

## Research Article

# Evaluation and Prediction of Wind Power Utilization Efficiency Based on Super-SBM and LSTM Models: A Case Study of 30 Provinces in China

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Although China's wind industry has made great progress in recent years, the wind abandonment phenomenon caused by the unbalanced development of regional wind power is still prominent. It is particularly important for the scientific development of wind power to accurately measure the utilization efficiency of wind power and understand its regional differences in China. This study establishes the improved super-efficiency slack-based measure (Super-SBM) model and long short-term memory (LSTM) network models, systematically and comprehensively measures and predicts the wind power utilization efficiency of 30 regions in China from 2013 to 2020, and explores regional differences in wind power utilization efficiency. Our results show the following: (1) China's overall wind power utilization efficiency is relatively low but has been on a steady upward trend since 2013. (2) Regional differences are obvious, showing that the spatial distribution pattern of wind power utilization efficiency is greatest in Northeast China, followed by North China, East China, South China, Northwest China, and Central China. The "Three-North" region with abundant wind energy resources has relatively high wind power utilization efficiency and exhibits a good development trend. East China, South China, and Central China, where wind energy resources are relatively poor, have low wind power utilization efficiency, and their development trends are not stable and are more prone to change. (3) The utilization efficiency of wind power in coastal areas is generally better than that in inland areas. There are also differences among the thirty Chinese regions studied. Inner Mongolia and Shandong have achieved real efficiency in wind power utilization efficiency, with optimal allocation of input and output, and a good development trend. The other 28 regions have varying degrees of inefficiency, and there is still room for improvement.

## 1. Introduction

Since the beginning of the 21st century, energy security issues, ecological protection issues, and climate change issues have developed into global issues and the power industry is closely related to them [1]. Improving the proportion of renewable energy is an important way for countries to achieve a low-carbon energy transition at this stage. Deepening the power market reform and accelerating the consumption of clean energy have become major issues facing countries worldwide [2]. Wind power is an energy generation method that can effectively save coal resources and reduce carbon emissions [3]. As an environmentally

friendly and socially beneficial power generation method, it is not only the main wind energy utilization form but also the best choice to replace conventional energy. In China, wind power has become the main form of renewable energy and has gradually developed into the main driver in the promotion of the low-carbon transition of energy [4]. In recent years, China's installed wind power capacity has shown a high growth, prompting China's renewable energy development to enter a new stage. At the same time, the substantial increase in wind power installed capacity will affect the stable operation of the entire power system, and the phenomenon of wind abandonment caused by regional wind power development imbalance has become

increasingly prominent, which could eventually become a major constraint to the healthy and sustainable development of wind power in China [5, 6]. By the end of 2019, China's wind power installed capacity exceeded 210 million kilowatts, which is nearly 10.4% of the national power generation capacity. However, wind power generation reached 405.7 billion kWh in 2019, and the ratio of wind power generation accounted for 5.5% of total power generation. This means that nearly half the wind power units were not operating, and the performance was worse in some major wind power regions.

Here, we develop a comprehensive and objective wind power utilization efficiency evaluation system. Based on this, we use the improved super-efficiency slack-based measure (Super-SBM) model and long short-term memory (LSTM) network to measure and predict wind power utilization efficiency in thirty Chinese regions and to study regional differences in the development of wind power utilization efficiency. We then provide a theoretical basis and suggestions for governments at all levels to formulate wind power development strategies.

Currently, there are relatively few studies on wind power efficiency. From the existing literature, Pan et al. [7] used a metafrontier data envelopment analysis (MA-DEA) model to measure and analyze the wind power efficiency of 30 regions in China from 2011 to 2014. On this basis, a symbolic regression model was used to test the influencing factors of wind power efficiency. Wang and Sun [8] used the clustering-analysis (CA) and data envelopment analysis (DEA) model to conduct an empirical analysis of the efficiency of 40 large-scale typical wind farms in China in 2012. It was found that the wind farms were relatively mature in terms of technology, but the scale was generally small. The next step should be to improve the management level and expand the industrial scale. Yang and Zhang [9] studied 30 wind power companies in China as examples, using the Malmquist productivity index method to measure the production efficiency of the wind power industry from 2007 to 2011. Their study found that the overall efficiency of the wind power industry was low and is still in the growth stage. The contribution of technological progress is greater than the contribution of internal management improvement. Liu et al. [10] analyzed and compared the efficiency level of the wind power industry in China from 2008 to 2012 based on the traditional DEA model. They pointed out that the efficiency of China's wind power industry is showing an upward trend, while the efficiency of the wind turbine manufacturing industry is on a downward trend. Pieralli et al. [11] used nonconvex efficiency analysis to study the production efficiency of 19 wind turbines across Germany and explained electricity losses by means of a bias-corrected truncated regression analysis. Wei et al. [12] and Gao et al. [13] conducted research on the efficiency of technological innovation in the wind power industry. Wei et al. used the DEA-Tobit model to measure the technical efficiency of China's wind power industry and conducted empirical tests on its influencing factors. Gao et al. used the three-stage DEA model to measure the innovation efficiency of China's wind power industry and conduct a convergence test on it. Li

and Wu [14] took 30 listed companies from the upper, middle, and lower reaches of China's wind power industry chain as samples and analyzed the financial support efficiency of China's wind power industry by DEA-Malmquist model from two perspectives (i.e., financing and distribution). The results show that the efficiency of financial support in China's wind power industry fluctuates greatly, with the problem that the industry lacks core technologies. Zhao et al. [15] used a super-efficiency DEA and Malmquist index model to measure and analyze the economic efficiency of wind power in China's Three-North region. Wang et al. [16] used the BCC model to analyze and evaluate the utilization efficiency of wind energy resources in 25 regions in China from 2014 to 2015 and analyzed the influencing factors of utilization efficiency. Sağlam [17–19] used a two-stage DEA model to calculate the wind power utilization efficiency of large wind farms in the United States.

Dong and Shi [20] built a DEA-TOPSIS-time series three-stage dynamic evaluation prediction model, which provides a new set of research ideas for wind power generation in China. Zhong et al. [21] constructed an SD model to simulate and evaluate China's regional wind power performance starting from the demand side and then looking at the grid and power generation sides. Papież et al. [22] constructed a wind power investment efficiency evaluation system consisting of wind power generation capacity; average wind power density; wind power generation; and environmental, economic, and energy security indicators. They used a two-stage deviation correction DEA model to evaluate the efficiency of wind power investment in EU countries in 2015 and empirically tested the impact of renewable energy policy on wind power efficiency. Zhao and Zhen [23] used a four-stage DEA model to analyze the technical efficiency of Chinese wind power companies based on the micro data of listed wind power companies. Studies have found that diseconomies of scale are the main reason for the low technical efficiency of wind power enterprises. Dong and Shi [24] constructed a DEA-TOPSIS model to evaluate the wind energy performance of 29 regions in China from 2011 to 2018. Based on this, they used the ANFIS forecasting model to predict and analyze the wind power performance of 29 regions in China in 2019 and established a regression model to test the main factors affecting China's wind performance. Yang et al. [25] designed and developed a bottom-up material flow analysis model to study the material efficiency of China's wind power infrastructure system from 1989 to 2018 to help China's wind power industry realize its green transformation. Aquila et al. [26] used an NBI-RSM-DEA model to optimize wind farm efficiency measures in order to maximize the overall welfare of the electricity sector. It can be seen that the existing literature mainly focuses on measurement research and the measurement model mainly focuses on the traditional DEA model. The research scope includes wind power utilization efficiency, technical efficiency, economic efficiency, and investment efficiency. The research scale includes countries, regions, wind power industries, and wind farms.

The above analysis shows that wind power research is still in its early stages, and there are still many deficiencies.

First, the existing research only uses regression models to examine the impact of wind curtailment rate and wind curtailment power on wind power utilization efficiency but does not include them in the efficiency evaluation framework and cannot accurately reflect the true level of wind power utilization efficiency. Second, the existing research does not consider the carbon dioxide emissions generated by wind power when measuring wind power utilization efficiency, which will bias the measurement results. Third, the measurement model of the existing research is mainly based on the traditional DEA model. This type of model cannot solve the problem of slack variables, and, at the same time, it cannot effectively sort units with an efficiency value of one. Fourth, the research mainly relies on simple measurement and methods to test its influencing factors and lacks more in-depth research such as time-space analysis, prediction, and simulation. In light of this, we attempt to expand the research by (1) taking wind curtailment power and carbon dioxide emissions as undesired outputs and including them in the wind power utilization efficiency evaluation framework, (2) using the unexpected output Super-SBM model to measure wind power utilization efficiency in 30 regions in China, and (3) using the LSTM model to predict and analyze the wind power utilization efficiency of 30 regions in China in 2020.

The rest of this paper is organized as follows. Section 2 introduces the DEA model and LSTM model. Section 3 describes the evaluation indicators and data sources. Section 4 provides the empirical results and specific analysis and consists of two main elements: wind power utilization efficiency measurement analysis and wind power utilization efficiency prediction analysis. Conclusion and policy suggestions are given in Section 5.

## 2. Materials and Methods

**2.1. Super-SBM Model with Undesirable Outputs.** Data envelopment analysis (DEA) is a nonparametric analysis method that uses linear programming to evaluate the relative effectiveness of comparable decision-making units. Since its introduction by American operations researchers Charnes and Cooper, it has been widely used in many fields and has become one of the most popular technical tools for evaluating relative efficiency [27]. Traditional DEA models mainly include CCR model and BCC mode [28, 29]. Although these two models can measure efficiency using both radial and angle parameters, they cannot solve the slack problem of input and output. Based on the shortcomings of the traditional DEA model, Tone proposed the SBM-DEA model in 2001 [30]. The SBM model can add slack variables to the target function directly, so that the slack problem can be solved. However, with the in-depth study, the shortcoming of the SBM model to ignore undesirable outputs gradually emerged. Thus, Tone constructed a new SBM program that can incorporate undesired outputs into the evaluation framework:

$$\begin{aligned} \rho^* = \min & \frac{1 - (1/m) \sum_{i=1}^m s_i^- / x_{ik}}{1 + (1/(p_1 + p_2)) (\sum_{r=1}^{p_1} (s_r^+ / y_{rk}) + \sum_{t=1}^{p_2} (s_t^{b-} / b_{rk}))} \\ & X\lambda + s^- = x_k \\ & Y\lambda - s^+ = y_k \\ \text{s.t.} & \\ & B\lambda + s^{b-} = b_k \\ & \lambda, s^-, s^+ \geq 0, \end{aligned} \quad (1)$$

where  $\rho^*$  represents the objective efficiency value;  $\lambda$  represents the intensity vector;  $m$  and  $s^-$  represent the numbers of inputs and the slacks in inputs, respectively;  $p_1$  and  $p_2$  stand for the numbers of desirable and undesirable outputs, respectively;  $s^+$  and  $s^{b-}$  stand for the slacks in desirable and undesirable outputs, respectively.

The objective efficiency value  $\rho^*$  measured from equation (1) is 0-1. If  $\rho^* = 1$  and  $s^- = 0$ ,  $s^+ = 0$ , and  $s^{b-} = 0$ , then the DMUs are efficient. If  $0 < \rho^* < 1$ , it means that the DMUs are inefficient. The input and output need to make the necessary improvements. However, the efficiency measurement results usually show that multiple DMUs are evaluated as effective. As the efficiency values of effective DMUs are all 1, it is impossible to further distinguish the efficiency ranking among effective DMUs. Therefore, Tone proposed a Super-SBM model that can effectively rank DMUs in 2002 [31].

The Super-SBM model cannot consider undesirable outputs. In order to measure wind power utilization efficiency more accurately, we used an improved Super-SBM model that can consider undesired outputs [32]:

$$\begin{aligned} \rho^* = \min & \frac{1 - (1/m) \sum_{i=1}^m (s_i^- / x_{ik})}{1 - (1/(p_1 + p_2)) (\sum_{r=1}^{p_1} (s_r^+ / y_{rk}) + \sum_{t=1}^{p_2} (s_t^{b-} / b_{rk}))} \\ & \sum_{i=1, j \neq k}^n x_{ij} \lambda_j - s_i^- \leq x_{ik} \\ & \sum_{j=1, j \neq k}^n y_{rj} \lambda_j + s_r^+ \geq y_{rk} \\ \text{s.t.} & \\ & \sum_{j=1, j \neq k}^n b_{tj} \lambda_j - s_t^{b-} \leq b_{tk} \\ & 1 - \frac{1}{p_1 + p_2} \left( \sum_{r=1}^p \frac{s_r^+}{y_{rk}} + \sum_{t=1}^p \frac{s_t^{b-}}{b_{rk}} \right) > 0 \\ & \lambda, s^-, s^{b-} \geq 0 \\ & i = 1, 2, \dots, m; r = 1, 2, \dots, p; j = 1, 2, \dots, n (j \neq k). \end{aligned} \quad (2)$$

**2.2. LSTM Model.** A recurrent neural network (RNN) is a recursive neural network that takes sequence data as the input recursively in the evolution direction of the sequence, and all nodes (recurrent units) are connected in a chain [33]. Its use began in the 1980s and 1990s, and it has developed into one of the most important algorithms of deep learning in the 21st century. The traditional recurrent neural network can solve the problem of short-term dependence, but, due to its lack of memory, when the span between the memory information and the predicted position is too large, the network cannot remember the longer time series values, which makes the RNN worse. It is getting harder to learn this information. Therefore, in response to the problem of time dependence, people have proposed some variants of recurrent neural networks, among which the most popular structure is the long short-term memory [34].

The long short-term memory (LSTM) network was proposed by Hochreiter and Schmidhuber in 1997 [35]. Its innovation lies in the design of memory modules to solve the long-term dependence of recurrent neural networks. The memory modules control the flow of information in sequences by introducing gate operations to increase the memory time, filtering out unimportant information [36]. The recurrent neural network based on LSTM units is composed of a series of repeated LSTM units. Each LSTM unit is equipped with a memory cell that judges whether the information is useful or not and includes three gates (i.e., input gate, output gate, and forget gate). The details are shown in Figure 1.

The forget gate determines whether to retain the memory from the previous moment. Opening the forget gate means keeping the memory of the previous moment. Closing the forget gate signifies clearing the memory of the previous moment. The input gate determines how much input to keep. The importance of the input information at each moment in the sequence input is different. When the input information is useless, the input gate is closed. The output gate determines whether to output the current memory information immediately; if the output gate is opened, the current memory information is output, while if the output gate is closed, the current memory information will not be output.

Figure 2 is a schematic diagram of the internal structure of the LSTM, where  $f_t$ ,  $i_t$ , and  $o_t$  represent the forget gate, input gate, and output gate, respectively.  $C$  is a memory cell,  $C_{t-1}$  represents the memory information of the previous moment,  $C_t$  represents the memory information of the current moment,  $h_t$  is the output of the LSTM unit, and  $h_{t-1}$  is the output of the previous moment. It can be seen from Figure 2 that the line from  $C_{t-1}$  to  $C_t$  through the LSTM unit can be called the memory cell state, which stores the data processed by the three gates.

The task of the LSTM unit is to receive the output data at the previous time and the input data at the current time, complete the modification and calculation of the cell state, and generate the output at the current time. The LSTM model has two hidden states, and the number of model parameters is almost four times greater than that in an RNN.

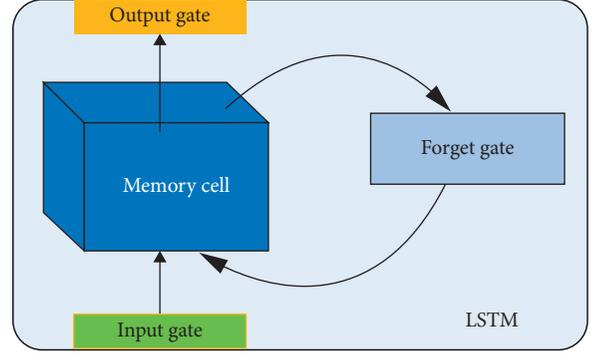


FIGURE 1: LSTM unit internal structure.

The following introduces the internal operation mode of LSTM and the specific representation of the input, forget, and output gates.

The calculation process for the forget gate first combines the network output  $h_{t-1}$  at time  $t-1$  with the network input  $x_t$  of this step. Then, a linear transformation is performed, and an activation function applies the result to a value between 0 and 1, which is denoted as  $f_t$ , also known as the memory attenuation coefficient. The specific calculation formula is as follows:

$$f_t = \sigma(W_f \cdot [h_{t-1}, x_t] + b_f). \quad (3)$$

The calculation process of the input gate is then entered. The calculation process is the same as the first step:

$$i_t = \sigma(W_i \cdot [h_{t-1}, x_t] + b_i). \quad (4)$$

Then, we calculate the memory learned at time  $t$ . It is calculated by a linear transformation  $W_C \cdot [h_{t-1}, x_t] + b_C$  and tanh activation function. The specific formula of the calculation process is as follows:

$$\bar{c}_t = \tanh(W_c \cdot [h_{t-1}, x_t] + b_c). \quad (5)$$

We then calculate the memory state at time  $t$ . The memory state  $C_t$  at time  $t$  is calculated on the basis of the above three steps. The specific formula is as follows:

$$c_t = f_t * c_{t-1} + i_t * \bar{c}_t. \quad (6)$$

The calculation process of the output gate uses a similar memory attenuation coefficient method to calculate the output gate coefficient  $o_t$ :

$$o_t = \sigma(W_o [h_{t-1}, x_t] + b_o). \quad (7)$$

We then calculate the output of the network.  $C_t$  and  $x_t$  jointly determine the output  $h_t$  at the current moment. Finally, the output of the network is calculated by the following:

$$h_t = o_t * \tanh(c_t). \quad (8)$$

Through the three gates in the internal structure of LSTM, the long-term dependence problem can be solved. Therefore, this paper uses the LSTM model to predict and

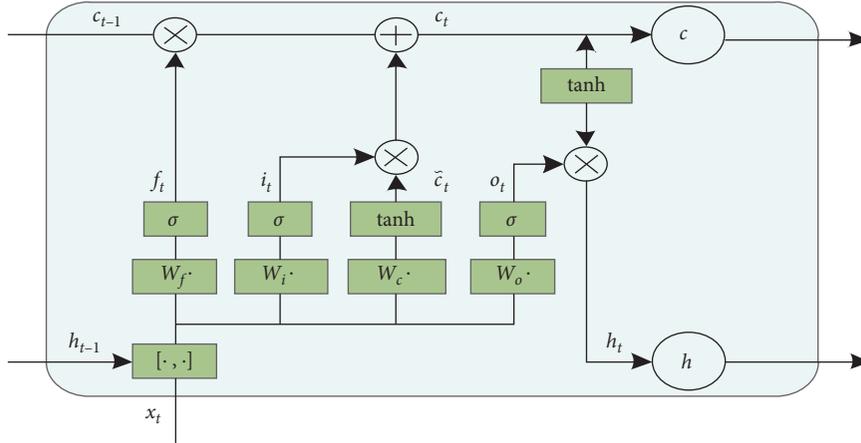


FIGURE 2: Development of the LSTM unit on the time axis.

analyze the wind power utilization efficiency for 30 regions in China in 2020.

### 3. Indicator Selection and Data Sources

In this study, three evaluation indicators of wind power utilization efficiency were used, input, desired output, and undesired output, as shown in Table 1.

Table 1 shows the variables used in this article. The input indicators include wind power installed capacity and wind power utilization hours, the desired output indicator is wind power generation, and the undesired output indicators are curtailed wind power and carbon dioxide emissions. Among them, the four indicators can be obtained directly from the China Electric Power Statistical Yearbook. The carbon dioxide emissions need to be estimated. This estimation is calculated as follows:

$$\text{CO}_2 = \text{wind power generation} \times \text{wind power carbon emission factor.} \quad (9)$$

The wind power generation can be obtained directly, and the wind power carbon emission coefficient refers to the median emission intensity of wind power given by the World Nuclear Energy Association and was set to 26 g/kWh.

This study covered 30 regions in China (four municipalities, four autonomous regions, and 22 provinces) from 2013 to 2020. Due to data availability, Tibet, Hong Kong, Macao, and Taiwan were excluded. For the convenience of research, these 30 regions are called provinces hereafter. At the same time, referring to the classification standard of the National Energy Administration of China, the 30 provinces are divided into six areas, as shown in Figure 3. The data mainly come from the “China Electric Power Yearbook” and the statistics of wind power grid-connected operation disclosed by the National Energy Administration of China.

## 4. Empirical Analysis

**4.1. Measurement and Analysis of Wind Power Utilization Efficiency.** According to the Super-SBM model considering undesirable output, we measured the wind power utilization

TABLE 1: Index system of wind power utilization efficiency.

Variable	Index	Unit
Input	Wind power installed capacity	100 million kW
	Wind power utilization hours	Hours
Desired output	Wind power generation	100 million kW
Undesired output	Curtailed wind power	100 million kW
	Carbon dioxide	10,000 tons

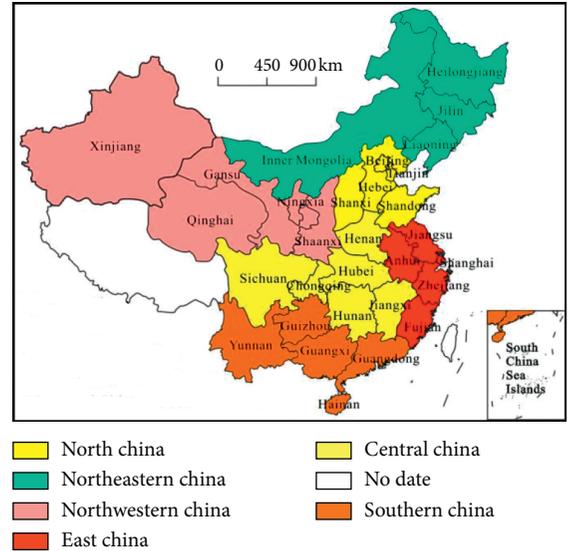


FIGURE 3: Six regions of China.

efficiency for 30 provinces between 2013 and 2019, which is displayed in Figure 4 and Tables 2 and 3.

According to Figure 2 and Table 3, at this stage, China’s overall wind power utilization efficiency is relatively low. The seven-year average efficiency is 0.5861, and the efficiency is between 0.5374 and 0.6454, showing an upward trend, with an average annual growth rate of 3.09%. It can be seen that while China has abundant wind energy resources and the

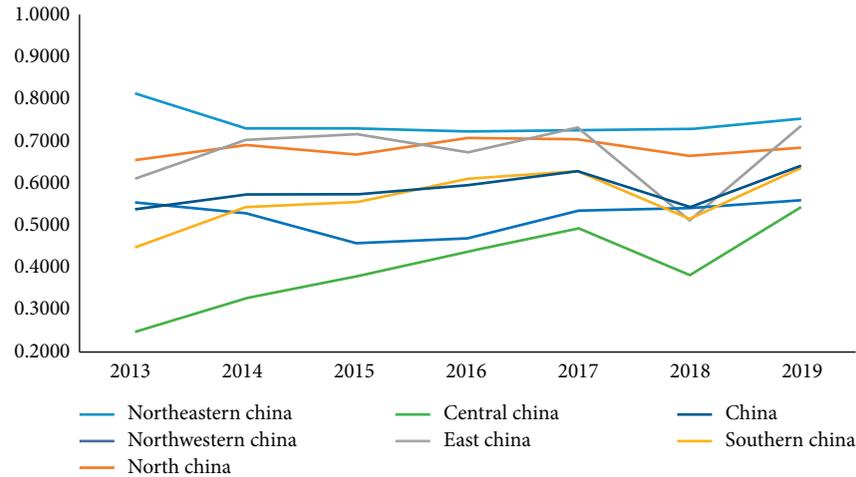


FIGURE 4: The development trend of wind power utilization efficiency in six regions in China.

TABLE 2: Wind power utilization efficiency of 30 provinces (2013–2019).

	2013	2014	2015	2016	2017	2018	2019	Means	Rank
Inner Mongolia	1.0628	1.2276	1.2068	1.1676	1.1657	1.1781	1.1495	1.1654	1
Shandong	1.2082	1.0733	1.1188	1.1410	1.1325	1.0299	1.0732	1.1110	2
Fujian	1.0884	1.0727	1.1190	1.0634	1.0841	0.5190	1.0278	0.9963	3
Yunnan	0.7269	1.0127	0.6789	1.0263	1.0574	1.0742	1.0832	0.9514	4
Jiangsu	0.6681	1.1232	1.1002	0.7318	1.0218	0.8032	1.1398	0.9412	5
Hebei	0.8524	0.6288	0.8145	1.0081	1.0134	0.9166	0.8716	0.8722	6
Ningxia	1.0054	0.8879	0.6067	0.6897	0.7854	0.7968	0.7006	0.7818	7
Shanxi	0.4841	1.0415	0.7174	0.7072	0.7667	0.9060	0.8377	0.7801	8
Liaoning	1.0061	0.7838	0.8231	0.7417	0.7113	0.6463	0.7461	0.7798	9
Guangdong	0.5420	0.6861	0.8391	0.6816	0.6892	0.4511	0.5724	0.6373	10
Xinjiang	0.5950	0.5409	0.4256	0.5693	0.6437	0.6182	0.6900	0.5833	11
Heilongjiang	0.6598	0.4868	0.4851	0.5698	0.5684	0.5691	0.5975	0.5624	12
Gansu	0.7467	0.5150	0.4642	0.4437	0.4894	0.5412	0.6040	0.5435	13
Anhui	0.3873	0.4490	0.5410	0.5884	0.5775	0.4263	0.5003	0.4957	14
Zhejiang	0.4844	0.4590	0.4594	0.5163	0.4911	0.3840	0.5502	0.4778	15
Hubei	0.2334	0.4467	0.4749	0.4823	0.6119	0.4492	0.6394	0.4768	16
Guizhou	0.3159	0.3473	0.6077	0.5189	0.6315	0.4263	0.4895	0.4767	17
Jilin	0.5189	0.4227	0.4033	0.4121	0.4604	0.5293	0.5141	0.4659	18
Hunan	0.2937	0.2988	0.5005	0.5304	0.6254	0.4121	0.4152	0.4395	19
Shanghai	0.4333	0.4224	0.3749	0.4670	0.4962	0.4115	0.4561	0.4373	20
Guangxi	0.2673	0.3377	0.2933	0.4434	0.4323	0.3967	0.7190	0.4128	21
Jiangxi	0.3308	0.3294	0.3877	0.4344	0.5058	0.3795	0.5206	0.4126	22
Sichuan	0.1527	0.2372	0.3147	0.4191	0.4682	0.4525	0.7987	0.4062	23
Shaanxi	0.3120	0.4150	0.4834	0.3091	0.4501	0.4260	0.4410	0.4052	24
Henan	0.3203	0.3499	0.3702	0.4287	0.3968	0.3482	0.5386	0.3932	25
Tianjin	0.3923	0.3778	0.3643	0.3983	0.3545	0.2468	0.3726	0.3581	26
Hainan	0.3994	0.3395	0.3673	0.3855	0.3409	0.2310	0.3186	0.3403	27
Beijing	0.3536	0.3410	0.3331	0.2900	0.2583	0.2387	0.2771	0.2988	28
Qinghai	0.1130	0.2805	0.3120	0.3437	0.3064	0.3207	0.3646	0.2916	29
Chongqing	0.1680	0.3103	0.2262	0.3541	0.3674	0.2544	0.3524	0.2904	30
China	0.5374	0.5748	0.5738	0.5954	0.6301	0.5461	0.6454	0.5861	

utilization efficiency of wind power has also shown an upward trend in recent years, the overall utilization efficiency is still relatively low. The main reason is that China's wind power resources are unevenly distributed in space and the policy environment for wind power development lacks stability. Key issues such as wind power consumption, wind curtailment, and wind power grid integration have not been

resolved, and the technological level and innovation capabilities are somewhat lacking. The current situation is a result of the combined influence of these issues.

From a regional perspective, the efficiency of wind power utilization in Northeast China is the highest. The average 7-year efficiency is 0.7434, and the efficiency is between 0.7228 and 0.8118 but shows a downward trend, with an average

TABLE 3: Wind power utilization efficiency of six regions (2013–2019).

	2013	2014	2015	2016	2017	2018	2019	Means	Rank
Northeast China	0.8119	0.7302	0.7296	0.7228	0.7265	0.7307	0.7518	0.7434	1
North China	0.6581	0.6925	0.6696	0.7089	0.7051	0.6676	0.6864	0.6840	2
East China	0.6123	0.7053	0.7189	0.6734	0.7341	0.5088	0.7348	0.6697	3
Southern China	0.4503	0.5446	0.5572	0.6111	0.6302	0.5159	0.6365	0.5637	4
Northwestern China	0.5544	0.5279	0.4584	0.4711	0.5350	0.5406	0.5600	0.5211	5
Central China	0.2498	0.3287	0.3790	0.4415	0.4959	0.3826	0.5441	0.4031	6
China	0.5374	0.5748	0.5738	0.5954	0.6301	0.5461	0.6454	0.5861	

annual growth rate of  $-1.27\%$ . North China is ranked second, with an average efficiency of 0.6840 for the past seven years and an efficiency value between 0.6581 and 0.7089 but shows a slight upward trend, with an average annual growth rate of 0.70%. Northeast China and North China have the most abundant wind power resources, with high economic development, advanced wind power technology and equipment, reasonable energy structure, and high demand for clean energy. They have more advantages in terms of technology, scale, and policies, so that their wind power utilization efficiency has always been in a leading position. East China is third, with an average 7-year efficiency of 0.6697 and an efficiency value between 0.5088 and 0.7348, showing an upward trend, with an average annual growth rate of 3.08%. South China is fourth, with an average efficiency of 0.5637 in the past seven years and an efficiency value between 0.4303 and 0.6365, showing an upward trend, with an average annual growth rate of 5.93%. East China and South China are located on the eastern coast, with long coastlines, high effective wind energy density, and faster wind speeds, making them rich in wind energy resources. In addition, their economy is highly developed, and their capital, equipment, technology, and talent advantages are clear. It has advantages over Northwest China and Central China in terms of wind power utilization efficiency. The fifth ranked area is Northwest China, with an average efficiency of 0.5211 in the past seven years and an efficiency value between 0.4711 and 0.5600, showing a slight upward trend, with an average annual growth rate of 0.16%. Although the Northwest region has abundant wind energy resources, its economic development is relatively lacking, its wind energy technology and equipment are outdated, and talent attraction is low. The energy structure is still dominated by fossil fuel energy, and the demand for clean energy is low, meaning its advantages in wind energy resources are not fully utilized, and wind power utilization efficiency cannot be effectively improved. The sixth ranked area is Central China, with a seven-year average efficiency of 0.4031 and an efficiency value between 0.2498 and 0.5451, showing a significant upward trend, with an average annual growth rate of 13.8%. Central China is located inland, with relatively scarce wind energy resources and low effective wind energy density. It also has no advantages in terms of capital, talents, technology, equipment, and so forth, making its wind power utilization efficiency far behind other regions. It can be seen that there are differences in the utilization efficiency of wind power across the six regions, showing a spatial distribution pattern of Northeast China > North China > East

China > South China > Northwest China > Central China, which is basically consistent with China's wind power resource endowment pattern. At the same time, the utilization efficiency of wind power in coastal areas is generally better compared with inland areas.

At the provincial level, the average wind power utilization efficiencies of Inner Mongolia and Shandong are 1.1654 and 1.1100, respectively, and the wind power utilization efficiencies in 2013–2019 were both greater than 1, which is truly effective. This shows that the utilization efficiency of wind power in these regions is high, and the input and output are in an effective state and reach the optimal configuration. Specifically, Inner Mongolia has superior wind power resources. The total wind energy resources account for 50% of the country. It is in a leading position in terms of scale and technology. Coupled with the key support of the country, the efficiency of wind power utilization is effective. Shandong has an advantageous geographical location, a long coastline, abundant wind energy resources, a well-developed electric power industry, and advanced wind power technology and equipment, making its wind power utilization efficiency effective. The provinces with high wind power utilization efficiency are Fujian, Yunnan, and Jiangsu. Their average wind power utilization efficiency is 0.9963, 0.9514, and 0.9412, respectively, and their wind power utilization efficiency is greater than 1, which is effective in most but not all years. It shows that the input and output of these regions are in an effective or close to effective state, and the input-output gap is small but not stable enough, so there is room for improvement. Specifically, as early as 2001, Fujian developed wind power in a joint venture with Spain, introduced and absorbed advanced technology earlier, and has maintained its advantage. At the same time, the range of available wind power in Fujian is relatively concentrated, which makes it easy to form scale advantages. Yunnan is located on the Yunnan-Guizhou Plateau, and, due to its high mountainous terrain, its wind energy resources are relatively high in China. In addition, Yunnan has consistently ranked among the best in terms of average annual wind power utilization hours, making its wind power utilization efficiency reach a high level. However, Jiangsu has similar development conditions to Shandong, resulting in a high level of wind power utilization efficiency. The provinces with relatively high wind power utilization efficiency are Hebei, Ningxia, Shanxi, Liaoning, and Guangdong. The average wind power utilization efficiency is above 0.6, which is higher than the national average, and can be effective in individual years. It shows that although the input and output

of these provinces are in an ineffective state, the gap between input and output is small and there is good room for improvement. These provinces are all located in the “Three-North” region or coastal areas rich in wind energy resources. They also have certain advantages in terms of capital, technology, and scale, which enable them to have high wind power utilization efficiency. The average wind power utilization efficiency of the other 20 provinces is below the national average. The average wind power utilization efficiency of Xinjiang, Heilongjiang, and Gansu is higher than 0.5, and the average wind power utilization efficiency of 11 provinces including Anhui and Zhejiang is between 0.4 and 0.5. The input and output of these provinces are in an ineffective state, and the input and output do not match, so it is difficult to upgrade. For example, although Gansu Province is located in an advantageous wind area, its grid structure is not optimal and the allocation of wind power resources is wasteful. In addition, the blind expansion of wind power scale makes it impossible to match power transmission and power sales capabilities, which directly leads to a decline in wind power utilization efficiency. The average wind power utilization efficiency of Henan, Tianjin, and Hainan is between 0.3 and 0.4, and the average wind power utilization efficiency of Beijing, Qinghai, and Chongqing is the lowest, at less than 0.3. This shows that the input and output of these provinces are in an ineffective state, and the input and output are mismatched, making it difficult to upgrade. For example, Hainan is dominated by offshore wind power, and the requirements of offshore wind power in terms of units, technology, personnel quality, and construction cost are much higher than those of onshore wind power; moreover, the stability of sea wind is poor, which makes it difficult to increase the hours of wind power utilization in Hainan. It can be seen that there are obvious differences in wind power utilization efficiency across China’s 30 provinces. Provinces with high wind power utilization efficiency are mainly distributed in the “Three-North” region and coastal areas, while provinces with low wind power utilization efficiency are mainly distributed inland.

From the perspective of the average annual growth rate of each province, the average annual growth rate of the 20 provinces is positive, showing an upward trend during the study period. Among them, the average annual growth rate of Sichuan, Qinghai, Hubei, Guangxi, and Chongqing is above 10%, showing a good upward trend. The average annual growth rate of eight provinces, including Shanxi and Jiangsu, is between 5% and 10%, showing a good upward trend, but the growth is not stable enough. The average annual growth rate of seven provinces, including Anhui and Xinjiang, is between 1% and 5%, showing a relatively stable upward trend. The average annual growth rate of 10 provinces is negative, showing a relatively stable downward trend during the study period. Among them, the average annual growth rates of Jilin, Tianjin, Fujian, Heilongjiang, and Shandong are between  $-0.155\%$  and  $-2\%$ , while the average annual growth rates of Gansu, Hainan, Beijing, Liaoning, and Ningxia are between  $-2\%$  and  $-6\%$ . It can be seen that provinces with low wind power utilization efficiency have higher average annual growth rates, showing a

good upward trend. Among the bottom 20 provinces in terms of wind power utilization efficiency, 14 provinces have a positive annual growth rate, showing an upward trend, accounting for 70%. Among the bottom 10 provinces in terms of wind power utilization efficiency, seven provinces have a positive average annual growth rate, and the average annual growth rate is higher than 5%, showing a significant upward trend. The 70% of provinces with high wind power utilization efficiency have low average annual growth rates, and some even show negative growth. Among them, Shanxi, Jiangsu, and Yunnan have relatively high average annual growth rates, showing an upward trend. Inner Mongolia, Hebei, and Guangdong have low average annual growth rates, showing a weak growth trend. However, the average annual growth rates of Fujian, Shandong, Liaoning, and Ningxia are negative, showing varying degrees of downward trends. At the same time, Beijing, Tianjin, Hainan, and other provinces also showed a downward trend.

## 4.2. Wind Power Utilization Efficiency Forecast

### 4.2.1. Application of the LSTM Model.

This paper takes the value of wind power utilization efficiency from 2013 to 2019 in 30 provinces as the known data and establishes an LSTM model using Python software. Since the LSTM neural network has higher requirements for input data, we used the z-score algorithm for standardization of all input data. LSTM processes  $X_{t-n}, X_{t-n+1}, \dots, X_{t-1}, X_t$ , these  $n$  time series data, including  $s$  features as input to predict the output at the  $(t+1)$ th time. We took the data from the previous three years as the input to predict the wind power utilization efficiency in the next year. We used a two-dimensional vector of  $n$  (time series)  $\times s$  (features per time series) as input ( $n = 6$  and  $s = 3$ ). The LSTM model in this paper contains six input indicators: the five input-output indicators used in Section 3 and the measurement value of wind power utilization efficiency and one output indicator, the forecasted value of wind power utilization efficiency. The model consisted of a total of 120 samples; we randomly selected 30% as test samples and 70% as training samples. In the prediction of deep neural networks, a single LSTM network cannot achieve prediction, and it is often necessary to connect a convolutional layer or a fully connected layer to achieve the output of the prediction result [37–39]. This paper adopts the method of constructing an LSTM network and fully connected layer to improve the model prediction accuracy. Generally speaking, the deeper the deep learning network, the better the expression effect of the neural network [40–42].

The Keras function in Python was used to obtain the membership function type. The training samples and the test samples were obtained as shown in Figures 5 and 6. The MAPE, MSE, and RMSE of the training sample set were 0.1668, 0.0119, and 0.1091, and the MAPE, MSE, and RMSE of the test sample set were 0.1428, 0.0158, and 0.1260, respectively. It can be seen that the prediction results of the training set and the test set of the LSTM model are highly accurate, and the predicted wind power utilization efficiency

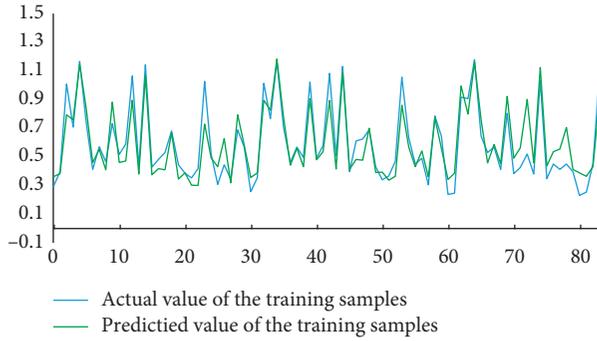


FIGURE 5: The training samples.

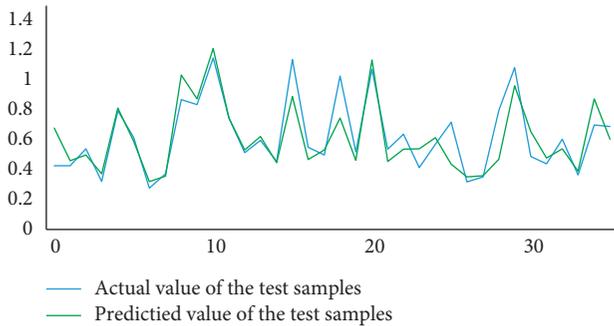


FIGURE 6: The test samples.

is credible. Therefore, based on the prediction results, this study gives further analysis of wind power utilization efficiency and regional differences in China's 30 provinces in 2020 were required.

**4.2.2. Analysis of Prediction Results.** According to the LSTM model, we forecast the wind power utilization efficiency for 30 provinces in 2020, which is displayed in Tables 4 and 5.

According to Table 4, the predicted value of China's overall wind power utilization efficiency in 2020 is 0.6383, meaning it has decreased since 2019, although the overall wind power utilization efficiency has shown an upward trend since 2013. Compared with the 8-year average of 2013–2020 and the 7-year average of 2013–2019, wind power utilization efficiency has still improved. This shows that although China's overall wind power utilization efficiency is not high at this stage, the development trend shows a steady upward trend.

From a regional perspective, the six regions still present a spatial distribution pattern of Northeast China > North China > East China > South China > Northwest China > Central China. However, compared with 2019, the utilization efficiency of wind power in Northeast China, North China, and Northwest China has improved, and all have shown an upward trend. The 8-year average of 2013–2020 has also increased compared with the 7-year average of 2013–2019. The forecasted value of wind power utilization efficiency in South China and Central China has declined compared with 2019, but the development trend is still good. The 8-year average of 2013–2020 has also

increased compared with the 7-year average of 2013–2019. The forecasted value of wind power utilization efficiency in East China has declined compared with 2019 and shows a weak downward trend. The 8-year average of 2013–2020 has also decreased compared with the 7-year average of 2013–2019. It can be seen that the wind power utilization efficiency rankings of the six regions are very stable, while the wind power utilization efficiency of the six regions is prone to fluctuations. The Three-North region that is rich in wind energy resources has high wind power utilization efficiency, good development trends, and great overall potential. East China, South China, and Central China, where wind resources are relatively poor, have low wind power utilization efficiency, and their development trends are not stable enough and are more prone to change.

At the provincial level, the predicted value of wind power utilization efficiency in 18 provinces has increased compared with 2019, accounting for 60%. Among them, the predicted values of wind power utilization efficiency in Inner Mongolia and Shandong are effective, and the predicted values of wind power utilization efficiency in Hebei, Ningxia, Shanxi, and Liaoning are relatively high. However, the development trend of these provinces since 2013 is not stable enough, showing a weaker up-and-down dynamic trend. The predicted value of wind power utilization efficiency in the other 11 provinces is low. Among them, Jilin and Qinghai have shown a relatively stable upward trend since 2013, while Hunan, Shaanxi, Guizhou, Chongqing, and Guangdong have shown upward trends since 2013, but these fluctuate up and down. Heilongjiang, Gansu, Beijing, and Hainan have exhibited worse trends since 2013. The predicted value of wind power utilization efficiency in 12 provinces has increased compared with 2019, accounting for 40%. Among them, the forecast value of wind power utilization efficiency in Jiangsu is effective, and the forecast value of wind power utilization efficiency in Yunnan and Fujian is relatively high. However, the development trend of these provinces since 2013 is not stable enough, and the trend fluctuates regularly. The predicted value of wind power utilization efficiency in the other nine provinces is low. Among them, Hubei, Sichuan, Guangxi, Jiangxi, and Henan have shown a steady upward trend since 2013, and only Xinjiang, Zhejiang, Shanghai, and Tianjin have been relatively stable since 2013. In terms of rankings, the ranking of 30 provinces in the 8-year average from 2013 to 2020 is basically the same as the ranking in the 7-year average from 2013 to 2019. Among them, 21 provinces have the same ranking, accounting for 70% of the rankings. There are nine provinces that have changed rank, accounting for 30%. The provinces whose rankings have changed are mainly up or down by 1-2 places, and the overall ranking has not changed much. It can be seen that the wind power utilization efficiency rankings of 30 provinces are relatively stable, and the overall performance is similar to the analysis results. First, Inner Mongolia, Shandong, and other provinces located in the Three-North region have relatively high wind power utilization efficiency, while Chongqing, Henan, Sichuan, and other provinces in Central China and Southern China have relatively low wind power utilization efficiency. Second, the utilization efficiency

TABLE 4: Predicted value of wind power utilization efficiency in 30 provinces (2020).

	2019	2020 prediction	Trend	Mean (2013–2019)	Rank	Mean (2013–2020)	Rank	Ranking changes
Inner Mongolia	1.1495	1.1832	Upward	1.1654	1	1.1677	1	No change
Shandong	1.0732	1.1375	Upward	1.1110	2	1.1143	2	No change
Fujian	1.0278	0.7501	Decline	0.9963	3	0.9656	3	No change
Yunnan	1.0832	0.9933	Decline	0.9514	4	0.9566	4	No change
Jiangsu	1.1398	1.0021	Decline	0.9412	5	0.9488	5	No change
Hebei	0.8716	0.9793	Upward	0.8722	6	0.8856	6	No change
Ningxia	0.7006	0.8676	Upward	0.7818	7	0.7925	8	Decline
Shanxi	0.8377	0.9086	Upward	0.7801	8	0.7962	7	Upward
Liaoning	0.7461	0.7535	Upward	0.7798	9	0.7765	9	No change
Guangdong	0.5724	0.6018	Upward	0.6373	10	0.6329	10	No change
Xinjiang	0.6900	0.5922	Decline	0.5833	11	0.5844	11	No change
Heilongjiang	0.5975	0.6306	Upward	0.5624	12	0.5709	12	No change
Gansu	0.6040	0.6087	Upward	0.5435	13	0.5516	13	No change
Anhui	0.5003	0.5134	Upward	0.4957	14	0.4979	14	No change
Zhejiang	0.5502	0.4835	Decline	0.4778	15	0.4785	17	Upward
Hubei	0.6394	0.5790	Decline	0.4768	16	0.4896	16	No change
Guizhou	0.4895	0.6202	Upward	0.4767	17	0.4947	15	Decline
Jiling	0.5141	0.5601	Upward	0.4659	18	0.4776	18	No change
Hunan	0.4152	0.5148	Upward	0.4395	19	0.4489	19	No change
Shanghai	0.4561	0.4310	Decline	0.4373	20	0.4365	20	No change
Guangxi	0.7190	0.5208	Decline	0.4128	21	0.4263	22	Decline
Jiangxi	0.5206	0.4983	Decline	0.4126	22	0.4233	23	Decline
Sichuan	0.7987	0.5679	Decline	0.4062	23	0.4264	21	Upward
Shaanxi	0.4410	0.5148	Upward	0.4052	24	0.4189	24	No change
Henan	0.5386	0.5265	Decline	0.3932	25	0.4099	25	No change
Tianjin	0.3726	0.3624	Decline	0.3581	26	0.3586	26	No change
Hainan	0.3186	0.3489	Upward	0.3403	27	0.3414	27	No change
Beijing	0.2771	0.3188	Upward	0.2988	28	0.3013	29	Decline
Qinghai	0.3646	0.4267	Upward	0.2916	29	0.3085	28	Upward
Chongqing	0.3524	0.3539	Upward	0.2904	30	0.2983	30	No change
China	0.6454	0.6383	Decline	0.5861		0.5927		

TABLE 5: Predicted value of wind power utilization efficiency in six regions (2020).

	2019	2020 Prediction	Trend	Mean 2013–2019	Rank	Mean 2013–2020	Rank	Ranking changes
Northeast China	0.7518	0.7819	Upward	0.7434	1	0.7482	1	No change
North China	0.6864	0.7413	Upward	0.6840	2	0.6912	2	No change
East China	0.7348	0.6360	Decline	0.6697	3	0.6655	3	No change
Southern China	0.6365	0.6170	Decline	0.5637	4	0.5704	4	No change
Northwest China	0.5600	0.6020	Upward	0.5211	5	0.5312	5	No change
Central China	0.5441	0.5067	Decline	0.4031	6	0.4161	6	No change
China	0.6454			0.5861		0.5927		

of wind power in the provinces in the eastern coastal areas, such as Fujian and Jiangsu, is relatively high, while the utilization efficiency of wind power in the provinces in the central and western inland areas, such as Xinjiang, Hunan, and Guizhou, is relatively low.

## 5. Conclusions and Policy Suggestions

This paper established an undesirable output Super-SBM model and LSTM model and combined the calculation and prediction methods to improve the research ideas of wind power efficiency. From this, the wind power utilization efficiency was systematically measured and predicted, and we scientifically measured the wind power utilization

efficiency of 30 provinces in China from 2013 to 2020 and came to the following conclusions:

- (1) At the national level, China's overall wind power utilization efficiency level is relatively low, but the development trend has shown a steady upward trend since 2013.
- (2) At the regional level, the wind power utilization efficiency of the six regions is different, showing a spatial pattern of Northeast China > North China > East China > South China > Northwest China > Central China. The ranking of wind power utilization efficiency by region is very stable. Among them, the Three-North region, which is rich in wind energy resources, has high wind power utilization

efficiency, good development trends, and great potential. However, the relatively poor wind energy resource regions of East China, South China, and Central China have low wind power utilization efficiency, and the development trend is not stable enough and is more prone to change. At the same time, the utilization efficiency of wind power in coastal areas is generally better than that in inland areas.

- (3) At the provincial and municipal level, there are differences in wind power utilization efficiency in China's 30 provinces. The utilization efficiency of wind power in Inner Mongolia and Shandong is truly effective. Input and output have reached the optimal allocation, and the development trend is good. The other 28 provinces have varying degrees of inefficiency, and there is still room for improvement. Provinces with low wind power utilization efficiency have higher average annual growth rates, showing a good upward trend. Provinces with high wind power utilization efficiency have lower average annual growth rates, and some even show negative growth. At the same time, the wind power utilization efficiency rankings of 30 provinces are relatively stable, showing two characteristics: First, Inner Mongolia, Shandong, and other provinces located in the Three-North region have relatively high wind power utilization efficiency, while Chongqing, Henan, Sichuan, and other provinces in Central China and Southern China have relatively low wind power utilization efficiency. Second, the utilization efficiency of wind power in the provinces in the eastern coastal areas, such as Fujian and Jiangsu, is relatively high, while the utilization efficiency of wind power in the provinces in the central and western inland areas, such as Xinjiang, Hunan, and Guizhou, is relatively low.

Based on the above conclusions, this paper proposes the following suggestions:

- (1) As far as the country is concerned, the first recommendation is to actively guide the construction of a technological innovation platform to effectively connect production, education, and research in the wind power industry to break through key technological blind spots. The second is to improve the power supply structure, reduce or slow down the construction of cogeneration units, release the capacity of cogeneration units, and improve the peak shaving capacity of these areas. The third is to establish a reasonable green power policy guidance system to make up for the shortcomings of pure new energy subsidy policies, open up the meridian of power generation, transmission, and power consumption networks, and improve the overall synergistic efficiency of the wind power supply chain.
- (2) As far as the Three-North region is concerned, the first recommendation is maintaining and expanding

its scale advantage. It is necessary to further coordinate and improve the input ratio of factors, continuously improve the grid structure, explore new ways of wind power consumption, and improve the relevant hardware and software required for wind power utilization. There should be an increase of investment in technology, and the technological content of wind energy resource utilization technology needs to be improved. The second is to speed up the construction of external transmission channels, smooth ventilation, and power transmission and utilization and to promote the overall planning and coordination of wind power development and grid construction planning, while reducing wind power development lagging behind grid construction, so as to better promote the sound operation of wind power resource utilization. The third recommendation is to build complementary power generation systems and wind energy storage systems that complement wind energy and other energy sources to reduce the adverse effects of large-scale wind power development on grid stability.

- (3) For East China, South China, and Central China, the first recommendation is to speed up the construction of supporting grids for wind power development and the implementation of consumption measures and to increase the investment in wind energy resource utilization and expand the scale of wind energy resource utilization. This will increase the cumulative installed capacity of wind power and produce scale effects. The second recommendation is to increase policy support and guidance for the wind power manufacturing industry, continuously enhance the wind power technology level of wind power companies, and gradually narrow the gap with foreign counterparts. The third recommendation is to continuously develop more efficient "low wind speed" and "high altitude" wind turbines to adapt to the characteristics of wind energy resources in these areas, so as to better increase their wind power capacity.

## Data Availability

The data used in this article can be found in the "China Electric Power Yearbook" and the statistics of wind power grid-connected operation disclosed by the National Energy Administration of China.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

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