第50卷第3期 中国科学技术大学学报 Vol. 50,No. 3
2020年3月 JOURNAL OF UNIVERSITY OF SCIENCE AND TECHNOLOGY OF CHINA Mar. 2020

文章编号:0253-2778(2020)03-0245-16

Measuring energy efficiency incorporating regional heterogeneities: A meta-frontier method with log-linear technology

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Abstract: China's provinces vary greatly in the economic development, resource endowments, and science and technology levels, which leads the heterogeneity of production technology. A data envelopment analysis model is proposed based on the log-linear energy technology and meta-frontier method, which considers the heterogeneity of production technology. Energy performances of China's 30 provinces during the 2006-2015 period were measured and causes of energy inefficiency were analyzed with the model. Empirical results indicate that, most of the provinces in China have great potential for energy efficiency improvement. It is also shown that the eastern region has the highest average annual energy efficiency while that of the western region is the lowest, with the central region somewhere in between. It is suggested to enhance management capabilities for the eastern provinces should be enhanced, improve both technology and management efficiency for central and western provinces, to improve their energy performances.

Key words: Energy efficiency; Data envelopment analysis; Meta-frontier; Log-linear technology

CLC number: F224 **Document code**: A doi:10.3969/j.issn.0253-2778.2020.03.001

2010 Mathematics Subject Classification: 94B15

Citation: ANG Sheng, DENG Fang, YANG Feng. Measuring energy efficiency incorporating regional heterogeneities: A meta-frontier method with log-linear technology[J]. Journal of University of Science and Technology of China, 2020,50(3):245-260.
昂胜,邓芳,杨锋. 考虑区域异质性的能源效率评价——基于线性对数技术的共同前沿方法[J]. 中国科学技术大学学报,2020,50(3):245-260.

考虑区域异质性的能源效率评价

——基于线性对数技术的共同前沿方法

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摘要:中国各区域经济发展、资源分布、科技水平存在巨大差异,这些差异导致不同区域之间生产技术存在异质性.为此,本研究将中国30个省份划分为东、中、西三个地区,基于线性对数技术的共同前沿方法,提出

Received: 2018-04-16; **Revised**: 2018-06-05

Foundation item: Supported by the National Natural Science Foundation of National Science Foundation(71631006,71601173), Special Fund for Basic Scientific Research Expenses of Central Universities.

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了考虑生产技术异质性的数据包络分析模型.利用该模型对各省份和各地区在 2006～2015 年间的能源效率进行了评价,并进一步分析了各省份能源无效的原因.研究结果表明,中国大部分的省份都有一定的能源效率提升空间.东部地区年平均能源效率最高,中部次之,西部地区最低.东部地区应该通过提高管理水平来提高能源效率,而中西部地区则需要同时提高技术和管理效率.

关键词:能源效率;数据包络分析;共同前沿;线性对数技术

0 Introduction

The fast development of China's economy has brought about a large energy consumption that has caused non-negligible environmental problems. Growing energy consumption and carbon emissions are serious threats to China's sustainable development strategy. China became the largest energy consumer country in 2010, and it has also become the largest emitter of carbon dioxide in the world[1]. Controlling energy consumption and reducing pollutant emissions is now assuming unprecedented strategic importance, and the alleviation of energy and environmental crisis is a problem that China has to face. Thus, the State Council of China[2] proposed some policies in the 13th Five-Year Plan for environmental protection. The targets include controlling total energy consumption within 5 billion tons (standard coal) and reducing CO_2 emissions (per unit of GDP) by 18% by 2020, which is one of the important ways for China to speed up the construction of a resource-conserving and environmentally-friendly society. The improvement of environmental efficiency is given central importance for it is an important way to reduce energy consumption and greenhouse gas emissions. The State Council[3] also allocated corresponding energy consumption and carbon emission targets for each province. Scientifically assessing regional environmental efficiency can effectively urge provinces to improve their energy utilization technology and environmental management, and achieve a harmonious development of the economy and environment.

Data envelopment analysis (DEA) method, first proposed by Charnes et al[4] in 1978, is a nonparametric frontier analysis method used in various field for relative performance evaluation for a set of decision making units (DMUs). In the field of energy efficiency analysis. Hu and Wang[5] used the DEA method to measure the total-factor energy efficiency (TFEE) in China's energy industry, and then various factors affecting the total-factor energy efficiency were analyzed[6-8]. Hu et al[9] used the DEA approach with the TFEE framework in APEC economies to determine their energy saving targets. Honma et al[10] employed the method to compute Japan's regional TFEE. Zhao et al[11] analyzed TFEE in the three-stage DEA method for 35 BRI countries.

It is known that an energy consumption process will produce pollutants, and the inclusion of these pollutants as undesirable outputs into efficiency measurement is conducive to the construction of a green ecological environment. Under the requirements of energy conservation and emission reduction with sustainable economic development, ignoringe pollutants is meaningless to evaluate energy efficiency and thus the estimation of energy will be efficiency biased[12]. Since Färe et al[13] and Färe et al[14] addressed undesirable outputs as by-products of production and manufacturing process, mangy energy efficiency studies usually include undesirable outputs in addition to traditional energy efficiency indicators[15-18]. Ramli et al[19] proposed a review on the undesirable outputs in efficiency measurement; they also brought up a discussion about environmental efficiency measurement. Valadkhani et al[20] used the multiplicative DEA approach based on the traditional energy indicators and various undesirable outputs to measure 46 countries' environmental efficiency. Zhou et al[21] used CO_2 as the desirable output to measure the energy efficiency under various DEA models. Liu et al[22] proposed a DEA model incorporating Malmquist index to evaluate the TFEE while CO_2 was selected as one of the undesirable outputs.

Although a lot of researches in the field of energy efficiency assessment based on DEA have been conducted, there are several limitations. One of the limitations is that previous studies rarely considered the heterogeneity of production technology. The gaps between economic development, resource endowments, and scientific and technological levels among different regions are ubiquitous which leads to technology heterogeneity. Meta-frontier method emphasizes the heterogeneity of production technology, which can solve this problem. Hayami[23] and Hayami et al[24] first proposed the meta production conception, and it is considered as the envelope curve of the general production function. Battese et al[25] developed meta-frontier theory and based it on the meta production. O'Donnell et al[26] further used the DEA models to construct the non-parametric meta-frontier, in which DMUs are divided into dissimilar groups in meta-frontier method. In application, Yu et al[27] applied the meta-frontier method to divide China's provinces into different regions to measure their efficiency. Wang et al[28] proposed a new TFEE indicator, and used the meta-frontier DEA method to calculate technology heterogeneity. Sun et al[29] considered management and technology heterogeneity to measure the EREC efficiency of 211 Chinese cities. Sun et al[30] considered technical-level differences to measure the heterogeneous Chinese bank supply chain system.

In this study we will further the meta-frontier method and combine it with Cobb-Douglas (namely log-linear) framework, which is under geometric convexity postulate in DEA. We propose the log-linear energy technology and construct the output-oriented DEA model under the two frontiers. Ordinary convexity postulate in the BCC model[31] permits various kinds of returns to scale situations in the production function while marginal products must be non-increasing. However, this restriction is inappropriate in non-concave regions or production possibility. Following Banker et al[32] and Valadkhani et al[20], we try to address the issue by converting the convexity postulate into a geometric convexity in BCC model, which means that Cobb-Douglas frontier replaces the piecewise linear frontier. We also propose a multiplicative environmental DEA approach based on the Multiplicative Environmental DEA Technology set and $T_{\mathrm{DEA}}^{\mathrm{ME}}$ its log-transformation $\log T_{\mathrm{DEA}}^{\mathrm{ME}}$. The multiplicative environmental DEA technology $T_{\mathrm{DEA}}^{\mathrm{ME}}$ is piecewise log-linear, and allows for all kinds of production structures.

The log-linear energy technology we proposed has several desirable features. First, the log-linear technology set breaks the limitation of the convexity assumption of technology. It allows for all kinds of production structures[33]. Second, the frontier of the log-linear energy technology set is to piecewise Cobb-Douglas type[34], which is widely used in practice. Third, we consider the heterogeneity of the production technology compared with former log-linear technology related researches.

For application we use the proposed models to measure energy efficiency in China's 30 provinces in 2006 ～ 2015. Since undesired output is an essential indicator in energy efficiency measurement to reflect the environmental conditions, and thus we choose the output-oriented model. Comparing the efficiency of the evaluated unit in the group frontier and the meta-frontier, we define a measure of technology gap ratio (TGR) to indicate the heterogeneity of the production technology[35]. Through the TGR, the gap between the energy efficiency of the provinces and different groups is analyzed. We further decompose the inefficiency of each unit into technical inefficiency and management inefficiency. From the perspectives of technology and management, the reasons for energy inefficiency in each province are analyzed.

Empirical results indicate that most of the provinces in China except Beijing, Shanghai and Guangdong have great potential for energy efficiency improvement. It also shows that the average annual energy efficiency is highest in the east, and the lowest in the western region, with the central region somewhere in between. The provinces in the east should improve their energy efficiency by improving their management capabilities, while the central and western provinces should improve both technology and management efficiency.

1 Methods

1.1 Log-linear energy technology

Suppose that there are N homogenous DMUs, whose inputs are as capital (k), labor force (l) and energy (e) and desirable output is GDP (y) while the undesirable output is CO_2 (u). Following Valadkhani et al[20], we formulate the output-oriented piecewise log-linear energy technology T as (1). Compared with the BCC model which, require convexity postulate, T allows for all kinds of production structures. $(\theta_1,\dots,\theta_n)^T$ are the reduction factors among DMUs while $(\lambda)_1,\cdots,\lambda_n)^T$ are the structural variables to connect all indicators[36].

$$T=\left\{(k,l,e,y,u):\prod_{n=1}^{N}k_n^{\lambda_n}\leqslant k,\prod_{n=1}^{N}l_n^{\lambda_n}\leqslant l,\prod_{n=1}^{N}e_n^{\lambda_n}\leqslant e,\prod_{n=1}^{N}y_n^{\theta_n\lambda_n}\geqslant y,\prod_{n=1}^{N}u_n^{\theta_n\lambda_n}\leqslant u;\lambda_n\geqslant 0;\theta_n\geqslant 0;\ n=1,\cdots,N\right\} \tag{1}$$

Transforming T into the log form as:

$$\log T=\left\{\begin{array}{l}(\log k,\log l,\log e,\log y,\log u)\mid\\(k,l,e,y,u)\in T\end{array}\right\} \tag{2}$$

The set $\log T$ is the log form of set T, and thus the inputs and outputs in T complete a log transformation. The two sets are of a mapping relationship for the strict monotonicity of the logarithmic function.

1.2 Log-linear energy efficiency measurement based on meta-frontier

It is generally assumed that each evaluated DMU has the same or similar technical level in traditional DEA models. However, for different provinces in a country, there are great differences in resource endowments, industrial structure and economic development. If these differences are not considered, comparisons of energy efficiency among the provinces based on the same technological level will not produce credible results. Assaf et al[37] and Chiu et al[38], We divide the provinces into J groups. The quantity of DMUs in the jth group is N_j, thus $\sum_{j=1}^{J}N_j=N$. Referring to the log-linear energy technology mentioned in Section 1.1, we present a log-linear energy efficiency measurement under the meta-frontier.

The production technology (T_l^j) under the jth group frontier is

$$T_l^j=\left\{(k^j,l^j,e^j,y^j,u^j):\prod_{n=1}^{N^j}k_n^{j\lambda_n^j}\leqslant k^j,\prod_{n=1}^{N^j}l_n^{j\lambda_n^j}\leqslant l^j,\prod_{n=1}^{N^j}e_n^{j\lambda^j}\leqslant e^j,\prod_{n=1}^{N^j}y_n^{j\theta_n^j\lambda_n^j}\geqslant y,\prod_{n=1}^{N^j}u_n^{j\theta_n^j\lambda_n^j}\leqslant u^j;\lambda_n^j\geqslant 0,\theta_n^j\geqslant 0;n=1,\cdots,N\right\} \tag{3}$$

The production technology under the meta-frontier (T_l^{meta}) is shown as following:

$$T_l^{\text{meta}}=\left\{(k,l,e,y,u):\prod_{j=1}^{J}\prod_{n=1}^{N^j}k_n^{j\mu_n^j}\leqslant k^j,\prod_{j=1}^{J}\prod_{n=1}^{N^j}l_n^{j\mu_n^j}\leqslant l^j,\prod_{j=1}^{J}\prod_{n=1}^{N^j}e_n^{j\mu_n^j}\leqslant e^j,\prod_{j=1}^{J}\prod_{n=1}^{N^j}y_n^{j\theta_n^j\mu_n^j}\geqslant y^j,\prod_{j=1}^{J}\prod_{n=1}^{N^j}u_n^{j\theta_n^j\mu_n^j}\leqslant u^j;\mu_n^j\geqslant 0;\theta_n^j\geqslant 0;\right.$$

$$n = 1, \cdots, N^j \Big\} \tag{4}$$

T_l^j and T_l^{meta} represent the technologies under two kinds of frontiers of each DMU. $\lambda_n^j \geqslant 0$ and $\mu_n^j \geqslant 0$ represent constant returns to scale assumption. Referring to O'Donnell et al[26], the two technologies have following properties:

A1. If $(k, l, e, y, u) \in T_l^j$ for any j then $(k, l, e, y, u) \in T_l^{\mathrm{meta}}$;

A2. If $(k, l, e, y, u) \in T_l^{\mathrm{meta}}$ then $(k, l, e, y, u) \in T_l^j$ for some k;

A3. $T_l^{\mathrm{meta}} = \{T_l^1 \cup T_l^1 \cup \cdots T_l^k\}$.

Based on the established energy production technology T_l^j and T_l^{meta}. we then present the following mathematical programming (5) and (6) to measure the energy performance of each DMU.

Log-linear energy model under group frontier is shown as:

$$\begin{aligned} &\rho^j = \mathrm{Max}\, \beta^{j\nu} \times \gamma^{j\omega} \\ \text{s. t.}\ &\prod_{n=1}^{N^j} k_n^{j\lambda_n^j} \leqslant k^j, \prod_{n=1}^{N^j} l_n^{j\lambda_n^j} \leqslant l^j, \prod_{n=1}^{N^j} e_n^{j\lambda_n^j} \leqslant e^j, \\ &\prod\nolimits_{n=1}^{n} y_j^{j\theta_j\lambda_j} \geqslant \beta^j y^j, \prod\nolimits_{n=1}^{n} u_j^{j\theta_j\lambda_j} \leqslant \gamma^{j-1} u^j; \\ &\lambda_j \geqslant 0, 0 \leqslant \theta_j \leqslant 1, \beta^j \geqslant 1, \gamma^j \geqslant 1 \end{aligned} \tag{5}$$

Log-linear energy model under meta-frontier is shown as:

$$\begin{aligned} \text{s. t.}\quad &\rho^{\mathrm{meta}} = \mathrm{Max}\, \beta^{\nu} \times \gamma^{\omega} \\ \text{s. t.}\ &\prod_{j=1}^{J}\prod_{n=1}^{N^j} k_n^{j\mu_n^j} \leqslant k^j, \prod_{j=1}^{J}\prod_{n=1}^{N^j} l_n^{j\mu_n^j} \leqslant l^j, \\ &\prod_{j=1}^{J}\prod_{n=1}^{N^j} e_n^{j\mu_n^j} \leqslant e^j, \\ &\prod_{j=1}^{J}\prod_{n=1}^{N^j} y_n^{j\theta_n^j\mu_n^j} \geqslant \beta y^j, \prod_{j=1}^{J}\prod_{n=1}^{N^j} u_n^{j\theta_n^j\mu_n^j} \leqslant \gamma^{-1} u^j; \\ &\mu_j \geqslant 0, 0 \leqslant \theta_j \leqslant 1, \beta \geqslant 1, \gamma \geqslant 1 \end{aligned} \tag{6}$$

In the models (5) and (6), ν and ω are weighted vectors which are often user-specified. The variables β and γ are used to enlarge outputs and reduce bad outputs. which indicate the inefficiency of output direction[39]. ρ^j and ρ^{meta} represent the maximum value of the objective function.

1.3 The definition of energy efficiency

If $\beta = 1, \gamma = 1$ for the DMU_j, the DMU is defined to be energy efficiency. We define the group frontier energy efficiency (GEE) as $\mathrm{GEE} = (\beta^{j*} \times \gamma^{j*})^{-1/2}$ and meta-frontier energy efficiency (MEE) as $\mathrm{MEE} = (\beta^* \times \gamma^*)^{-1/2}$.

Definition 1.1 DMU_j is energy-efficient if and only if MEE=1.

Since the production technology of the meta-frontier contains the group frontier, that GEE $\geqslant$ MEE. A DMU achieve energy-efficient when MEE=1, and its GEE must be 1.

Theorem 1.1 *MEE* $=1$ if and only if $\beta = 1$, $\gamma = 1$. GEE $=1$ if and only if $\beta^j = 1, \gamma^j = 1$.

When $\beta = 1, \gamma = 1$, the slacks of the desirable output and the undesirable output are both zero under meta-frontier. This means the evaluated unit does not have room for improvement in the direction of output in this output-oriented model, thus the DMU_j is energy-efficient. So it is the GEE in the group frontier. When the evaluated DMU attains energy full efficiency, it suggests that there is no shortfall of desirable output and excessive undesirables. From the definition of the energy efficiency, we can conclude that the best way to improve the efficiency is to gain desirable output and reduce undesirable output as much as possible while keeping the input unchanged. That is to say, the value of β, γ should be controlled as small as possible to improve energy efficiency.

1.4 Technology gap ratio of energy efficiency

To evaluate the performance of each DMU under different frontiers, technology gap ratio of energy efficiency is defined. The TGR of the nth DMU in the jth group is described in Eq. (7). Following Wang et al[40], we define the average TGR of the jth group, which is shown in Eq. (8).

$$\mathrm{TGR}_n^j = \frac{\mathrm{MEE}_n^j}{\mathrm{GEE}_n^j} \tag{7}$$

$$\mathrm{TGR}^j = \frac{\sum_{n=1}^{N^j} \mathrm{TGR}_n^j}{N^j} \tag{8}$$

Since GEE$\geqslant$MEE e have that the value of TGR_n^j belongs to $(0,1]$. TGR_n^j is the performance difference under two kinds of frontiers of the nth DMU, while TGR^j presents the jth group's average technology gap. A smaller TGR^j means a greater heterogeneity of the production technology. Based on the existence of such differences, we can further decompose TGR to analyze reasons for the inefficiency.

As Lin et al[41] and Chiu et al[38] described the energy inefficiency of the meta-frontier, we decompose the technology inefficiency of meta-frontier (MTI) into two parts in a similar way. If the unit under the group frontier is inefficient, its inefficiency source in the inner-group can be considered as a management inefficiency. Thus, MTI is composed of group frontier managerial inefficiency (GMI) and technology gap inefficiency (TGI).

$$TGI_n^j = GEE_n^j \times (1 - TGR_n^j) \tag{9}$$

$$GMI_n^j = 1 - GEE_n^j \tag{10}$$

$$TGI^j = \frac{\sum_{n=1}^{N^j} TGI_n^j}{N^j} \tag{11}$$

$$GMI^j = \frac{\sum_{n=1}^{N^j} GMI_n^j}{N^j} \tag{12}$$

1.5 Computational procedure for solving models (5) and (6)

Models (5) and (6) presented above are complicated and hard to solve for they are nonlinear. Taking the natural logarithm of models (5) and (6), we get the energy efficiency model under group frontier as Eq. (13) and the energy efficiency model under meta-frontier as Eq. (14).

We define the linear programming of the log-linear energy model under the group frontier as:

$$\ln\rho^j = \mathrm{Max}\,\nu\ln\beta^j + \omega\ln\gamma^j$$

$$\begin{aligned} \text{s.t.}\ & \sum_{n=1}^{N^j}\lambda_n^j \ln k_n^j \leqslant \ln k^j, \sum_{n=1}^{N^j}\lambda_n^j \ln l_n^j \leqslant \ln l^j, \\ & \sum_{n=1}^{N^j}\lambda_n^j \ln e_n{}^j \leqslant \ln e^j, \\ & \sum_{n=1}^{N^j}\theta_n^j\lambda_n^j \ln y_j^j \geqslant \ln y_j^j + \ln\beta^j, \\ & \sum_{n=1}^{N^j}\theta_n^j\lambda_n^j \ln u_n^j \leqslant \ln u^j - \ln\gamma^j \\ & \lambda_j \geqslant 0, 0 \leqslant \theta_j \leqslant 1, \ln\beta^j \geqslant 0, \ln\gamma^j \geqslant 0, \end{aligned} \tag{13}$$

Similarly, the linear programming of the log-linear energy model under meta-frontier is defined as:

$$\ln\rho^{\mathrm{meta}} = \mathrm{Max}\,\nu\ln\beta + \omega\ln\gamma$$

$$\begin{aligned} s.t.\ & \sum_{j=1}^{J}\sum_{n=1}^{N^j}\mu_n^j \ln k_n^j \leqslant \ln k^j, \sum_{j=1}^{J}\sum_{n=1}^{N^j}\mu_n^j \ln l_n^j \leqslant \ln l^j, \\ & \sum_{j=1}^{J}\sum_{n=1}^{N^j}\mu_n^j \ln e_n{}^j \leqslant \ln e^j, \\ & \sum_{j=1}^{J}\sum_{n=1}^{N^j}\theta_n^j\mu_n^j \ln y_n^j \geqslant \ln y^j + \ln\beta, \\ & \sum_{j=1}^{J}\sum_{n=1}^{N^j}\theta_n^j\mu_n^j \ln u_n^j \leqslant \ln u^j - \ln\gamma; \\ & \mu_j \geqslant 0, 0 \leqslant \theta_j \leqslant 1, \beta \geqslant 1, \gamma \geqslant 1 \end{aligned} \tag{14}$$

Supposing that $(\ln\beta^{j*}, \ln\gamma^{j*}, \lambda_n{}^*)$ is an optimal solution to Eq. (13), $(\ln\beta^*, \ln\gamma^*, \mu_n{}^*)$ is an optimal solution to Eq. (14), $(\beta^{j*}, \gamma^{j*}, \lambda_n{}^*)$ and $(\beta^*, \gamma^*, \mu_n{}^*)$ are the optimal solution to Eqs. (5) and (6), respectively. MEE and GEE are both belong to (0,1] .

2 Empirical analysis

2.1 Data and groups

Data of 30 provinces in China in the period of 2006～2015 are collected (Tibet and Hong Kong, Macao and Taiwanare excluded due to lack of data). The energy consumption index includes all kinds of consumption, such as coal and crude oil. The consumption data are derived from the energy statistics yearbook of China (2006～2015). The labor force and GDP data are derived from the statistical yearbook of China (2006～2015). GDP has been adjusted as the 2 000 constant-price to remove the influence of price fluctuations. Since the energy consumption will bring the undesired output of greenhouse gases, the carbon dioxide emissions from various provinces are selected as undesired output[42]. Following Zhang et al[43], we convert various energy consumption into corresponding carbon emissions based on their respective conversion coefficients to estimate the carbon emissions of each province. We use the perpetual inventory method to calculate capital stock $K_{it} = I_{it} + (1 - \delta_i)K_{i,t-1}$, in which K_{it} is the capital stock of the region i in the year t, $I_{i,t}$ is the investment of the regional i in the year t, and δ_i is the depreciation of fixed assets of the region i in the year t[44-45]. Here, the capital stock is converted into the corresponding data based on the 2 000 basis. Tab. 1 summarizes the statistical characteristics of the inputs and desirable and undesirable outputs.

Tab. 1 Statistical summary summary of the inputs and outputs data, 2006～2015

Parameters	Index	Unit	Average	Max	Min	St. Dev
Input	Labor	10^4 Persons	2 600	6 636	294	1 721
	Capital	10^9 Yuan	26 728	117 106	1 712	21 440
	Energy	10^4 Tons	12 914	38 899	920	8 060
Desirable output	GDP	10^9 Yuan	11 464	54 143	527	9 762
Undesirable output	CO_2	10^4 Tons	7 546	22 647	512	5 033

According to the division of the three major economic regions of the National Bureau of Statistics, provinces are divided into three major groups, eastern, central and western regions[40,46]. The eastern region includes 11 provinces, the central region includes 8 provinces, and the western region includes 11 provinces. Tab. 2 shows the average of the various indicators of inputs and outputs in these three regions over five years. From Tab. 2, it is seen that the eastern region has the best economic situation, with the highest energy consumption and carbon dioxide emissions. Tables 1 and 2 also show that the indicators in the eastern region are above the average. The western region has the worst economic situation but relatively lower energy consumption and carbon dioxide emissions, which is of a typical low-input and low-output type. The difference in these indicators suggests the imbalance in economic development. As a result, the technical heterogeneity of each region should be considered when evaluating the energy efficiency.

Tab. 2 The annual average value of input-output in three regions, 2006～2015

Parameters	Index	East	Central	West
Input	Labor	2 954	3 165	1 836
	Capital	38 366	25 637	15 883
	Energy	16 856	12 846	9 022
Desirable output	GDP	18 256	10 155	5 623
Undesirable output	CO_2	9 619	7 787	5 298

2.2 Energy efficiency under meta-frontier and group frontier

Before analyzing the energy efficiency of China in 2006～2015, we first use the data of 2015 to compare our log-linear method with the directional meta-frontier DEA approach. The directional meta-frontier method is widely used in efficiency evaluation[47-48]. In the Appendix details of the directional meta-frontier method are introduced. We calculate the energy efficiency under both group frontier and meta-frontier to compare the two methods. Tab. 3 shows the energy efficiency of these two methods.

In Tab. 3, we can find that the energy efficiency under the directional meta-frontier method is less than our proposed log-linear method within meta-frontier. The efficiency using direct group frontier is almost less than the efficiency using the log-linear method, except for Hubei. Obviously, the efficiency values obtained through these two methods are quite different. The reason for this disparity is the difference between their production possible sets. The results obtained through our method are more realistic since that the frontier of our method is piecewise Cobb-Douglas type. For example, Tianjin and Guangdong are inefficient in directional distance method, but they are on the Cobb-Douglas production frontier in our method.

Tab. 3 Comparison of the log-linear and directional meta-frontier DEA methods

Province	MEE		GEE		TGR	
	Log-linear	Directional-distance	Log-linear	Directional-distance	Log-linear	Directional-distance
Beijing	1.000	1.000	1.000	1.000	1.000	1.000
Tianjin	1.000	0.805	1.000	0.805	1.000	1.000
Hebei	0.445	0.302	0.445	0.302	1.000	1.000
Shanxi	0.366	0.182	0.581	0.398	0.630	0.457
Inner Mongolia	0.355	0.181	0.478	0.219	0.742	0.826
Liaoning	0.533	0.315	0.533	0.315	1.000	1.000
Jilin	0.555	0.318	1.000	1.000	0.555	0.318
Heilongjiang	0.568	0.327	1.000	1.000	0.568	0.327
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000
Jiangsu	0.674	0.470	0.674	0.470	1.000	1.000
Zhejiang	0.768	0.601	0.768	0.601	1.000	1.000
Anhui	0.542	0.302	1.000	0.719	0.542	0.420
Fujian	0.733	0.583	0.733	0.583	1.000	1.000
Jiangxi	0.640	0.397	1.000	1.000	0.640	0.397
Shandong	0.543	0.366	0.543	0.366	1.000	1.000
Henan	0.467	0.309	0.740	0.569	0.631	0.543
Hubei	0.619	0.417	0.980	1.000	0.632	0.417
Hunan	0.654	0.457	1.000	1.000	0.654	0.457
Guangdong	1.000	0.964	1.000	0.964	1.000	1.000
Guangxi	0.641	0.430	0.888	0.746	0.721	0.576
Hainan	0.642	0.323	0.642	0.323	1.000	1.000
Chongqing	0.728	0.514	1.000	1.000	0.728	0.514
Sichuan	0.749	0.606	1.000	1.000	0.749	0.606
Guizhou	0.450	0.256	0.586	0.310	0.768	0.826
Yunnan	0.634	0.409	0.854	0.675	0.742	0.606
Shaanxi	0.543	0.302	0.729	0.398	0.745	0.759
Gansu	0.499	0.298	0.644	0.361	0.774	0.825
Qinghai	0.523	0.273	0.663	0.330	0.790	0.827
Ningxia	0.296	0.090	0.376	0.108	0.786	0.833
Xinjiang	0.339	0.151	0.444	0.183	0.763	0.825
Average	0.617	0.432	0.777	0.625	0.805	1.000
East	0.758	0.612	0.758	0.612	1.000	1.000
Central	0.551	0.339	0.913	0.836	0.606	0.417
West	0.523	0.319	0.697	0.494	0.755	0.729

Next, we will calculate the energy efficiency MEE and GEE with the log-linear models introduced. The average results of MEE and GEE in 2006～2015 are shown in Tab. 4.

Tab. 4 Annual average energy efficiency under different frontiers

Province	MEE	GEE	TGR
Beijing	1.000	1.000	1.000
Tianjin	0.829	0.829	1.000
Hebei	0.486	0.486	1.000
Shanxi	0.407	0.599	0.678
Inner Mongolia	0.394	0.716	0.590
Liaoning	0.594	0.594	1.000
Jilin	0.566	0.982	0.579
Heilongjiang	0.662	1.000	0.662
Shanghai	1.000	1.000	1.000
Jiangsu	0.711	0.711	1.000
Zhejiang	0.773	0.773	1.000
Anhui	0.609	0.976	0.625
Fujian	0.788	0.788	1.000
Jiangxi	0.710	1.000	0.710
Shandong	0.582	0.582	1.000
Henan	0.561	0.817	0.686
Hubei	0.615	0.891	0.692
Hunan	0.691	0.993	0.696
Guangdong	1.000	1.000	1.000
Guangxi	0.676	0.963	0.703
Hainan	0.827	0.827	1.000
Chongqing	0.727	0.988	0.736
Sichuan	0.718	1.000	0.718
Guizhou	0.432	0.575	0.753
Yunnan	0.585	0.792	0.739
Shaanxi	0.585	0.797	0.733
Gansu	0.535	0.706	0.758
Qinghai	0.571	0.742	0.770
Ningxia	0.338	0.440	0.766
Xinjiang	0.448	0.601	0.743
Average	0.647	0.806	0.811
East	0.781	0.781	1.000
Central	0.603	0.907	0.666
West	0.546	0.756	0.728

In Tab. 4, we can see that only three provinces are efficient under the meta-frontier, namely Beijing, Shanghai and Guangdong. They are all in the east region. However, under the group frontier, there are six efficient provinces, namely Beijing, Heilongjiang, Shanghai, Jiangxi, Guangdong, and Sichuan. Since the meta-frontier production possibility set contains all units, the measured efficiency value under meta-frontier is less than or equal to the group frontier efficiency value. We can see that the efficiency score under the group frontier is higher in the western region and the central region. Beijing, Shanghai and Guangdong are all efficient under both group frontier and meta-frontier. It shows they are the best-performing provinces in energy efficiency evaluation, which has nothing to do with technological heterogeneity. For the technology gap ratio, we can see that the ratio of all provinces in the eastern region is 1. It means that the group frontiers of all provinces in the eastern region are part of the meta-frontier. The reason for this phenomenon is that the two provinces that are efficient under meta-frontier are both in the eastern region. As a result, when the group evaluation is conducted, the reference units of the ineffective provinces in the eastern region are still the three efficient provinces. As a result, there is a coincidence between the group frontier and part of meta-frontier, resulting in the consistent performance of the eastern region under both frontiers. Take Inner Mongolia in western provinces as an example. Its meta-frontier efficiency is 0.394, but the group efficiency has increased to 0.716. This big gap means that technological heterogeneity has a greater impact on the energy efficiency evaluation in Inner Mongolia. It is worth noting that despite the technical heterogeneity, there is still 28.4% potential room for improvement in Inner Mongolia within the group frontier. In contrast, there is as much room for improvement as 60.6% under the meta-frontier. In either case, this space for improvement is large. In other words, Inner Mongolia has a relatively low energy efficiency value. It needs to improve efficiency by reducing energy consumption, increasing GDP and reducing carbon dioxide emissions. The average meta-frontier efficiency of the eastern region is the highest, the central region is the second and the west is the lowest, as seen from Tab. 4. The average efficiency of the central region is the highest under group frontier, which is related to the small number of provinces in the central region. In general, energy is higher in areas with better economic development.

Fig. 1 reflects the trend of the meta-frontier efficiency in each province yearly. From the figure, we can see that most provinces have had relatively stable efficiency values over the ten years. The annual energy efficiency of Beijing, Shanghai and Guangdong are 1, and thus they are benchmarks of all provinces. Taking Tianjin as an example. The energy efficiency values grew every year except 2009 in Tianjin during the 2006～2015 period, which indicates increasing energy use technology with economic development and environmental protection are coordinated in Tianjin. The reason for the decline in 2009 is that there was a lot of growth in Tianjin's capital stock and carbon emissions in that year, but the GDP growth rate was smaller than other provinces in the same period. In general, energy efficiency in most provinces shows a declining-rising trend, such as Jilin and Guangxi. One situation that calls for attention is that the energy efficiency of most provinces was declining, compared with the initial energy efficiency during the period. Managers need to give some attention to this phenomenon and find out the reasons for the decline. Compared with the energy-efficient provinces, most provinces have considerable room for improvement.

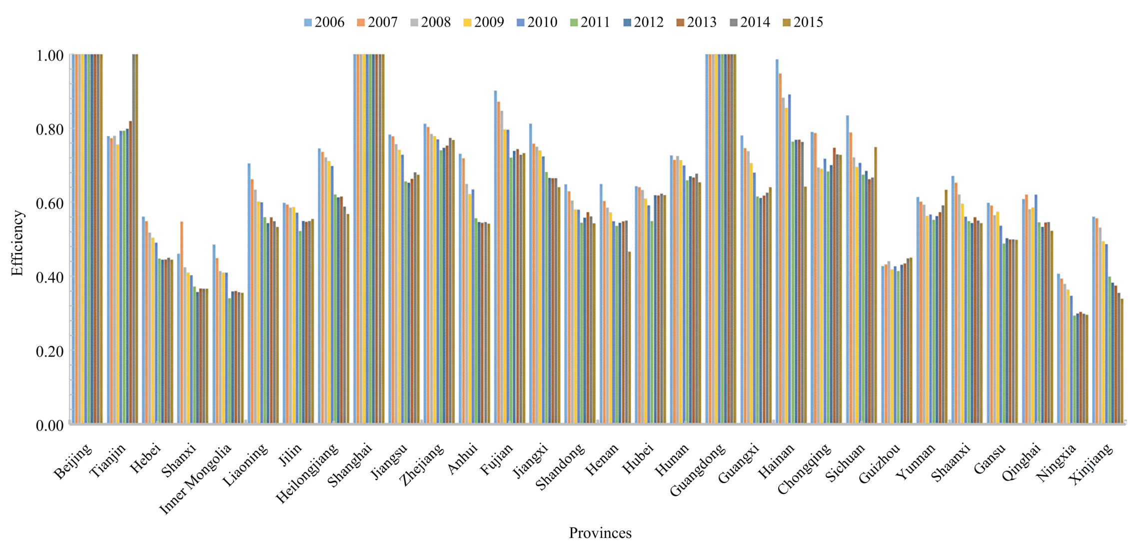

Fig. 1 Energy efficiency under meta-frontier in 2006～2015

Fig. 2 reflects the trend of the group frontier efficiency in each province yearly. Combined results in Tab. 1, we can see that the provinces that are energy efficient have increased greatly. The group frontier energy efficiency values of the 6 provinces are all 1 from 2006 to 2015, which are Beijing, Heilongjiang, Shanghai, Jiangxi, Guangdong and Sichuan. Thirteen provinces achieved at least one-time energy efficient during the ten years. In some provinces like Hebei, Shandong, Guizhou and Ningxia, the annual intra-group energy efficiency values are much lower than those of other provinces. Excluding the causes of technological heterogeneity, these provinces should strengthen the level of energy management, reduce energy consumption and reduce undesirable output to improve energy efficiency.

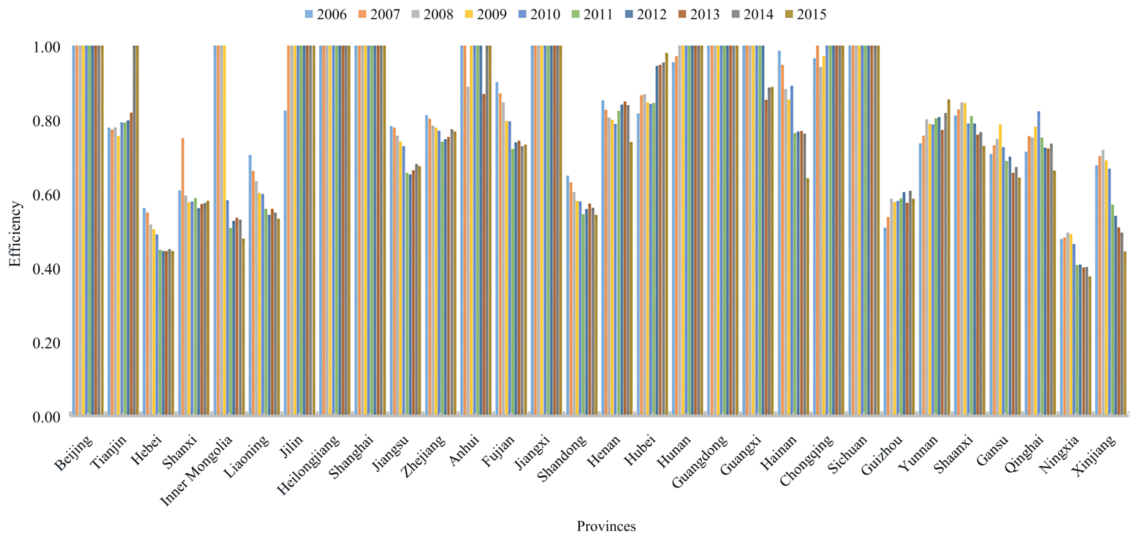

Fig. 2 Energy efficiency under group-frontier in 2006～2015

2.3 Technology gap and energy inefficiency decomposition

We have already shown in Tab. 4 the annual average TGR of each province. Detailed inefficient decomposition of all province will be discussed in this section. From Fig. 3, we can see each region's annual technology gap ratio trends. The eastern region is undifferentiated under the two types of frontiers, which was analyzed in the previous section. The TGR between the central and western regions is almost the same. However, both of them are far less than the eastern region, which indicates that they had a greater influence of technological heterogeneity.

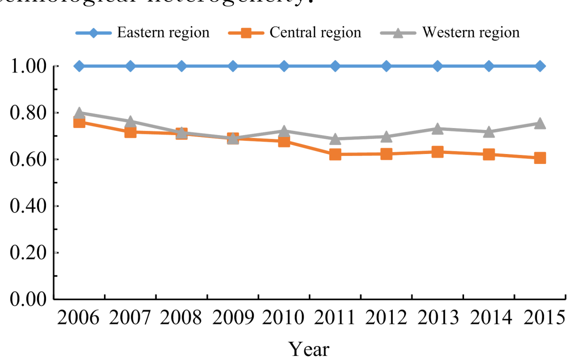

Fig. 3 Technology gap ratio in eastern, central and western region in 2006－2015

We divide the energy inefficiency into technology inefficiency and managerial inefficiency. The TGI and GMI are calculated according to Eqs. (9) and (10). The average value of TGI and GMI is shown in Tab. 5. The TGR

Tab. 5 Decomposition of energy inefficiency for all provinces

Province	TGI	GMI
Beijing	0.000	0.000
Tianjin	0.000	0.156
Hebei	0.000	0.468
Shanxi	0.174	0.365
Inner Mongolia	0.293	0.258
Liaoning	0.000	0.369
Jilin	0.379	0.016
Heilongjiang	0.308	0.000
Shanghai	0.000	0.000
Jiangsu	0.000	0.262
Zhejiang	0.000	0.206
Anhui	0.333	0.022
Fujian	0.000	0.193
Jiangxi	0.264	0.000
Shandong	0.000	0.380
Henan	0.233	0.167
Hubei	0.252	0.099
Hunan	0.275	0.007
Guangdong	0.000	0.000
Guangxi	0.261	0.034
Hainan	0.000	0.158
Chongqing	0.237	0.011
Sichuan	0.256	0.000
Guizhou	0.130	0.386
Yunnan	0.189	0.189
Shaanxi	0.193	0.184
Gansu	0.155	0.267
Qinghai	0.156	0.234
Ningxia	0.093	0.509
Xinjiang	0.140	0.362
Average	0.144	0.177

values of all eastern provinces are 1, and thus all the TGI values in eastern provinces are 0. Namely, the eastern region only has management inefficiency. Take Hunan in the Central region as an example, its total energy inefficiency is 0.282, which contains 0.275 TGI value and 0.007 GMI value. The inefficiency caused by the technical gap is far greater than the management inefficiency. This also happens to provinces such as Jiangxi and Anhui. These provinces can reduce the energy inefficiency by improving their management efficiency.

Fig. 4 shows the decomposition of the energy inefficiency of the three regions. The Eastern region has only management inefficiency, while TGI takes up a larger proportion of inefficiency in the central and western regions. Especially in the central region, the inefficiency caused by technological heterogeneity is far greater than that caused by management inefficiency. However, in the western region, it is worth noting that management inefficiency has shown an upward trend. Management inefficiency in 2010 went beyond technical gap inefficiency and has become the main source of inefficiency since then. Therefore, reducing energy consumption and reducing pollutant emissions are of great importance to improving the energy efficiency of the western region. As a whole, the proportion of management inefficiency grows year by year. There is much room for potential improvement in China's energy efficiency. This also explains the fact that China's energy management must be coordinated with economic development.

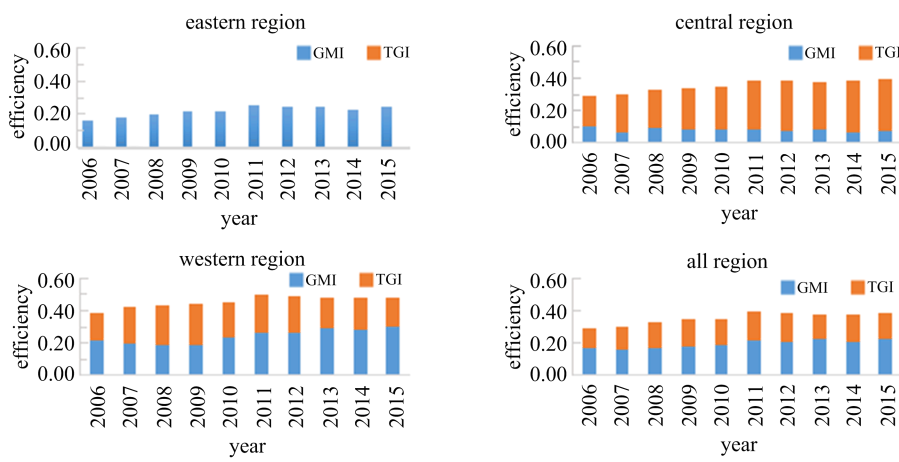

Fig. 4 Decomposition of energy inefficiency

3 Conclusion

For a sustainable development strategy of energy-saving and emission-reduction, energy efficiency measurement has gradually taken the environment into consideration. Reducing energy consumption and carbon emissions are important ways to improve energy efficiency. Considering the heterogeneity of technology among China's provinces due to economic development and geographical factors, we propose a log-linear energy technology based and output-oriented DEA model combining the meta-frontier method. In the study, we use a panel data in China from 2006 to 2015 to measure the energy efficiency of 30 provinces under meta-frontier and group frontier. We select energy consumption, capital stock, and labor input as input factors, regional GDP as expected output and CO_2 emission as undesired output. After calculating the group efficiency and meta-frontier efficiency of each province, we analyze the reasons for their inefficiencies: technology inefficiency and management inefficiency.

Through empirical study, we find most provinces have great potential for energy efficiency improvement, and there are significant differences between different regions.

Comparing the annual average meta-frontier efficiency of each province, it was found there are only three provinces, namely Beijing, Shanghai and Guangdong, that have reached energy efficiency, which means there is room for improvement for most provinces. The energy efficiency of the eastern region is higher than the average efficiency of 20.7%, and it is ahead of the other two regions. When it comes to the comparison of meta-frontier and group frontier, the efficiency in the eastern region is the same under two types of frontiers. Nevertheless, there are significant differences between the two frontiers in the central and western provinces. The main reason is that the high level of energy utilization technology in the eastern provinces represents a potential optimal level of energy efficiency in China, while the energy utilization levels of the provinces in the central and western regions are relatively low.

Second, the results show that the sources of inefficiency among different regions are different. The main reason for energy inefficiency in the eastern region is low management efficiency, while that of the central and western regions is due to the technology gap. However, it is worth noting that the management efficiency of the western region has shown a trend of decline year by year.

Third, the energy efficiency of different regions varies from high to low according to the degree of economic development. Most of the provinces in the central and western regions are economically underdeveloped. Economic development is related to energy consumption, and the level of energy technology in the central region and western region being lower than that of the eastern region results in higher energy consumption and pollution emissions.

Based on the above analysis, some managerial suggestions are given. First, different regions should reduce their energy inefficiency in different directions. The provinces in the eastern region should improve their energy efficiency by improving their own management capabilities and complete energy conservation and emission reductions effectively. The provinces in the western and central regions should improve both their management and technology capabilities.

Finally, exchanges between different regions should be strengthened to reduce the gap in energy utilization technology and environmental protection technology caused by poor economic development, which resulted in low energy efficiency. In particular, in trying to eliminate poverty and boost economic development in the western region, energy saving and emission reduction work face greater difficulties. The government should fully consider the differences in the technical levels of various regions when formulating policies related to energy-saving and emission-reduction. Governments and enterprises in the eastern region should exchange experiences in the utilization of energy and environmental management with other regions to promote the efficiency of the utilization of energy in the central and western regions. At the same time, the concept of eco-energy consumption should be adhered to so as to prevent the widening gap in energy efficiency in the central and western regions. In short, in the process of economic development, all provinces should control energy consumption to protect our common living environment.

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Appendix

Following Refs. [40,47-48], we introduce the directional-distance meta-frontier method to compare with our log-linear method. The production possibility sets under group frontier and meta-frontier are shown as Eqs. (15) and (16), respectively.

$$T=\Big\{(k,l,e,y,u):\sum_{n=1}^{N_j}\lambda_n k_n\leqslant k,\sum_{n=1}^{N_j}\lambda_n l_n\leqslant l,\sum_{n=1}^{N_j}\lambda_n e_n\leqslant e,$$
$$\sum_{n=1}^{N_j}\lambda_n y_n\geqslant(1+\beta_y^j)y,\sum_{n=1}^{N_j}\lambda_n u_n\leqslant(1-\beta_u^j)u,\lambda_n\geqslant 0,n=1,\cdots,N_j\Big\}$$
$$T^{\text{meta}}=\Big\{(k,l,e,y,u):\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n k_n\leqslant k,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n l_n\leqslant l,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n e_n\leqslant e,$$

$$\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n y_n\geqslant(1+\beta_y)y,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n u_n\leqslant(1-\beta_u)u,\lambda_n\geqslant 0,n=1,\cdots,N_j\Big\}\tag{16}$$

Based on the production possibility sets, the directional DEA models under group frontier and meta-frontier are shown as models (17) and (18), respectively.

$$\begin{aligned}&\overrightarrow{D}^j=(k,l,e,y,u;g)=\mathrm{Max}\,\omega_y\beta_y^j+\omega_u\beta_u^j\\ \text{s. t.}\ &\sum_{n=1}^{N_j}\lambda_n k_n\leqslant k,\sum_{n=1}^{N_j}\lambda_n l_n\leqslant l,\sum_{n=1}^{N_j}\lambda_n e_n\leqslant e,\\ &\sum_{n=1}^{N_j}\lambda_n y_n\geqslant(1+\beta_y^j)y,\sum_{n=1}^{N_j}\lambda_n u_n\leqslant(1-\beta_u^j)u,\\ &\lambda_j\geqslant 0,\beta_y^j\geqslant 0,0\leqslant\beta_u^j<1\end{aligned}\tag{17}$$

$$\begin{aligned}&\overrightarrow{D}^j=(k,l,e,y,u;g)=\mathrm{Max}\,\omega_y\beta_y+\omega_u\beta_u\\ \text{s. t.}\ &\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n k_n\leqslant k,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n l_n\leqslant l,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n e_n\leqslant e,\\ &\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n y_n\geqslant(1+\beta_y)y,\sum_{j=1}^{J}\sum_{n=1}^{N_j}\lambda_n u_n\leqslant(1-\beta_u)u,\\ &\lambda_j\geqslant 0,\beta_y\geqslant 0,0\leqslant\beta_u<1,\end{aligned}\tag{18}$$

Through models (17) and (18), the energy efficiency under group frontier as GEE and meta-frontier as MEE are computed as follows.

$$\mathrm{GEE}=\frac{1-\beta_u^j}{1+\beta_y^j}\tag{19}$$

$$\mathrm{MEE}=\frac{1-\beta_u}{1+\beta_y}\tag{20}$$