selection

Most researchers prefer to consider the interaction between energy, labor, science and technology, capital input, economic output, and the substitution relationship of the total factor energy efficiency index when constructing the energy efficiency index system. Drawing on the actual research, this paper selects three indicators including capital input, labor input, and technology input as input elements. Local fiscal revenue is used to calculate capital input, employment termination is used to measure labor input, and research and development personnel are counted for technology input. Per capita GDP is used as the desired output, and carbon dioxide emissions serve as the undesired output. The specific input-output index system is shown in the following Table 1.

Table 1: Index selection and unit.

Indicator type	name of index	Index unit
Investment index	Local fiscal revenue	100 million
	Number of people employed at the end of the year	human being
	Research and trial development personnel	human being
Expect output indicators	Per capita GDP	first
Undesired output indicators	Carbon dioxide emissions	Ten thousand tons

2.3 Research Method

DEA-BCC Model measures the pure technical efficiency by assuming a variable return of scale, it is also called the variable return of scale (VRS) model. BCC The model is shown as follows:

When σ =1, then the pure technical efficiency of DMU is DEA effective. If the comprehensive technical efficiency is θ and the pure technical efficiency is σ, then the scale efficiency of DMU = θ / σ (Yang et al, 2023).

Malmquist Model: The Malmquist Index method is a helpful tool for analyzing efficiency changes across multiple samples. It can show the relationship between comprehensive efficiency, technical efficiency, and total factor production efficiency index. This method can dynamically track the changes in efficiency values of sample data over different time periods. The Malmquist index was first proposed in 1953 to solve the problem of variations in the consumption bundle in the consumption function. CAVES applied the Malmquist index to analyze energy production efficiency (Asche, 2013).

$$M(y_{t+1}, x_{t+1}, y_t, x_t) = \frac{1}{2}\left[\frac{D^t(x_{t+1},y_{t+1})}{D^t(x_t,y_t)} * \frac{D^{t+1}(x_{t+1},y_{t+1})}{D^{t+1}(x_t,y_t)}\right] \tag{2}$$

Where $(x_{t+1}, y_{t+1})(x_t, y_t)D^{t+1}D^t$ For input and output variables in $t+1$ and t; for decision unit distance function in $t+1$ and t.

3 RESULTS AND DISCUSSION

Energy plays a crucial role as a material foundation for human survival and social progress. With the increasing energy demand, environmental problems caused by energy shortage and excessive energy consumption have gradually attracted people's attention.

3.1 Descriptive Statistics

Based on previous data comparing energy consumption and carbon emissions. In this research, the DEA-Malmquist method is applied to measure the energy efficiency of China from 2010-2020 from both static and dynamic perspectives, and to compare the efficiency differences of the seven regions (Figure 1).

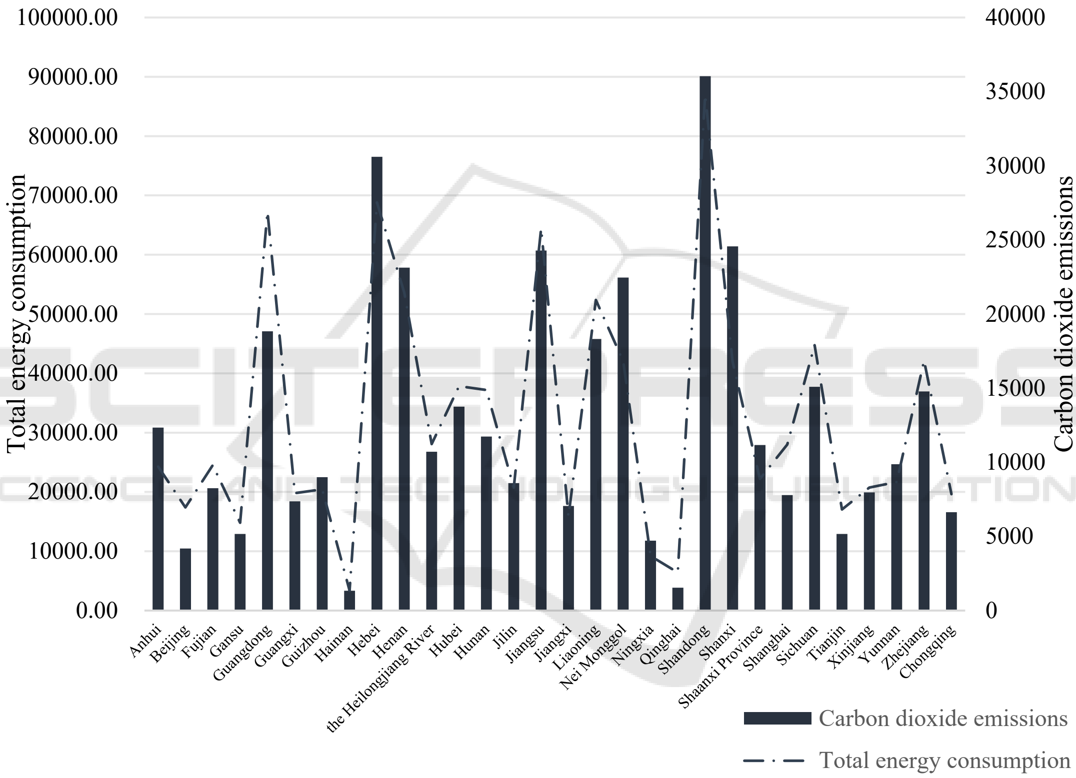

Figure 1: Comparing energy consumption and carbon emissions plot (Picture credit: Original)

Using the original input and output data and Deap2.1 software, the total energy factor productivity and decomposition index were calculated for the 30 provinces in China. and municipalities from 2010 to 2020. Combined with the Malmquist index, the total factor production efficiency is used to evaluate it dynamically. As shown in Table 2., the average total factor production efficiency of 30 provinces and municipalities in China from 2010 to 2020 is 0.951, indicating that the energy efficiency of these 30 provinces and municipalities has not yet reached the effective state. From 2010 to 2014, tfp increased year by year, with a significant decrease in 2014-2015. From 2015 to 2016, it recovered to the level of 2013-2014 and probably decreased from 2016 to 2019.

From 2010 to 2020, the development of energy efficiency in all regions of China will be divided into three phases: the first from 2010 to 2014, the second from 2014 to 2016, and the three from 2016 to 2019. (Table 2).

Table 2: Malmqusit index decomposition of energy efficiency.

year	eff	tech	peh	sec	tfp
2010-2011	1.027	0.870	1.015	1.012	0.894
2011-2012	1.021	0.910	1.023	0.998	0.928
2012-2013	1.000	0.961	1.005	0.996	0.962
2013-2014	1.016	0.962	1.016	1.000	0.977
2014-2015	0.994	0.932	0.995	0.999	0.927
2015-2016	1.022	0.958	1.033	0.989	0.979
2016-2017	0.972	0.995	0.960	1.012	0.967
2017-2018	1.010	0.961	1.006	1.003	0.970
2018-2019	1.035	0.929	1.105	0.936	0.961
mean	1.011	0.941	1.017	0.994	0.951

According to the principle of the Malmquist index method, the total factor production efficiency is the product of the comprehensive technical efficiency change index and the technical change index.

In the first stage, the contribution to the growth of total factor production efficiency is technological changes. The sudden decline of total factor production efficiency in the second stage is mainly due to the decline of technological changes, while the scale also decreases in efficiency. Combined with the literature research, environmental protection was valued in 2014.31 provinces and the Ministry of Environmental Protection signed the "Target Responsibility Letter for Air Pollution Prevention and Control", and the policy had a great impact on the technical change index, thus affecting the total factor productivity. In the third stage, the total factor productivity index continued to decline, but from 2018 to 2019, the technical change index increased. The scale efficiency index decreased, indicating that the development of new energy technology in China is effective. The technology application is in scale, and it is in the stage of energy technology transformation and development after the environmental protection policy.

In general, technical changes play a leading role in the total factor efficiency of production. In contrast, the change is relatively flat at present, which may require further optimization of resource allocation and scale expansion strategy.

3.2 Regional Trend

Without the influence of environmental effects and random factors, the total factor growth rate decreased by 1% annually from 2010 to 2020 (table 3). Surgical efficiency (TECH) increased by 2.4% annually; technological progress level. TCH decreased by 3.2% annually. This shows that the decline in the productivity of environmental service enterprises is mainly caused by the relative decline of technology. From the perspective of segmentation, only the average annual productivity of environmental monitoring enterprises has seen a small improvement, and the main driving force is the obvious improvement in the technical efficiency of enterprises. However, the productivity of enterprises in the other five categories showed a small downward trend, with a decline rate of 0.56% ~2.25%.

Between, the main reason is the negative impact of the technological relative regression on productivity. The results of the first stage show that, without considering the influence of environmental factors and random factors, the improvement of correct management decisions is not enough to offset the adverse impact of the relative decline of technology level on the production efficiency of enterprises.

From the perspective of regional analysis, the results under environmental constraints energy efficiency and overall technology progress level are low (only 0.94) has not reached the equilibrium degree. The efficiency difference between provinces, regions, in the study period of Beijing, Shanghai province energy efficiency mean is 1, every year reached the effective state, and the average energy efficiency in Guizhou is only 0.87.

Energy efficiency in North China and Eastern China is significantly higher than in other regions. In this regard, the differences in resource endowment of different regions, as well as the supply and demand of different resources and the development degree of utilization, and relevant policies should be formulated according to local conditions.

From a dynamic point of view, between 2010-2020 our country's energy total factor productivity changed overall downward trend, and gradually in the good direction in recent years, the technological progress is the main factor of driving energy efficiency growth, should adhere to resource orientation and science and technology, and attach importance to technology research and development, actively develop clean coal utilization technology, unconventional oil and gas exploration and development technology, but also to promote the development of energy conservation and emissions reduction technology, intensify mining environment monitoring, increase the proportion of clean energy consumption, under the condition of low carbon environmental protection improve energy efficiency (table 4).

Table 3: Static index analysis of energy efficiency.

area	firm	crste	vrste	scale
Sichuan	25	0.135	0.135	1.000
Henan	10	0.165	0.165	1.000
Guangdong	5	0.169	0.169	1.000
Shandong	21	0.196	0.196	1.000
Jiangsu	15	0.207	0.207	1.000
Hebei	9	0.209	0.209	1.000
Hunan	13	0.212	0.212	1.000
Anhui	1	0.221	0.221	1.000
Hubei	12	0.243	0.243	1.000
Yunnan	28	0.251	0.251	1.000
Liaoning	17	0.265	0.291	0.913
the Heilongjiang River	11	0.268	0.268	1.000
Shaanxi Province	23	0.271	0.271	1.000
Guangxi	6	0.287	0.287	1.000
Shanxi	22	0.289	0.289	1.000
Jiangxi	16	0.299	0.299	1.000
Zhejiang	29	0.314	0.314	1.000
Guizhou	7	0.349	0.349	1.000
Xinjiang	27	0.351	0.351	1.000
Chongqing	30	0.365	0.365	1.000
Jilin	14	0.387	0.474	0.816
Gansu	4	0.393	0.393	1.000
Nei Monggol	18	0.430	1.000	0.430
Fujian	3	0.479	0.479	1.000
Shanghai	24	0.672	1.000	0.672
Beijing	2	1.000	1.000	1.000
Hainan	8	1.000	1.000	1.000
Ningxia	19	1.000	1.000	1.000
Qinghai	20	1.000	1.000	1.000
Tianjin	26	1.000	1.000	1.000

Table 4: Total factor energy efficiency.

area	firm	effch	techch	pech	sech	tfpch
Anhui	1	1.01	0.89	1.02	7.00	0.90
Beijing	2	1.00	1.08	1.00	1.99	1.08
Fujian	3	1.04	0.95	1.08	0.97	0.99
Gansu	4	1.02	0.88	1.02	2.00	0.90
Guangdong	5	1.01	0.97	1.03	0.98	0.97
Guangxi	6	1.01	0.89	1.01	2.00	0.89
Guizhou	7	0.98	0.88	0.98	1.10	0.87
Hainan	8	1.00	0.96	1.00	2.00	0.96
Hebei	9	0.99	0.92	0.99	1.09	0.91
Henan	10	1.01	0.90	1.01	2.00	0.91

Table 4: Total factor energy efficiency (cont.).

area	firm	effch	techch	pech	sech	tfpch
The Heilongjiang River	11	1.03	0.92	1.03	2.00	0.94
Hubei	12	1.03	0.95	1.04	9.98	0.98
Hunan	13	1.01	0.93	1.01	7.00	0.94
Jilin	14	1.02	0.96	1.00	1.92	0.98
Jiangsu	15	1.05	0.95	1.09	8.96	0.99
Jiangxi	16	0.99	0.89	0.99	1.01	0.88
Liaoning	17	1.01	0.96	1.01	1.10	0.97
Nei Monggol	18	0.99	1.00	1.00	0.99	0.99
Ningxia	19	1.00	0.98	1.00	1.90	0.98
Qinghai	20	1.00	0.99	1.00	2.00	0.99
Shandong	21	1.00	0.96	1.01	9.99	0.96
Shanxi	22	1.01	0.91	1.01	1.10	0.91
Shaanxi Province	23	1.03	0.95	1.04	10.00	0.98
Shanghai	24	1.02	1.04	1.00	1.18	1.06
Sichuan	25	1.03	0.89	1.03	1.99	0.92
Tianjin	26	0.98	0.97	1.00	6.98	0.96
Xinjiang	27	1.01	0.94	1.02	9.99	0.95
Yunnan	28	1.01	0.88	1.01	1.09	0.89
Zhejiang	29	1.01	0.95	1.05	9.97	0.96
Chongqing	30	1.04	0.96	1.06	0.98	0.99
	mean	1.01	0.94	1.02	9.99	0.95

3.3 Discussion

According to the above studies, the paper puts forward the following suggestions:

Chinese energy enterprises should increase their investment in new energy technology innovation, and attach importance to the important role of technological innovation in improving energy efficiency, to improve China's energy efficiency. The government and enterprises should increase their investment in technological innovation, increase the allocation of research and development funds and human resources, and cultivate internationally competitive energy technologies.

China needs to work on optimizing its energy mix by promoting the use of clean energy in place of traditional energy sources, and increasing the proportion of clean energy in the total energy consumption. It is also important for enterprises to focus on researching clean coal utilization technology to improve the efficiency of coal utilization and reduce carbon emissions. Strengthening environmental protection policies. The Chinese government will further improve environmental protection policies, increase penalties for polluting enterprises, and guide them to take the path of green development. At the same time, enterprises are encouraged to carry out carbon emission rights trading, increase the cost of carbon emission, and promote enterprises to improve energy efficiency.

Strengthen the training of energy talents. China aims to provide comprehensive training for a diverse pool of energy professionals, equipping them with a global perspective and enhancing their expertise in areas such as energy technology research and development, as well as energy management. Simultaneously, the Chinese government will prioritize the enhancement of professional development programs for individuals already employed within the energy industry, thereby elevating the overall quality standards across the sector.

Strengthen regional coordination. The Chinese government should strengthen energy cooperation among regions and promote rational allocation of energy resources. Through regional coordination, China can improve energy efficiency and reduce national energy consumption.

4 CONCLUSION

Based on the measurement of energy data from various regions in China from 2010 to 2020, this paper finds that China's energy efficiency has not yet reached its overall effective state, and there are significant fluctuations in energy efficiency from 2014 to 2016. Under this premise, this paper puts forward policy suggestions such as increasing investment in technological innovation, optimizing energy structure and strengthening environmental protection policies to provide reference for improving energy efficiency and green and low-carbon development in China. Through the implementation of these policies, China's energy enterprises can help to improve production efficiency, reduce carbon emissions, and achieve sustainable development. At the same time, the government, enterprises and scientific research institutions should make joint efforts to contribute to improving energy efficiency and green and low-carbon development in China.

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