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Research on the utilization efficiency of new energy technologies in China^{*}

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Abstract: Energy is an important driving force of human social progress and national economic development and makes crucial the concept of energy utilization efficiency. This paper uses panel data of the DEA model to measure China's thirty provinces from 2010 to 2019 against the energy efficiency index, a new technology to describe the energy efficiency of new technology in Chinese provinces. The empirical study found that the efficiency of China's new energy technology contains obvious regional characteristics, and that the provinces' domain energy new technology using comprehensive efficiency and technical efficiency is highly uneven. Compared with the average level, the comprehensive efficiency and technical efficiency of the new energy technologies in the eastern and western regions of China from 2010 to 2019 showed a significant downward trend.

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1. Introduction

Energy is an important driving force for the progress of human society and the development of the national economy. Every great leap in human productivity is accompanied by a revolution in energy production and consumption. The new round of energy revolution is emerging, with the development of innovative energy technology as its distinguishing characteristic, as is the promotion of human society to the new energy age,^[1] which is characterized by high efficiency, low carbon emission, clean and intelligent. The scope of new energy technologies includes not only new technologies in nuclear and renewable energy, but also new and disruptive technologies related to fossil energy. Generally, we have the following characteristics^[2] through the innovation of technical principles. It puts forward solutions to the restrictive problems in the development of the field of technology. It has excellent competitiveness and shows strong technical advantages. The new technology relies on mature technology for development, has strong technical feasibility, and offers the prospect of great cost efficiency. In order to ensure the rapid expansion of the scale of technology development, the cost will decrease rapidly, and the ability to compete with traditional technology and capture a large amount of market share can be obtained in the short term. Based on the characteristics of strategic new industries, on the industrial level the strategic emerging industries in the energy field can be collectively referred to as new energy technology.^[3] The development of new energy technology has become the focus of attention in modern society. It is important in all countries to improve the efficiency of new energy technology innovation and reduce energy consumption as a sustainable development strategy. In recent years, with the improvement of the market, industrialization and internationalization of China's economy, the imbalance between the supply and demand of energy in China will be further intensified. In order to improve the efficiency of new energy technology innovation, the Chinese government pledged at the Copenhagen Summit in 2009 that the emission of GDP carbon dioxide in 2020 would be 40%-45% lower than that in 2005. In September 2014, the National Development and Reform Commission, the Ministry of Ecology and Environment and the National Energy Administration jointly issued an action plan for upgrading and reforming coal energy use and reducing emissions (2014-2020), and put forward the atmosphere of coal-fired generating units. The pollution achieved the requirements of the emission limits for gas turbines, that is, the "ultra-low emission" requirement for coal-fired power plants. In 2015, the government work report established clearly the "big number of energy saving and

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emission reduction and environmental governance." In its 12th Five-Year Plan, China increased its support for fuel cell direct power generation (Integrated Gasification Fuel Cell) technology. The "863" and "973" programs were funded by the Ministry of Science and Technology for research on the solid oxide fuel cell (SOFC) electric reactor, power generation system and related scientific problems. Therefore, strategies for improving the efficiency of new energy technology innovation and reducing carbon dioxide emissions are critically necessary. The data demonstrate inefficiency in new energy utilization in China and uneven development of new energy utilization efficiency in various provinces, and there is a combination of high investment, low production and low efficiency. Accordingly, it is of great theoretical and practical importance to study the efficiency of new energy utilization.

2. A review of related studies

From the perspective of economics, innovation efficiency refers to the efficiency of innovation activities from the elements of innovation to the transformation of innovation results and product output, that is, the innovative output,^[4,5] obtained by the unit innovation elements. At present, the research on efficiency conducted by foreign scholars is more mature. The research methods are divided into two main categories: the parameter method, such as the matter-element analysis method,^[6] the ratio ranking method^[7] and the random frontier method;^[8] and the nonparametric method, such as the data envelopment analysis (DEA) method.^[9] The research of domestic scholars on innovation efficiency is mostly found in the literature of regional innovation efficiency^[10,11] and technological innovation efficiency.^[12-15] Wang Xiuli et al.^[16] used data envelopment analysis to measure the efficiency of collaborative innovation at the provincial level in China. Although there are some deficiencies in index selection and research methods in this literature, it has opened the beginning of using data envelopment analysis to measure the efficiency of collaborative innovation; Fan Xia et al.^[17] On the basis of MTCR and MTCL. Introduced SPM method to discuss the innovation efficiency of industry, University and Research Institute on the common technology of biological industry. Although it provides a reference for the relevant empirical research, but the field has certain characteristics, which can not reflect all the characteristics of industry commonness. Wu Hecheng et al.^[18] used super efficiency DEA and nonparametric statistical method to measure the efficiency of collaborative innovation in Colleges and universities. The disadvantage is that the empirical literature did not put forward specific measures to improve the technical efficiency of colleges and universities. At present, the most commonly used method in industrial efficiency research in domestic and foreign literature is "frontier efficiency analysis method"^[19]. Usually, the parameters in the frontier production function are estimated according to whether it is necessary or not. Many scholars have studied and proved that external environmental factors such as macro-economy also have a significant impact on industrial efficiency. Industrial inefficiency may be caused by internal mismanagement or by external environment. The former is endogenous, while the latter is exogenous.^{[20] [21] [22]} Therefore, the impact of exogenous factors on efficiency will lead to the problem of selecting an efficiency evaluation method, and the efficiency value cannot be real management efficiency. In this regard, some scholars, such as Akhighe and McNulty^[23] and Berger and Mester,^[24] have proposed that multiple exogenous factors which may affect efficiency should be directly introduced into the frontier analysis method of calculating efficiency using SFA methods to analyze American banking efficiency, and variables representing exogenous factors should be used, such as concentration index, flat index and leveling index. The rate of bad loans, the growth rate of state income and some control factors of the bank branches are directly added to the efficiency estimation equation, and the distribution of inefficiency is expressed as a function of possible factors. Lozano-Vivas et al. used the DEA method to study the bank efficiency of the ten countries in the Organisation for Economic Co-operation and Development (OECD). The per capita income, per capita wage, population density, deposit density, average income of the branch, average deposit of the branch, ratio of equity capital, and rate of return on net assets were taken as output variables, and the per capita branches and density of the branches in the environment variables were introduced into the DEA model as input variables.^[25] For example, Yan Li introduced three innovative environmental variables into the efficiency evaluation equation^[26] in the study of regional innovation efficiency, such as the total number of postal and telecommunications, the number of ordinary higher education schools, the number of research and development and the number of development institutions. However, the disadvantage of this method is that we usually do not know the influence of environmental variables on efficiency in advance. If the environmental variable is classified as an input or output item, the value of the efficiency will be altered. In order to improve the development and utilization efficiency of new energy technology and improve the defects of single factor indexes such as carbon emission intensity and energy intensity, an efficiency measurement method based on all-factor production theory is widely used. This

method is derived from the concept of efficiency measurement established by Farrell^[27] and by using data envelopment analysis proposed by Charnes et al.^[28] Methods to build the production frontiers and measure the energy and environmental efficiency of different economic units. Zaim and Taskin used DEA data to create environmental performance indicators of OECD countries and, on this basis, verify the environmental Kuznets curve hypothesis.^[29] Hu and Wang^[30] have proposed an all-factor energy efficiency index. An empirical study of the data was carried out, and Hu^[31] was used to measure the total factor energy efficiency of the Asia-Pacific Economic Corporation (APEC) countries by using the TFEE index, and constructed the quantitative analysis index of the energy saving target ratio (ESTR), which reflects the energy saving potential. Moon h and min d^[32] expand the Two-stage DEA model to verify the relationship between energy efficiency and financial performance. Guo y, Yu y and Ren h^[33] evaluate the energy-saving technology of the whole supply chain based on DEA and life cycle theory, and conclude that the key factors affecting energy efficiency are different under different additional considerations. Wang LW, Le KD and Nguyen TD^[34] used DEA Malmquist model to measure the energy efficiency of 25 carbon dioxide emitting countries, and found that the development of developed countries between GDP growth and CO2 emissions is more balanced. Similar studies include Iftikhar y, Wang Z, Zhang B^[35]; Zhao h, Lin B^[36]; Ya C, Zhiqiang Z, Zhixiang Z^[37]; bampatsou C, halkos G^[38]. In general, in the study of industrial efficiency, the use of the DEA method to study the relationship between environmental factors and industrial efficiency has been widely recognized by scholars at home and abroad, but the lack of this method is applied to the study of the efficiency of new energy utilization.

Therefore, this paper applies the related theory of the generalized DEA method of panel data^[39], constructs a possible set of production with a technical level of data, and gives the DEA method based on panel data. Secondly, this method is used to estimate the 2010-2019 energy efficiency index of China's thirty provinces and to describe the new energy technology in various provinces of China. Through empirical research, it is found that the reference set of the DEA model based on panel data is more stable and the efficiency index and corresponding improved information are more in line with actual circumstances. On this basis, the empirical measure of the technological efficiency, institutional efficiency and scale efficiency of the new energy technologies in various provinces and regions of China is explained in accordance with the regional -overall -average analytical framework.

3. Research methods and data sources

3.1 The meaning of energy efficiency index

The first total factor energy efficiency (TFEE) based on the DEA method used by Hu^[30] and others has become the mainstream tool for measuring energy efficiency. The traditional TFEE index considers only one output, that is, economic output, such as gross domestic product (GDP) or industrial added value, also known as expected output. In recent years, as concern has grown about environmental pollution, many scholars have introduced the environmental impact (such as pollution or greenhouse gas emissions) generated by energy utilization into TFEE, which is defined as the TFEE^[40] considering the environmental effect or the TFEE^[41] under the environment constraint, which enriches the connotation of TFEE and makes energy efficiency. The rate of research is more scientific and systematic, and it also reflects the ideals of sustainable development. However, few studies have placed traditional TFEE and TFEE considering environmental pollution in a unified research framework. In order to divide the two kinds of TFEE effectively according to whether or not the environmental factors are introduced, Wang Ke Liang^[42] studies the two energy efficiency indicators energy economic efficiency (EEE) and energy and environmental prediction (EEP) based on the total factor method and the DEA method. Wei Yiming's^[43] research OF energy efficiency is usually measured by the ratio of energy service output to energy input, but different methods are used in different application fields determine or calculate energy input and service output, thus generating different energy utilization efficiency measure indicators, etc., to put forward energy as a kind of birth. The factor of production is to participate in the production process together with other factors such as capital, labor, raw material and so on. Energy utilization efficiency reflects the energy demand that can be reduced under the established combination of elements. In the economic category, there are two kinds of energy efficiency indicators: all-factor energy efficiency, that is, to consider various input factors, including the energy efficiency of interaction; and single-factor

energy efficiency, in which only the energy factors and output are compared, and other production factors are not considered. The total factor energy efficiency of this method is closer to reality.^[44]

In this paper, the efficiency of new energy technology innovation is defined as the ratio between optimal energy consumption and actual energy consumption to achieve the established economic goals. The consumption of the best new energy technology is the energy consumption that best meets the conditions of Pareto efficiency, that is, the new energy consumption on the boundary of production possibility. Under this production theory, according to the variability of the input factors the production possibility curve and the corresponding optimal energy consumption can be divided into short and long term. In the short term, the production possibility boundary can be expressed as $Y=f(X_i)=f(X_{i-1}, E)$, where Y represents output, i represents the type of input elements, E represents energy input, and X_{i-1} represents input elements other than energy. As shown in Figure 1, the surface PAOB is a production possibility boundary; the actual production point in the surface is M , and at the same time, it is on the equal output plane CHD , and the over point M is perpendicular to the bottom AOBG at the plane PGB, and the production possibility curve CD is given to the point D , and the point D is the short-term optimal energy dissipation point corresponding to the point M . Under the given output conditions, other input factors remain unchanged in the short term, and the minimum energy input required by the economic system is the optimal new energy consumption. The point on the possibility of production is the best advantage of resource allocation, and the resources are fully utilized. Under the given output conditions, the gap between the observation points and the most advantages is the inefficiency of the utilization of energy elements. Therefore, the short-term utilization efficiency of energy can be expressed as BF/BN . In the long run, all input factors can be changed, and the production possibility frontier can be expressed as $Y=f(E)$. In Figure 1, the curve KF is the projection of the production possibility curve CD at the bottom, the line TF is parallel to the OB , the curve KF is tangent to the point T , and the T point is the long-term optimal consumption point corresponding to the M point. In other words, under the established output conditions the minimum energy input required by the economic system is the long-term optimal new energy consumption, and the long-term utilization efficiency of the corresponding new energy elements can be expressed as JT/JL .

Figure 1. Innovative utilization efficiency of new energy technology.

The above results deepen our understanding of energy utilization efficiency and have high reference value. At the same time, however, two problems are worthy of note. The first is how to overcome the defect of the DEA method itself. Ignoring the effects of random factors on output, for example, the basic data is too sensitive to produce "extreme" frontier, etc. The second concerns the choice of influence factors. The index method is limited by decomposition methods, can only be constrained by several fixed-factor analyses, and even to some factors to define the connotation of controversial, such as technical contribution and Divisia index in structure. According to the above problem, this article examines mainly the energy, human, capital and economic growth-to-energy-efficiency problem to evaluate new technology innovation in China's energy use efficiency, namely, the selection of the province of the total amount of capital formation, employment, total energy consumption as inputs, with GDP as a new technology innovation output element for energy efficiency evaluation

and analysis of the application of the DEA model based on panel data, the selection of data as a control group of 2007, to evaluate new technology innovation in China's energy efficiency. Compared with previous methods, this method not only provides a stable reference frame, but deals effectively with the time changes in the conditions. Thus it has certain advantages as compared with the complement in the field of the study.

3.2 Research model: panel data generalized DEA model and validity analysis

Assumptions have used input index m and output index s to reflect the status of input and output of the decision-making units and have measured the decision-making units in an L index on the time series data.

If the data of the $n(k)$ decision unit is measured in the k time period, the input of the p decision unit is:

$$x_p^{(k)} = (x_{1p}^{(k)}, x_{2p}^{(k)}, \dots, x_{mp}^{(k)})^T,$$

The output index value is:

$$y_p^{(k)} = (y_{1p}^{(k)}, y_{2p}^{(k)}, \dots, y_{sp}^{(k)})^T,$$

and

$$x_p^{(k)} > 0, y_p^{(k)} > 0, p = 1, 2, \dots, n^{(k)}, k = 1, 2, \dots, L.$$

If the data of the $n(0)$ decision unit is measured in the base time period (control group), and the input index value corresponding to the J TH decision unit is:

$$x_j^{(0)} = (x_{1j}^{(0)}, x_{2j}^{(0)}, \dots, x_{mj}^{(0)})^T,$$

the output index value is:

$$y_j^{(0)} = (y_{1j}^{(0)}, y_{2j}^{(0)}, \dots, y_{sj}^{(0)})^T,$$

and both are positive.

Based on the data of the base time period, the efficiency of each decision unit relative to the base time period is taken into account, and the production of the base time period can be set as T .

$$T = \{(x, y) \mid x \geq \sum_{j=1}^{n^{(0)}} x_j^{(0)} \lambda_j, y \leq \sum_{j=1}^{n^{(0)}} y_j^{(0)} \lambda_j, \delta \sum_{j=1}^{n^{(0)}} \lambda_j \delta_j = \delta, (\lambda_1, \dots, \lambda_{n^{(0)}})^T \geq 0\}$$

Define 3.2.1 The index value of the p decision unit in the K TH time period $x_p^{(k)}, y_p^{(k)}$. If it doesn't exist $(x, y) \in T$, make

$$x_p^{(k)} \geq x, \quad y_p^{(k)} \leq y,$$

In addition, at least one inequality is strictly established, and it is said that the production of the P decision unit in the K TH time period is effective compared with the production of the base time period, which is called a DEA -panel.

Define 3.2.1 Show that if there is no more production status than the input of the evaluation unit in the base time period, it is considered that the evaluation unit is a DEA panel.

To further measure the effectiveness of the evaluation unit, the following mathematical models are given:

$$\begin{aligned} \min \quad & \theta - \varepsilon(e^T S^- + e^T S^+) \\ \text{s.t.} \quad & X\lambda + S^- = \theta X_k \\ & Y\lambda - S^+ = Y_k \\ & \lambda_j \geq 0, j = 1, 2, \dots, N, \\ & S^+ \geq 0, S^- \geq 0 \end{aligned}$$

Define 3.2.2 If a DEA panel has no solution or its optimal solution $\lambda^0, s^{+0}, s^{-0}, \theta^0$ meet $\theta^0 \geq 1$, it is said that the production of the p decision unit in the k time period is more effective than the production of the base time period. The abbreviation for weak DEA panel is valid.

Theorem 2.2.1 The optimal solution of a DEA-panel $\lambda^0, s^{+0}, s^{-0}, \theta^0$, meets one of the following conditions:

a. $\theta^0 > 1$ or (DEA-panel) No line solution;

b. $\theta^0 = 1$, and $s^{+0} = 0, s^{-0} = 0$,

The efficiency of the P decision unit in the KTH time period is effective for the DEA panel.

(1) When $\theta^0 > 1$, it shows that we are $y_p^{(k)}$ keeping the original output constant as long as the input of the p decision unit is not greater than that in the KTH time period $\theta^0 x_p^{(k)}$, Its production will not be inferior to the effective productivity of the base period. When the model DEA panel is not feasible, it indicates that the output of the evaluation unit is too large to reach the level of the sample unit. At this moment, provisions $\theta^0 = 1$,

(2) When $\theta^0 = 1$ and $s^{+0} = 0, s^{-0} = 0$, it shows that the production efficiency of the P decision unit in the KTH time period is equivalent to some effective production efficiency of the base time period.

(3) When $\theta^0 = 1$ 且 $(s^{+0}, s^{-0}) \neq 0$, it is shown that the production efficiency of the P decision unit in k time period is weak and effective compared with that of the base period.

(4) When $\theta^0 < 1$, it indicates that the production efficiency of the P decision unit in the KTH time period is invalid compared with the production efficiency of the base period.

Define 2.2.3 Set: $\lambda^0, s^{-0}, s^{+0}, \theta^0$ It is the optimal solution of the DEA panel. Make

$$\hat{x}_p^{(k)} = \theta^0 x_p^{(k)} - s^{-0}, \quad \hat{y}_p^{(k)} = y_p^{(k)} + s^{+0},$$

According to $(\hat{x}_p^{(k)}, \hat{y}_p^{(k)})$, the projection of the decision unit P on the effective front surface of the base time period.

Theorem 3.2.2 If the optimal solution of the DEA panel is planned $\lambda^0, s^{+0}, s^{-0}, \theta^0$ meet

$$\theta^0 < 1,$$

or

$$\theta^0 = 1, (s^{+0}, s^{-0}) \neq 0$$

the

$$\theta^0 x_p^{(k)} - s^{-0}, \quad y_p^{(k)} + s^{+0}$$

The DEA-panel works.

3.3 Research data

The DEA method, therefore, has been widely applied to the evaluation of new technology innovation efficiency. Jianghong [45] et al. Used DEA game cross efficiency model to study the energy efficiency of 30 provinces in China from 2002 to 2016, and concluded that the energy efficiency between provinces in China has obvious spatial dependence, and different factors have different effects on energy efficiency. Chen Xing [46] et al. Used the four stage bootstrap DEA Malmquist model to verify the inter provincial differences of energy consumption and output efficiency under the unexpected output. Zou

Yanping ^[47] and others used the improved DEA method to calculate the energy and environmental efficiency of 30 provinces in 2016. The one belt, one road, and other countries along the belt and road ^[48] measure the total factor productivity and the trend of change based on the super efficiency DEA model and GML index. Because of the traditional DEA models (e.g., the C2R model and BC2 model), further thought is necessary to determine the general requirements of decision-making units with the same external environment and how to deal effectively with panel data information and with the different time conditions of data. As a result of the application of the DEA model based on panel data, this paper selected data as a control group for 2010 to evaluate new technology innovation in China's energy efficiency. Compared with previous methods, this method provides a stable reference frame and deals effectively with the time changes in the condition of data.

3.4 Data source: evaluation of the comprehensive index of China's new energy technology innovation efficiency

3.4.1 Selection of evaluation indicators

At present, the reflected energy new technology innovation efficiency has a variety of indicators, depending on the object and purpose of evaluation. Selection of the index system is also different. According to the above problem, this article examines mainly the energy, human, capital and economic growth-to-energy-efficiency problem to evaluate new technology innovation in China's energy use efficiency, namely, the selection of the province of the total amount of capital formation, employment, total energy consumption as inputs, with GDP as output factors to evaluate the efficiency of the new energy technology innovation and analysis.

3.4.2. The data collection

In order to effectively evaluate and analyze the innovation efficiency status of energy and new energy industries in China's provinces, according to the availability of data This chapter selected data from 30 provinces in China from 2010 to 2019 (not included in the evaluation packet analysis and its application case unit due to the lack of new energy data in Tibet), all data are derived from the China Energy Statistics Yearbook and the China Statistical Yearbook and the New China Sixty Years Compilation. And the data according to the 2010 constant price was converted.

3.4.3. Calculation of results

Take the following as $d=1$, $\delta=0$, Data in various provinces in 2010 as the control group ($>$ sample data, using DEA - the panel model on the comprehensive efficiency of China's provinces from 2010 to 2019 value measurement, the comprehensive efficiency for each province energy new technology index as shown in Table 1.

Table 1. Comprehensive efficiency (CE) status of energy new technology innovation efficiency based on 2010 technology level in China.

Region	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Beijing	1.066	1.069	1.108	1.130	1.080	1.071	1.069	1.038	1.022	1.000
Tianjin	1.064	1.070	1.046	1.021	0.999	0.975	0.916	0.884	0.850	0.798
Hebei	0.753	0.747	0.799	0.847	0.887	0.884	0.849	0.796	0.764	0.734
Shanxi	0.832	0.836	0.852	0.826	0.774	0.755	0.734	0.704	0.669	0.653
Inner Mongolia	0.868	0.901	0.894	0.960	0.889	0.735	0.625	0.537	0.525	0.510
Liaoning	1.307	1.340	1.288	1.266	1.228	1.084	0.897	0.849	0.788	0.742
Jilin	0.952	0.943	1.062	1.014	1.006	1.019	0.952	0.845	0.672	0.625
Heilongjiang	1.048	1.165	1.230	1.182	1.107	1.209	1.147	1.159	1.120	1.000
Shanghai	1.334	1.316	1.313	1.257	1.209	1.150	1.124	1.068	1.030	1.000
Jiangsu	0.882	0.866	0.843	0.847	0.859	0.798	0.756	0.780	0.828	0.848
Zhejiang	0.909	0.899	0.888	0.908	0.878	0.802	0.782	0.795	0.840	0.847
Anhui	0.821	0.852	0.860	0.864	0.883	0.885	0.802	0.787	0.763	0.747
Fujian	0.978	0.946	0.890	0.914	0.908	0.853	0.841	0.818	0.786	0.746
Jiangxi	1.087	1.065	1.019	1.041	0.956	0.799	0.783	0.772	0.753	0.750
Shandong	0.837	0.823	0.771	0.799	0.799	0.790	0.775	0.795	0.813	0.803
Henan	0.828	0.817	0.818	0.824	0.813	0.812	0.775	0.734	0.700	0.651
Hubei	0.785	0.758	0.759	0.810	0.840	0.859	0.834	0.839	0.819	0.818
Hunan	1.126	1.171	1.193	1.118	1.040	0.985	0.900	0.879	0.833	0.818
Guangdong	0.943	0.949	0.982	0.963	1.004	0.964	0.954	0.971	1.003	1.000
Guangxi	1.035	1.036	1.026	1.003	0.957	0.895	0.838	0.777	0.729	0.690
Hainan	0.994	0.950	0.915	0.865	0.829	0.801	0.792	0.766	0.767	0.763
Chongqing	0.879	0.886	0.827	0.759	0.723	0.666	0.633	0.609	0.607	0.592
Sichuan	0.932	0.936	0.896	0.878	0.842	0.801	0.801	0.768	0.734	0.722
Guizhou	0.838	0.718	0.676	0.595	0.601	0.601	0.624	0.644	0.653	0.655
Yunnan	0.830	0.865	0.896	0.785	0.827	0.731	0.724	0.622	0.604	0.632
Shanxi	0.801	0.838	0.781	0.747	0.720	0.662	0.675	0.644	0.622	0.631
Gansu	0.809	0.778	0.782	0.729	0.707	0.702	0.710	0.726	0.733	0.729
Qinghai	0.701	0.683	0.672	0.616	0.580	0.578	0.610	0.622	0.614	0.633
Ningxia	0.676	0.663	0.650	0.607	0.575	0.539	0.510	0.493	0.504	0.511
Xinjiang	0.697	0.817	0.908	0.804	0.779	0.725	0.702	0.685	0.662	0.684

The following apply $d=1$, $\delta=1$, Data in various provinces in 2010 as control group, this is the application model (DEA - a panel) of China's provinces from 2010 to 2019 technical efficiency value measure, for each province's energy new technology innovation efficiency index as shown in Table 2.

Table 2 Technical efficiency (TE) status of China's provincial energy new technologies based on 2010 technology level

Region	2010 年	2011 年	2012 年	2013 年	2014 年	2015 年	2016 年	2017 年	2018 年	2019 年
Beijing	1.113	1.115	1.149	1.166	1.100	1.089	1.077	1.046	1.031	1.000
tianjin	1.191	1.194	1.193	1.174	1.171	1.135	1.095	1.074	1.051	1.000
Hebei	0.755	0.751	0.803	0.853	0.896	0.886	0.850	0.797	0.765	0.735
Shanxi	0.856	0.860	0.863	0.833	0.782	0.762	0.740	0.709	0.674	0.657
Inner Mongoli a	0.935	0.971	0.963	1.030	0.924	0.737	0.629	0.541	0.530	0.515
Liaoning	1.278	1.340	1.288	1.267	1.228	1.085	0.897	0.849	0.794	0.786
Jilin	1.005	0.998	1.116	1.069	1.060	1.038	0.972	0.865	0.678	0.631
Heilongji ang	1.012	1.169	1.234	1.186	1.111	1.217	1.152	1.162	1.122	1.000
Shanghai	1.328	1.318	1.314	1.260	1.212	1.152	1.114	1.061	1.031	1.000
Jiangsu	1.087	1.017	0.994	0.992	0.975	0.944	0.928	0.966	0.990	1.000
Zhejiang	0.910	0.898	0.872	0.886	0.852	0.765	0.737	0.776	0.825	0.834
Anhui	0.828	0.861	0.870	0.873	0.894	0.895	0.809	0.794	0.770	0.753
Fujian	1.020	0.988	0.917	0.952	0.935	0.883	0.870	0.846	0.813	0.770
Jiangxi	1.134	1.111	1.061	1.085	0.997	0.835	0.812	0.791	0.771	0.767
Shandon g	1.159	1.093	0.984	1.064	1.015	0.905	0.941	0.968	0.995	1.000
Henan	0.808	0.799	0.801	0.811	0.803	0.813	0.770	0.730	0.716	0.703
Hubei	0.787	0.762	0.762	0.812	0.845	0.865	0.837	0.843	0.821	0.819
Hunan	1.128	1.173	1.193	1.120	1.042	0.988	0.901	0.880	0.832	0.808
Guangdo ng	0.968	0.928	1.000	0.992	0.995	0.960	0.961	0.979	1.002	1.000
Guangxi	1.069	1.062	1.052	1.028	0.983	0.920	0.860	0.797	0.748	0.706
Hainan	1.634	1.574	1.489	1.440	1.349	1.258	1.188	1.119	1.064	1.000
Chongqi ng	0.940	0.928	0.870	0.801	0.764	0.722	0.675	0.646	0.644	0.628
Sichuan	0.929	0.932	0.892	0.875	0.843	0.802	0.802	0.767	0.730	0.711
Guizhou	0.842	0.765	0.721	0.637	0.643	0.643	0.665	0.678	0.672	0.668
Yunnan	0.854	0.891	0.924	0.811	0.854	0.757	0.748	0.643	0.624	0.650
Shanxi	0.838	0.875	0.833	0.782	0.754	0.694	0.705	0.673	0.648	0.655
Gansu	0.887	0.856	0.860	0.806	0.781	0.774	0.779	0.772	0.775	0.774
Qinghai	1.472	1.386	1.386	1.323	1.255	1.206	1.145	1.086	1.046	1.000
Ningxia	1.377	1.340	1.311	1.244	1.189	1.009	0.930	0.898	0.873	0.819
xinjiang	0.754	0.875	0.949	0.853	0.822	0.742	0.701	0.685	0.662	0.687

4. Empirical analysis and results discussion

4.1 Analysis of the average comprehensive efficiency of new energy technology innovation in China

In order to better understand the state of China's new energy technology innovation efficiency, it has been found that the efficiency of the new energy technology innovation on average changes, as seen in the data in Table 1. The average comprehensive efficiency of thirty Chinese provinces (ACE) can be determined, as shown in Table 3.

Table 3. The average comprehensive efficiency index of energy new technology innovation and utilization in Chinese provinces relative to 2019.

Year	2010	2011	2012	2013	2014
ACE	0.920	0.923	0.921	0.899	0.877
Year	2015	2016	2017	2018	2019
ACE	0.838	0.804	0.780	0.760	0.745

As can be seen from Table 3, the comprehensive efficiency of China's use of new energy technology innovation is on an overall downward trend. The efficiency index for 2010-2012 was 0.9~1, showing that the average over the past few years demonstrates that the comprehensive efficiency of new energy utilization in China's provinces was close to its best level in 2019. The pace of decline accelerated after 2013. The efficiency index for 2013-2016 was 0.8 to 0.9, and fell below 0.8 from 2017-2019, and the trend of decline has accelerated. The above analysis shows that although China in recent years has increased the intensity of its energy conservation and emissions reduction efforts, but rapid economic and social developments as well as the huge demand for energy has fueled a continued decline. Especially as China's rapid development has presented a challenge for meeting the country's energy conservation and emissions reduction goals, there is still a need to explore ways to improve the efficiency of China's use of new energy technology.

4.2 Analysis of the average technical efficiency of energy new technology innovation efficiency in China's provinces

Taking into account the data in Table 2, the average technical efficiency (ATE) of new energy technology innovation of each province in China can be given, as shown in Table 4.

Table 4. The average technical efficiency index of new energy technology innovation and utilization in China's provinces relative to 2019.

Year	2010	2011	2012	2013	2014
ATE	1.030	1.028	1.022	1.001	0.969
Year	2015	2016	2017	2018	2019
ATE	0.916	0.876	0.848	0.823	0.803

As can be seen in Table 4, the average technical efficiency of new energy technology innovation in thirty provinces is similar to the basic trend of comprehensive efficiency, but it is still slightly different. From 2010 to 2013, the average technical efficiency level of each province exceeds 1, which is better than the best level in 2019. Despite the decline in 2015, the average efficiency index is still more than 0.9. After 2016, however, the level dips below 0.9, and the trend is toward decline. This shows that although in recent years the province's average technical efficiency has been relatively good, the ten-year technical efficiency index fell by 22% on average, suggesting that improvement is needed in the energy efficiency of the new technology.

4.3 Analysis of the regional characteristics of China's new energy technology innovation efficiency

The regional characteristics of China's new energy technology innovation and utilization efficiency are evident. The new energy utilization efficiency of technological innovation and regional distribution were analyzed by division in eastern, central and western China, as well as the relationship between the eastern region and its twelve provinces, Beijing, Shanghai, Guangdong, Tianjin, Hebei, Liaoning, Jiangsu, Zhejiang, Fujian, Shandong, Guangxi and Hainan; the central region and its nine provinces, Shanxi, Inner Mongolia, Jilin, Heilongjiang, Anhui, Jiangxi, Henan, Hubei and Hunan; and

the western region and its ten provinces, Chongqing, Sichuan, Guizhou, Yunnan, Tibet, Shaanxi, Gansu, Qinghai, Ningxia and Xinjiang. According to the results of Table 1 and Table 2, thorough calculations produced the results shown in Table 5.

Table 5. State of new energy utilization efficiency in eastern, central and western China.

Year	The national average		In the east		In the middle		In the west	
	ACE	ATE	ACE	ATE	ACE	ATE	ACE	ATE
2010	0.920	1.030	1.008	1.126	0.927	0.944	0.796	0.988
2011	0.923	1.028	1.001	1.106	0.945	0.967	0.798	0.983
2012	0.921	1.022	0.989	1.088	0.965	0.985	0.787	0.972
2013	0.899	1.001	0.985	1.090	0.960	0.980	0.725	0.904
2014	0.877	0.969	0.970	1.059	0.923	0.940	0.706	0.878
2015	0.838	0.916	0.922	0.998	0.895	0.905	0.667	0.817
2016	0.804	0.876	0.883	0.960	0.839	0.847	0.666	0.794
2017	0.780	0.848	0.862	0.940	0.806	0.813	0.646	0.761
2018	0.760	0.823	0.852	0.926	0.761	0.768	0.637	0.742
2019	0.745	0.803	0.831	0.903	0.730	0.739	0.643	0.732

As can be seen from the data in Table 5, the regional characteristics of China's new energy technology innovation and utilization efficiency are obvious, as manifested in the following.

(1) The comprehensive efficiency and technical efficiency of the eastern region is significantly higher than that of the central and western regions, and the central region is also significantly better than the western region. In particular, the efficiency gap between the eastern coastal areas and the western regions is large.

(2) On average, the eastern and midwestern comprehensive efficiency and technical efficiency in 2010-2019 showed significantly lowering trends. Among them, the eastern region was average, and the western region was far below the national average. This shows a significant gap with that of the central regions.

5. Four main conclusions

Based on the panel data of thirty provincial-level administrative regions in China from 2010 to 2019, this paper uses the generalized DEA model to measure the innovation efficiency of new energy technologies in China.

(1) Although countries in recent years have increased the intensity of energy conservation and emissions reduction efforts, rapid economic and social development as well as the huge demand for energy has still led to a decline in energy efficiency. Especially given China's rapid development, energy conservation and emissions reduction remain difficult tasks and there is still a need to explore ways to improve China's energy efficiency.

(2) Although in recent years the average technical efficiency and comprehensive efficiency of each province has been relatively good, a downward trend is still evident. In the last decade the average technical efficiency index fell by 22%, suggesting that the efficiency of new energy utilization technology must be improved.

(3) The comprehensive efficiency and technical efficiency of the eastern region is significantly higher than that of the central and western regions, and the efficiency of the central region is significantly better than that of the western region. In particular, the efficiency gap between the eastern coastal areas and the western regions is large. Therefore, the comprehensive efficiency and technical efficiency of new energy technologies in China's provinces are extremely unbalanced.

(4) The comprehensive efficiency and technical efficiency of the eastern and western regions showed a significant downward trend from the average level between 2010 and 2019. This demonstrates a significant gap in energy use efficiency between the western and central regions. Therefore, it is extremely important to adjust the energy consumption structure and increase the energy utilization efficiency of the western region.

The technical efficiency and comprehensive efficiency gap between the east and west are very large. It will be extremely beneficial for the country to reduce this gap and improve the efficiency of new energy technology innovation. The government must further promote energy conservation and emissions reduction through policy, laws and regulations, to strengthen the ecological environment and construct an ecologically conscious built environment. The government can leverage relevant new technologies and renewable energy policies toward the furtherance of these goals.

Although our research has some theoretical and practical significance, it does contain some shortcomings. First, no in-depth research has been conducted on the evaluation and analysis by energy enterprises of new energy technology innovation efficiency, which has resulted in incomprehensive research on the innovation efficiency of new energy technologies. Secondly, because of the lack of a professional energy database, this paper takes into account the availability of data in the selection of variables, which is bound to cause errors in measurement results.

Declarations

(1) Availability of data and materials

Data sharing not applicable to this article as the data of the paper is too long to save.

(2) Competing Interest

There is no interest competition in this paper.

(3) Funding

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(4) Authors Contribution

LMY drafted the manuscript, WYL is the Corresponding author and Responsible for revising the relevant wording. HYZ Conceived this paper.

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