CHEMICAL ENGINEERING TRANSACTIONS
VOL. 70, 2018
A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet
Guest Editors: Timothy G. Walmsley, Petar S. Varbanov, Rongxin Su, Jiří J. Klemeš

ISBN 978-88-95608-67-9; **ISSN** 2283-9216
DOI: 10.3303/CET1870256

Analysis of China's Regional Wind Power Generation Efficiency and its Influencing Factors

Xiongfeng Pan*, Jing Zhang, Changyu Li, Xianyou Pan

No.2 Linggong Road, Ganjingzi District, Dalian, Department of management and Economics, Dalian University of Technology, 116024
xiongfengpan@163.com

In order to objectively evaluate the current situation of wind power generation in China and identify the key factors, based on the data of 30 Chinese provinces from 2011 to 2014, this study use a meta-frontier data envelopment analysis (DEA) model and a symbolic regression method to study wind power generation efficiency and its influencing factors. The results show: (1) The wind power generation efficiency of the eastern region is the highest, followed by the western region, and the wind power generation efficiency of the central region is the lowest. (2) The wind power generation efficiency in the eastern region has great room for improvement in internal management; the wind power generation efficiency in the central region and western region has great room for improvement not only at a technical level but also in internal management. (3) Technical progress has the most impact on wind power generation efficiency, followed by carbon regulation, while wind energy reserve has the least impact on wind power generation efficiency.

1. Introduction

Wind power, which produces a negligible amount of harmful substances and barely consumes mineral resources and water resources (Mesarić and Krajcar, 2015), has gained enormous attention in the electricity generation sector of each country all over the world. However, at present, the speed of development of installed wind capacity in China is much higher than the speed of development of the power grid, leading to a "wind power curtailment" phenomenon. In addition, wind power endowments and wind power construction differ greatly in different regions, which leads to the level of wind power generation in different regions presenting different characteristics. Therefore, taking the regional differences into account, objectively evaluating China's current wind power status, and identifying key factors will become the fundamental steps required to improve the wind power generation efficiency, implement a clean energy development strategy, and alleviate environmental problems.

With the high-speed of development of the wind power industry, the wind power generation efficiency and its influencing factors have gradually attracted the attention of scholars. Iribarren et al. (2013) compared the operational and environmental performance of 25 wind farms in Spain by using life cycle assessment (LCA) and DEA and only four of the evaluated farms were found to be comparatively efficient. They also combined energy analysis with DEA to investigate ecocentric bench-marking of multiple resembling entities of 25 wind farms in Spain and the result showed only 3 wind farms were deemed efficient (Iribarren et al., 2014). Wu et al. (2016) developed two-stage DEA and Tobit analysis to assess the efficiency of 42 wind farms in China. The findings showed that most of the wind farms operate efficiently. They also found that installed capacity and wind power density were the most important factors for the efficiency of wind farms. Saglam (2017) extended the previous work by examining the relative efficiency of the 39 states' wind power performances for electricity generation, using a two-stage DEA and Tobit analysis. The DEA results indicated that more than half of the states operated wind power efficiently, and Tobit regression showed that early installed wind power was more expensive and less productive than the relative currently installed wind power.

From the aforementioned literature, we can see that scholars have achieved a certain level of progress in the field of wind power generation efficiency but that some questions require further exploration. First, most previous studies are based on the assumption that all the decision-making units (DMUs) which are required to be measured share a common production technology. The assumption of homogeneous technology may inevitably lead to a biased result (O'Donnell et al., 2008). Second, numerous scholars adopted Tobit model to explore influencing factors of wind power generation efficiency, which need to assume a predefined structure between those factors, which is usually described by a linear function.

The study contributes to the literature in two ways: first, this study uses the meta-frontier method with homogeneous technology hypothesis to estimate and analyze the wind power generation efficiency in contrast to the existing studies that assumed that all DMUs possess the same level of production technology. Second, this study uses symbolic regression, which can automatically discover either linear or nonlinear relations without a predefined regression structure, to study the influential factors of wind power generation efficiency in addition to showing the important factors.

2. Methods and data

2.1 Meta-frontier model and SBM model

Data envelopment analysis (DEA) is a strong tool in the evaluation of relative efficiency. Nevertheless, the conventional DEA approach is limited by the presupposed similar production technology of each DMU (Hang et al., 2015). The data analysis method adopted in this study combines the concept of meta-frontier, proposed by Hayami (1969) and adapted by Tone, with the SBM approach to evaluate efficiency in different groups to compare the most efficient technology in wind power generation, avoiding the bias of evaluation by taking group differences into account. The distance function based on input minimization is:

$$0 \le \overrightarrow{D^g}(x,y) = \sup_\theta \left\{ \theta > 0; \frac{y}{\theta} \in P^g \right\} = GTE(x,y) \le 1 \tag{1}$$

and the distance function based on the meta-frontier is:

$$0 \le \overrightarrow{D^m}(x,y) = \sup_\theta \left\{ \theta > 0; \frac{y}{\theta} \in P^m \right\} = MTE(x,y) \le 1 \tag{2}$$

2.2 TGR and IE

O'Donnell et al. (2008) pointed out that the meta-frontier technical efficiency can be decomposed into technical efficiency within the group and the TGR. TGR is the ratio of the technical efficiency of the production units under meta-frontier and group frontiers, as shown in eq. (3), which reflects the gap between the group frontier and the meta-frontier technology.

$$0 \le MTR = \frac{\overrightarrow{D^m}(x,y,b)}{\overrightarrow{D^g}(x,y,b)} = \frac{MTE(x,y,b)}{GTE(x,y,b)} \le 1 \tag{3}$$

Chiu et al. (2012) pointed out that, based on the meta-frontier, inefficiency (IE) could be decomposed into two components: technology gap inefficiency (TIE) and group-specific managerial inefficiency (MIE), as described in eqs. (5) and (6).

$$IE = 1 - MTE = TIE + MIE \tag{4}$$

$$TIE = GTE - MTE \tag{5}$$

$$MIE = 1 - GTE \tag{6}$$

2.3 Symbolic regression

Symbolic regression, an evolutionary function discovery method based on genetic programming, was first proposed by Koza (1992). Different from traditional regression methods, symbolic regression can determine both parameters and structures of the regression models simultaneously (Vladislavleva et al., 2009). In symbolic regression, the task is to automatically find a suitable functional form in the complex data, either linear or nonlinear, and simultaneously determine the coefficients of the functions, the occurrence of each factor shows its ability to describe the data, and higher frequency indicates more importance (Yang et al., 2016).

This study selects three indexes and analyze their influence on wind power generation efficiency: these are carbon regulation, technical progress, and wind energy reserve. Then, this study builds the following model to analyze their impact on wind power generation efficiency:

$$E = f(C\_reg, wind\_tec, wind\_res) \tag{12}$$

2.4 Variable descriptions and data sources

In the measurement of wind power generation efficiency, the data set includes two input variables: (1) installed wind capacity, (2) wind energy reserve and one output variable: wind power generating capacity. In the symbolic regression model, E represents wind power generation efficiency, C_reg represents carbon regulation and is measured by the ration of carbon dioxide emissions to the real GDP (2000 constant price). The calculation process of carbon dioxide emissions refers to Fan (2013), with the difference that this study eliminates the material input and do not consider the carbon emissions from crude oil; wind_tec represents technical progress and is measured by the number of wind power patents; wind_cap represents wind energy reserve and is measured by the total amount of wind energy resources that can be developed (Xue et al., 2001).
Given the lack of relative data in Tibet, Hong Kong, Macau, and Taiwan, this study selects the other 30 provinces as the research objective, and the study period is from 2011 to 2014. The data come from the China Electric Power Yearbook, the China Energy Statistical Yearbook and the China Statistical Yearbook for Regional Economy.

3. Empirical analysis

3.1 Analysis of difference in wind power generation efficiency in three regions

Through the SBM and meta-frontier models, this study calculates the wind power generation efficiency of each province under the meta–frontier and the group frontier. As shown in Table 1, China's wind power generation efficiency level is generally low, and there are obvious regional differences. Under the meta–frontier, the wind power generation efficiency of the eastern region is the highest, followed by the western region, and the wind power generation efficiency of the central region is the lowest. Under the group frontier, the wind power generation efficiency of the eastern region is the highest, followed by the central region and the western region, showing a scalariform spatial distribution.

Table 1: Statistical description of wind power generation efficiency under meta-frontier and group frontier

Region	Meta-frontier efficiency				Group frontier efficiency			
	Max	Min	Average	SD	Max	Min	Average	SD
Eastern region	0.672	0.611	0.647	0.029	0.672	0.611	0.647	0.029
Central region	0.420	0.310	0.373	0.047	0.662	0.622	0.645	0.017
Western region	0.466	0.301	0.375	0.069	0.649	0.483	0.561	0.068
Nationwide	0.528	0.440	0.474	0.038	0.657	0.576	0.615	0.034

Note: SD stands for standard deviation.

This study uses TGR to analyze the differences and changes of wind power generation efficiency in China's three regions. As shown in Table 2, Kruskal–Wallis test shows that TGRs are different among different regions. The wind power generation of the eastern region represents the highest level of the national wind power generation. In contrast, the TGR of the central and western regions are lower than is that of the eastern region. Compared with the meta-frontier, the improvement space for wind power generation technology in these two regions is 40.0 % and 27.5 %, respectively.

Table 2: Statistical description of TGR and difference test results

Region	Max	Min	Average	SD
Eastern region	1.000	1.000	1.000	0.000
Central region	0.657	0.494	0.600	0.075
Western region	0.857	0.543	0.725	0.140
Nationwide	0.856	0.698	0.793	0.071
Kruskal-Wallis test	Chi-Square=23.446		Asymp.Sig=0.0001***	

Note: *, **, *** represent 10 %, 5 %, 1 % of the significance level.

3.2 Decomposition of wind power generation inefficiency in three regions

This study uses the above inefficient decomposition method to decompose the wind power generation inefficiency in three regions into two dimensions: technology gap inefficiency TIE and managerial inefficiency MIE. The results are shown in Table 3.

Taking the central region as our example, the figures show that total wind power generation inefficiency is 0.627. Its TIE is 0.272 and its MIE is 0.355. Obviously, the TIE of the central region comprises a larger portion of the wind power generation efficiency loss than that of the eastern and western regions. It can be seen that the technology gap is an important cause of wind power generation inefficiency in the central region. This is driven largely by China's preferential economic policies, as well as by complex geographical environment and climatic conditions in different regions. As for the eastern and western regions, the wind power generation inefficiency is mainly caused by MIE. The preceding analysis reveals that the eastern region possesses the highest technical level in wind power utilization and that wind power generation inefficiency in this region is mainly from management ineffectiveness. The inefficiency incurred by the technology gap is the smallest in contrast to other regions. However, on the whole, both the technology gap and management effectiveness are important sources of the efficiency loss in the western and central regions.

Table 3: Decomposition of wind power generation inefficiency in three regions

Regions	IE	TIE and its proportion		MIE and its proportion	
Eastern region	0.353	0.000	0.00 %	0.353	100 %
Central region	0.627	0.272	45.43 %	0.355	54.57 %
Western region	0.625	0.186	36.18 %	0.439	63.82 %
Nationwide	0.526	0.141	25.38 %	0.385	67.95 %

3.4 Influencing factors of wind power generation efficiency

For symbolic regression problems, this study chooses the following most common symbols that can appear in the regression models: constant, the input variable, + (addition), — (subtraction), and * (multiplication).

We build the Pareto front first, and then focus on the limited number of optimal solutions, which are provided in detail in Table 4, to evaluate the comparative importance of each factor.

Figure 1 shows how many models contain the factor and how many times the factor appears in the models in total. From Figure 6, it can be observed that the order of influence of each factor on wind power generation efficiency is $wind\_tec > C\_reg > wind\_res$. Technical progress is the most frequent factor appearing in the Pareto optimal models, while wind energy reserve is the least frequent factor, that is, technical progress has the most impact on wind power generation efficiency, while wind energy reserve has the least impact.

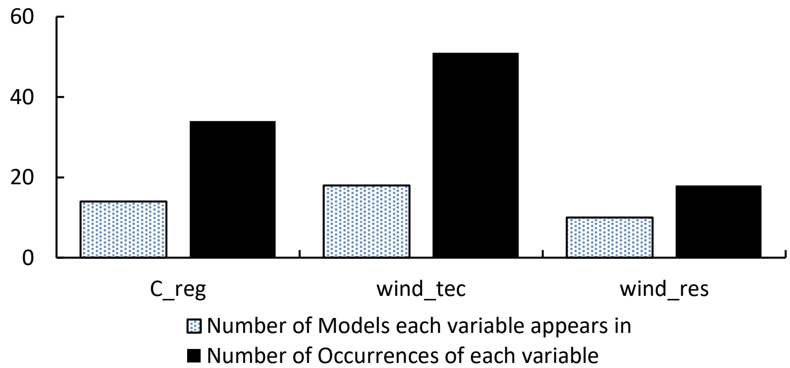

Figure 1: The occurrence of each factor in the Pareto optimal models

Technical progress is conducive to the improvement of the whole innovation environment. In recent years, with the growth of energy demand, coupled with the lack of energy in China, all regions are committed to the development of new energy and renewable energy. Wind energy is one of these. The emergence of new equipment and new technology has greatly improved wind energy utilization efficiency and wind power generation efficiency.

With regard to the influence of carbon regulation on wind power generation efficiency, maybe carbon regulation will improve wind power generation efficiency. Traditional thermal power generation uses coal and oil as raw materials, and, while producing chemical pollution, also produces a large amount of carbon dioxide. Through the introduction of carbon regulation and low-carbon constraint, the government will shoulder more carbon emission reduction responsibilities and rely more on new energy sources, such as wind energy. Local governments are likely to focus more on the new energy generation efficiency on the basis of publishing many policies supporting new energy power generation and expanding installed capacity. However, as an indirect influencing factor, carbon regulation has less impact on wind power generation efficiency than technical progress.

Table 4: Regression models

Index	Complexity	MAE	Models
1	1	0.2152	$y=-0.371$
2	5	0.1724	$y=0.147x_2-0.741$
3	7	0.1606	$y=0.0215{x_2}^2-0.543$
4	9	0.1380	$y=0.0803{x_2}^2-0.382x_2$
5	11	0.1370	$y=0.0772{x_2}^2-0.0373-0.36x_2$
6	13	0.1284	$y=0.149{x_1}^2+0.0194{x_2}^2-0.578$
7	15	0.1246	$y=0.631x_1+0.199x_2-0.944-0.131x_1x_2$
8	17	0.1199	$y=0.133{x_1}^2+0.0484{x_2}^2-0.303-0.189x_2$
9	19	0.1168	$y=0.37x_1+0.0262{x_2}^2-0.593-0.0162x_1{x_2}^2$
10	21	0.1108	$y=0.0682{x_2}^2-0.353x_2-0.0548x_1x_2-0.101x_1x_3$
11	23	0.1096	$y=0.0949+0.0777{x_2}^2-0.415x_2-0.0502x_1x_2-0.0942x_1x_3$
12	27	0.1064	$y=0.0816{x_2}^2+0.0156x_1x_3{x_2}^2-0.387x_2-0.0743x_1x_2x_3$
13	29	0.1060	$y=0.0774{x_2}^2+0.0159x_1x_3{x_2}^2-0.0412-0.36x_2-0.0759x_1x_2x_3$
14	31	0.1036	$y=0.26{x_1}^2+0.0269{x_2}^2+0.0381x_3x_2{x_1}^2-0.62-0.0355x_1x_2x_3$
15	33	0.1029	$y=0.241{x_1}^2+0.00455{x_2}^3+0.0379x_3x_2{x_1}^2-0.529-0.0379x_1x_2x_3$
16	35	0.0998	$y=0.0639{x_2}^2-0.353x_2-0.103x_1x_2x_3-0.03x_1{x_2}^2-0.0135x_1x_2{x_3}^2$
17	37	0.0972	$y=0.066{x_2}^2-0.35x_2-0.083x_1x_2x_3-0.00559x_1{x_2}^3-0.011x_1x_2{x_3}^2$
18	41	0.0904	$y=0.131{x_1}^2+0.0831{x_2}^2-0.248x_1-0.406x_2-0.0757x_1x_2x_3-0.0028{x_1}^2{x_2}^2{x_3}^2$
19	43	0.0871	$y=0.192+0.129{x_1}^2+0.101{x_2}^2-0.309x_1-0.533x_2-0.089x_1x_2x_3-0.00314{x_1}^2{x_2}^2{x_3}^2$

Wind energy reserve also affects the wind power generation efficiency, but the influence of this factor is weaker than that of the other three factors. There is no doubt that wind energy reserve is one of the most important factors affecting wind power generation efficiency. And with the change of wind energy reserve in a region, wind power generation efficiency is bound to change, that is, the region has enjoyed “resource blessing” because of its rich resources. However, according to the “resource curse”, the more abundant the natural resources, the less the ability of capital and labor force to be used in the natural resources sector, which will lead to a risk of missing technical progress and reduction of resources utilization efficiency. Besides, the economic rent obtained by various departments in the acquisition of natural resources has contributed to the “greedy effect”, which, to a certain extent, will counteract the positive effect of energy reserve. The above reasons make the effect of wind energy reserve on wind power generation efficiency relatively small.

4. Conclusions

Based on the data of 30 Chinese provinces from 2011 to 2014, this study uses a meta-frontier DEA model and the symbolic regression method to study wind power generation efficiency and its influencing factors. The main conclusions are as follows.

Firstly, China's wind power generation efficiency level is generally low, and there are obvious regional differences. The TGR shows that the wind power generation efficiency of the eastern region represents the highest level of the national wind power generation efficiency. The wind power generation efficiency of central region and eastern region is 40 % and 27.5 % lower than eastern region, respectively. Secondly, the wind power

generation efficiency in the eastern and western region has great room for improvement in internal management, such as optimizing the allocation of human resources, providing information and management platform to facilitate the timely feedback of production and operation information; the wind power generation efficiency in the central region has great room for improvement, not only in terms of technical level but also in internal management. Thirdly, technical progress has the greatest impact on wind power generation efficiency, followed by carbon regulation, while wind energy reserve has the least impact on wind power generation efficiency.
On the basis of the above conclusions, the following policy recommendations are proposed: Firstly, the eastern region should pay more attention to summing up and popularizing the experience of wind energy utilization and fully excavating the potential of the existing production technology. In addition, the eastern region should formulate and implement a benign system to improve the management efficiency. The central region should learn from the advanced production technology in the eastern region and improve wind power generation efficiency through upgrading technology and improving management ability. The western region should give full play to its own resource advantages, accelerate the construction of large wind power infrastructure, and increase the R & D investment of energy storage technology. Secondly, government departments should promote the diffusion of advanced production technology from the eastern region to the central and western regions through various means, such as financial assistance, technical assistance, tax reduction, and subsidy. The central and western regions should improve technological absorptive capacity and narrow the technological gap with the eastern region. Thirdly, all regions should comb and optimize existing energy and low-carbon policies, and put forward relevant countermeasures to improve low-carbon regulation to link up the mechanism of low carbon regulation and energy consumption saving policy and provide a favorable institutional environment for the development of wind and other new source energy generation.

Acknowledgments

This paper is the stage achievement of National Natural Science Foundation Project in China (71303029). The authors thank for the support of National Natural Science Foundation in China.

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