

## **Multi-Criteria Decision Analysis of China's Energy Security from 2008 to 2017 based on Fuzzy BWM-DEA-AR model and Malmquist Productivity Index**

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**Abstract:** Energy security has become one of the growing concerns of many countries as well as the policy makers and decision-makers. This study aims to investigate the energy security performances of 30 Chinese provinces within the period of 2008-2017 by proposing a hybrid model that integrated Fuzzy Best-Worst Method, Data Envelopment Analysis and Assurance Regions. The dynamic trend of energy security performances of these provinces during this period has also been analysed by using Malmquist Productivity Index. It was found that China's provincial energy security have shown great variance, and the eastern and southern coastal provinces have experienced better energy security performance than that of the western and northern regions. In addition, China still improved its energy security performance during this period even it has been the country with the fastest growth in world energy consumption in recent decades. Specifically, energy security performance in the middle and western provinces seems to have made more progress than the coasts. Technological progress and energy innovations can help to improve China's energy security by diversifying the energy supply sources/pathways and improving the energy efficiency, which is of great significance for the development of clean and sustainable energy.

**Key Words:** Energy security; Fuzzy Best Worst Method; Data Envelopment Analysis; Assurance Regions; Malmquist Productivity Index; technology and innovation

## Nomenclature

### *Abbreviations and acronyms*

AR	Assurance Region
BWM	Best-Worst Method
CI	consistency index
CPI	Consumer Price Index
CR	consistency ratio
CRS	constant returns to scale
CV	Coefficient of Variation
DEA	Data Envelopment Analysis
DMUs	Decision Making Units
Effch	changes in technical efficiency
FTN	fuzzy triangular numbers
GDP	Gross Domestic Product
GMIR	graded mean integration representation
GRA	Grey Relation Analysis
MCDM	multi criteria decision making
MPI	Malmquist Productivity Index
Pech	pure technical efficiency change
Sech	scale efficiency change
SWA	Simple Weighted Average
SWI	Shannon Winer Index
Techch	technology change
TEch	technical efficiency change
TFPch	total factor productivity change
TOE	tons of oil equivalent
TOPSIS	Technique for Order Preference by Similarity to an Ideal Solution
VRS	variable returns to scale

### *Parameters and variables*

$x_{ij}$	Value of the $i_{th}$ input criterion with respect to the $j_{th}$ DMU
$y_{rj}$	Value of the $r_{th}$ output criterion with respect to the $j_{th}$ DMU
$v_i$	Weight of the $i_{th}$ input criterion
$u_r$	Weight of the $r_{th}$ output criterion
$h_k$	Efficiency score of the $k_{th}$ DMU
$u_0$	Free sign
$\varepsilon$	Non-Archimedean element

## 1. Introduction

As the world's largest developing country, China has experienced unprecedented flourishing economic growth during the past decades, accompanied by ever-growing demands for energy resources. The energy consumption increased from 977.2 million TOE in 1999 to 3273.5 million TOE in 2018, with an annual growth rate of 6.6% [1]. Consequently, it has been the largest energy consumer globally for a decade by taking over the United States in 2010. To meet the increasing energy demands, it has to import energy products from overseas, resulting in expanding gap between domestic energy supply and demand, and increasingly rising dependence on energy imports [2]. Besides, the coal-dominated energy mix (accounting for more than 60% in total primary energy supply) in China is also criticized for leading to large amount of greenhouse gas emissions. In 2009, the Chinese government promised to reduce its intensity of carbon emissions by 40% to 45% on 2005 level by 2020 [3], and even pledged to peak carbon emissions, reduce carbon intensity from 60% to 65% on 2005 level, and increase the share of non-fossil fuels in primary energy consumption to approximately 20% around 2030 [4]. To achieve these targets and ensure energy security without cumbering economic development, China is facing unprecedented challenges and pressure. In addition, the massive consumption of fossil fuels is also criticized for leading to energy inefficiency and serious environmental problems [5,6], which causes great damages to economic development. Some studies revealed that that an increase of  $5 \mu\text{g}/\text{m}^3$  in PM2.5 concentrations may lead to a decrease of 2500 Yuan RMB in GDP per capita in China [7]. Environmental pollution caused by fossil fuels combustion is also a main threat to public health. Song *et al.* (2017) found that in China, PM2.5 contributed about 40.3% to total stroke deaths, 26.8% to ischemic heart disease deaths, 33.1% to acute lower respiratory infection deaths, 18.7% to chronic obstructive pulmonary disease deaths, 23.9% to lung cancer deaths, and 15.5% to all caused deaths [8]. All the above issues are within the scope of energy security, which makes it a broad and inclusive concept [2,9-11]. To tackle the ever-growing energy consumption and the derived social and environmental issues, and achieve energy efficiency, it is necessary to make an assessment for China's energy security.

Up to now, plentiful studies have investigated regional energy security. With the explosive growth of global economy in the early 21<sup>st</sup> century, energy security has been an increasingly hot topic all over the world [12-15]. Since the 4A (Availability, Accessibility, Affordability, and Acceptability) framework for energy security assessment was put forward by Asia Pacific Energy Research Centre (2007) [16], energy security has been the focus of researchers and policymakers, and its concept also becomes more and more inclusive [17-25].

Based on that, Vivoda (2010) proposed 44 indicators for evaluating national or regional energy security [26]. Cohen *et al.* (2011) measured energy security for OECD countries from the perspective of diversification in energy supply sources [27]. Sovacool and his team conducted a series of studies to evaluate energy security for countries all over the world by using the dimensions and metrics they developed [28-30]. Aslani *et al.* (2012) discussed energy security situation for the Nordic countries by comparing with other developed countries [31]. Kanchana and Unesaki (2014)

employed 35 indicators for evaluating energy supply security of nine ASEAN states during the past decades [32]. By using three different aggregated energy indices, Narula and Reddy (2015) measured energy security and energy sustainability of different countries [33]. Based on three energy scenarios, Phdungsilp (2015) made a future energy security measurement in Thailand between 2012 and 2030 [34]. Erahman *et al.* (2016) also proposed an energy security index by aggregating 14 indicators and evaluated energy security performance in Indonesia during the period of 2008–2013 [35]. Narula *et al.* (2017) used 23 metrics to compose a sustainable energy security index to assess Indian energy security in 2002, 2007 and 2012 [36]. Zeng *et al.* (2017) evaluated energy security trends of three Baltic States during 2008–2012 with MCDM methods [37]. Wang and Zhou (2017) developed a framework for measuring global national energy security by proposing a set of indicators and using MCDM methods [38]. Zhang *et al.* (2017) measured the provincial energy security within China [2]. Matsumoto *et al.* (2018) analyzed energy security of EU countries based on the Shannon–Wiener diversity index from 1978 to 2014 [39]. By constructing a comprehensive index, Le *et al.* (2019) evaluated energy security for 24 Asian countries during 1990–2014 [40]. Song *et al.* (2019) designed a China energy security index by integrating 18 indicators with banding approach [41]. Gasser (2020) reviewed 63 indices for measuring national energy security. Most of these studies focused on the selection of indicators or metrics, and then aggregated them into an index to represent energy security performance, either by simple aggregation or by using MCDM techniques [42]. However, just like Narula and Reddy (2015) pointed out in their study - different indices resulted in different results [33], which means when using different indicators or indices to assess energy security for the same sample, inconsistent energy security performance may appear. Even for the same group of indicators, different aggregation methods or indicator weights can also lead to inconsistency of rankings. Besides, they are also criticized for lack of transparency in selecting indicators and aggregating methods [42]. Thus, a more rigorous and holistic methodology is prerequisite for helping researchers and policymakers to measure energy security performance from an overall perspective.

DEA, developed by Charnes *et al.* (1978), is a novel non-parametric method for efficiency measurement [43]. It has been widely used for assessing the relative efficiency of a set of DMUs, and is especially commonly used for the scenarios with multiple inputs and outputs [44]. Some studies have been carried out to investigate energy efficiency with DEA model. For instance, Mandal and Madheswaran (2011) analyzed energy use efficiency of Indian cement companies [45]. Houshyar *et al.* (2012) investigated the efficiency of energy consumption in corn production of Southwest Iran [46]. Zhou *et al.* (2014) evaluated energy efficiency of China's transport sector [47]. Dogan and Tugcu (2015) assessed energy efficiency in electricity production of the G20 countries [48]. Liu and Wang (2015) evaluated energy efficiency of China's industry sector [49]. Song *et al.* (2015) analyzed energy efficiency of coal-fired power units in China [50]. Jebali *et al.* (2017) studied the energy efficiency of the Mediterranean states [51]. Gökgöz and Güvercin (2018) measured the renewable energy efficiency and productivity of several EU member states during the period 2004

to 2014 from a perspective of energy security [52]. However, they mainly focused on efficiency of energy consumption in different sectors [53], and failed to evaluate energy security performance from a more systematic and comprehensive prospective. In addition, the weights of the input and output indicators in DEA model are determined by solving the programming model instead of being determined in advance, and a very large weight value may be allocated to one criterion while the rest share very small weights [54]. However, energy security in real world is a complex system with the involvement of many elements, and each of them play an import role in it. Thus, the traditional DEA model is also criticized by giving extreme weight values to inputs or outputs [54].

The objective of this study is to establish an integrated and efficient methodology to evaluate China's energy security performance from 2008 to 2017. The contribution of this study lies in the following aspects:

- A hybrid model that integrated Fuzzy BWM, DEA and AR was developed in this study. The Fuzzy BWM is used to determine multiple criteria weights for generating Assurance Regions, which are then added to the DEA model as constraints to avoid extreme and unreasonable weight values.
- Comparisons between the proposed Fuzzy BWM-DEA-AR model and traditional DEA as well as other MCDM techniques was conducted. (including SWA, TOPSIS, and GRA), and the results indicate that the proposed Fuzzy BWM-DEA-AR model has better discriminative power than traditional DEA model, and it is capable of measuring energy security performance from an economic and technological efficiency perspective rather than the perspective of compromise among indicators.
- With the proposed input and output indicators for measuring energy security, both the cross-sectional comparison and changing trend analysis are performed. The former is accomplished with the proposed Fuzzy BWM-DEA-AR model, and the latter is completed with Malmquist Productivity Index.

The remaining parts of this study are organized as following: Section 2 describes the methodology of Fuzzy BWM-DEA-AR and MPI. Section 3 presents the input and output indicators as well as the corresponding data for measuring China's energy security performance. Section 4 analyzes the results of China's energy security performance with the proposed Fuzzy BWM-DEA-AR model and MPI, Section 5 makes some further discussions on the comparisons between traditional DEA and hybrid model proposed in this study, and Section 6 draws some conclusions for this study and proposes some policy implications for enhancing energy security.

## 2. Methodology

DEA, firstly developed by Charnes, Cooper and Rhodes, also called CCR or C<sup>2</sup>R model, a linear programming-based technique, can be used to measure the relative performance for a group of DMUs [43]. Compared with other techniques, DEA model doesn't require specific function relationships between the inputs and outputs [55], and showed great promise for analyzing energy efficiency and productivity [53]. However, the traditional DEA model is criticized for the unreasonable weight determination with occasional occurrences of extreme weight values [54]. Thus, we introduced AR

proposed by Thompson et al. (1986) to define the ranges of criteria weights, and introduced a highlighted DEA-AR model to conduct the performance evaluation [56].

To determine ARs for the indicators, it's necessary to calculate multiple weights for them. Therefore, it needs a weighting method based on multiple experts' judgement. In fact, AHP is usually used to determine criteria weights, however, this method frequently encounters intensive pairwise comparisons and the problems of inconsistency [57,58]. So, we introduced Fuzzy BWM to determine weight values of indicators. BWM is a newly developed MCDM technique introduced by Rezaei (2015) [59], and can determine criteria weights with less and easier pairwise comparisons and improve their consistency. Since human qualitative judgments of BWM usually contain a certain degree of ambiguity and uncertainty [60], we combined fuzzy logic with BWM to derive criteria weights, which makes it suitable for solving uncertain and vague problems [60]. So, here we use Fuzzy BWM based on multiple experts' judgement to define ARs for the criteria in DEA model, which is a major innovative contribution in this paper.

In this section, the specific model is presented as displayed in Figure 1. To start, it determines weight values of the input and output indicators with Fuzzy BWM based on multiple experts' judgement, and then, ARs are formed from the pairwise weight comparisons. By adding these ARs as constraints in DEA model, the efficiency performance scores of the DMUs can be derived and analyzed from a static perspective by solving the models. Finally, the method of MPI has been introduced to examine the performance change trends over time [61].

### 2.1 Fuzzy BWM

The steps for executing Fuzzy BWM is presented as follows [60]:

**Step 1:** Analyze decision problems and select decision criteria.

We assume  $C:(c_1, c_2, \dots, c_n)$  are the  $n$  criteria in the decision-making problem.

**Step 2:** Identify the best and worst criterion.

The best and worst criterion, or the most and least important, need to be identified from all the  $n$  criteria, and are represented by  $C_B$  and  $C_W$ , respectively.

**Step 3:** Make fuzzy comparisons for the best and worst criterion.

Experts are invited to use linguistic terms in Table 1 to make comparisons for the preferences of the best criterion over all the others and all the others over the worst criterion, which are then translated into FTNs. The derived fuzzy Best-to-Others and fuzzy Others-to-Worst vectors are shown in Eqs. (1)-(2).

Table 1. Linguistic terms and the corresponding FTNs in Fuzzy BWM [60].

Linguistic terms	FTNs
Equally important (E)	(1, 1, 1)
Weakly important (W)	(2/3, 1, 3/2)
Fairly important (F)	(3/2, 2, 5/2)
Very important (V)	(5/2, 3, 7/2)
Absolutely important (A)	(7/2, 4, 9/2)

$$\tilde{A}_{BO} = (\tilde{a}_{B1}, \tilde{a}_{B2}, \dots, \tilde{a}_{Bn}) \quad (1)$$

$$\tilde{A}_{OW} = (\tilde{a}_{1W}, \tilde{a}_{2W}, \dots, \tilde{a}_{nW}) \quad (2)$$

where  $\tilde{a}_{Bj}$  and  $\tilde{a}_{jW}$  refers to the fuzzy preferences of the best criterion  $C_B$  over criterion  $j$  and criterion  $j$  over the worst criterion  $C_W$ , respectively. We define that  $\tilde{a}_{BB} = (1, 1, 1)$  and  $\tilde{a}_{WW} = (1, 1, 1)$ .

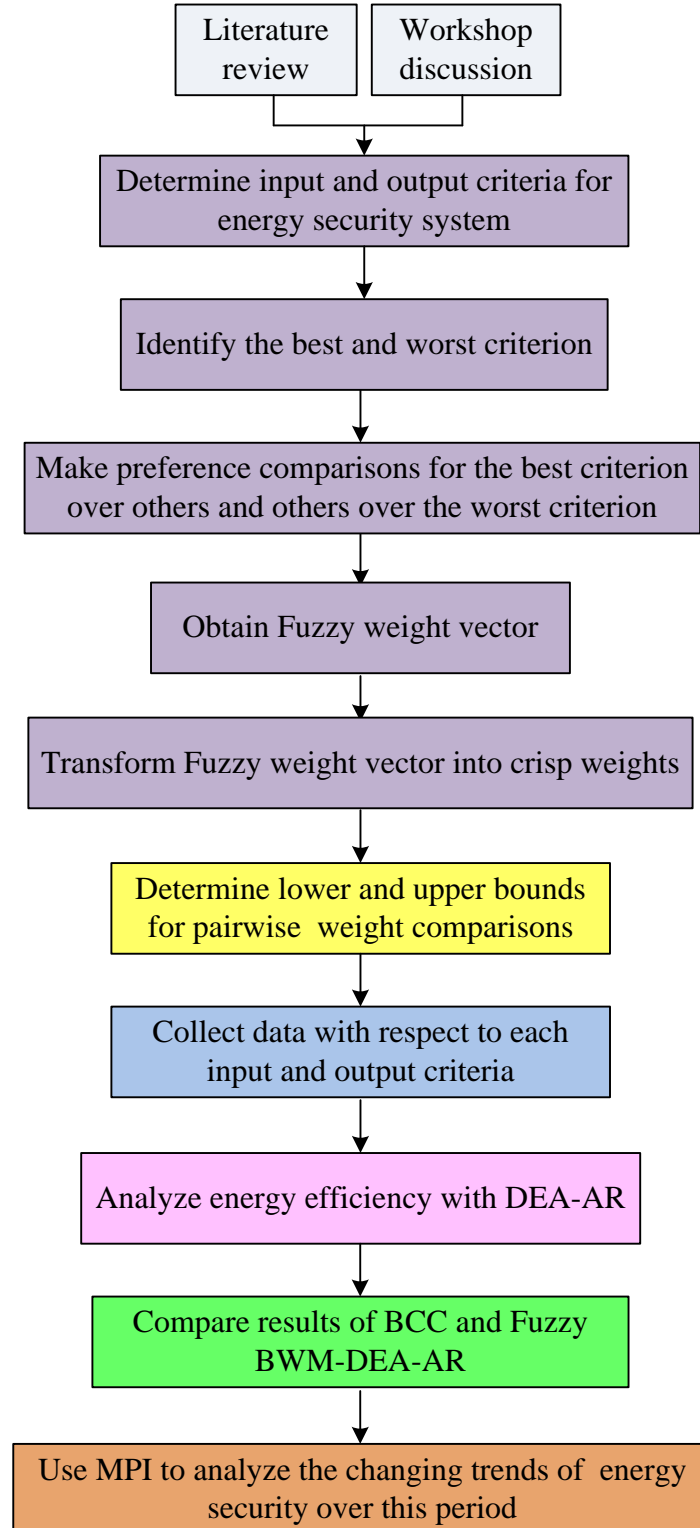


Figure 1. Flow chart of the methodology in this study.



**Step 4:** Calculate the optimal fuzzy weight  $W = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)$ .

In order to derive the optimal fuzzy criteria weights, the following programming model in Eq. (3) can be established [60].

$$\begin{aligned} & \min \tilde{\xi} \\ & s.t. \left\{ \begin{array}{l} \left| \frac{\tilde{w}_B}{\tilde{w}_j} - \tilde{a}_{Bj} \right| \leq \tilde{\xi} \\ \left| \frac{\tilde{w}_j}{\tilde{w}_W} - \tilde{a}_{jW} \right| \leq \tilde{\xi} \\ \sum_{j=1}^n R(\tilde{w}_j) = 1 \\ l_j^W \leq m_j^W \leq u_j^W \\ l_j^W \geq 0 \\ j = 1, 2, \dots, n \end{array} \right. \end{aligned} \quad (3)$$

where  $\tilde{w}_B = (l_B^W, m_B^W, u_B^W)$ ,  $\tilde{w}_j = (l_j^W, m_j^W, u_j^W)$ ,  $\tilde{w}_W = (l_W^W, m_W^W, u_W^W)$ ,  $\tilde{a}_{Bj} = (l_{Bj}, m_{Bj}, u_{Bj})$ ,  $\tilde{a}_{jW} = (l_{jW}, m_{jW}, u_{jW})$ ,  $\tilde{\xi} = (l^\xi, m^\xi, u^\xi)$ , and  $l^\xi \leq m^\xi \leq u^\xi$ . It is assumed  $\tilde{\xi}^* = (k^*, k^*, k^*)$  and  $k^* \leq l^\xi$ .

The programming model in Eq. (3) can be rewritten as model in Eq. (4) [60].

$$\begin{aligned} & \min \tilde{\xi}^* \\ & s.t. \left\{ \begin{array}{l} \left| \frac{(l_B^W, m_B^W, u_B^W)}{(l_j^W, m_j^W, u_j^W)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{(l_j^W, m_j^W, u_j^W)}{(l_W^W, m_W^W, u_W^W)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^n R(\tilde{w}_j) = 1 \\ l_j^W \leq m_j^W \leq u_j^W \\ l_j^W \geq 0 \\ j = 1, 2, \dots, n \end{array} \right. \end{aligned} \quad (4)$$

By solving the programming model in Eq. (4), the optimal fuzzy weights vector  $W = (\tilde{w}_1, \tilde{w}_2, \dots, \tilde{w}_n)$  and  $\tilde{\xi}^*$  can be calculated [60]. For further understanding the operations of fuzzy numbers, [62] and [63] can be referred to.

**Step 5:** Compute CR for the fuzzy weight vector.

CR can be calculated by Eq. (5) [60].

$$CR = \frac{\tilde{\xi}^*}{CI} \quad (5)$$

where CR varies in the range [0,1], and better consistency of the fuzzy weight vector is achieved with smaller CR. CI is determined by the preference comparison of the best criterion over the worst, and the value is shown in Table 2 [60].

Table 2. CI for Fuzzy BWM [60].

$\tilde{a}_{BW}$	(1,1,1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(5/2, 3, 7/2)	(7/2, 4, 9/2)
CI	3.00	3.80	5.29	6.69	8.04

**Step 6:** Transform the optimal fuzzy weight into crisp value.

If all fuzzy comparisons have been considered as consistent, the fuzzy weights vector in Step 5 can be transformed to a crisp value by adopting GMIR in Eq. (6) [64].

$$R(\tilde{a}_i) = \frac{l_i + 4m_i + u_i}{6} \quad (6)$$

where  $R(\tilde{a}_i)$  is the GMIR of  $\tilde{a}_i = (l_i, m_i, u_i)$ .

## 2.2 DEA

DEA is a popular programming model used to evaluate the relative efficiency of DMUs with multiple inputs and outputs based on the efficiency frontier [43]. The DEA-CCR model has an assumption of CRS, so it is also called DEA-CRS model. If it assumes VRS, the DEA-VRS model can be derived, which is also known as DEA-BCC model [65].

Let's assume that there are  $m$  input indicators and  $s$  output indicators for a group of  $n$  DMUs.  $x_{ij}$  is the attribute value of the  $i$ th input indicator with respect to the  $j$ th DMU, with a weight of  $v_i$ , where  $i=1,2,\dots,m, j=1,2,\dots,n$ .  $y_{rj}$  is the attribute value of the  $r$ th output indicator with respect to indicator of the  $j$ th DMU, with a weight of  $u_r$ , where  $r=1,2,\dots,s, j=1,2,\dots,n$ . Among them,  $x_{ij}$  and  $y_{rj}$  are known parameters, while  $v_i$  and  $u_r$  are unknown variables, which can be expressed in matrix format as following:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \quad Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1n} \\ y_{21} & y_{22} & \cdots & y_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ y_{s1} & y_{s2} & \cdots & y_{sn} \end{bmatrix} \quad V = \begin{bmatrix} v_1 \\ v_2 \\ \vdots \\ v_m \end{bmatrix} \quad U = \begin{bmatrix} u_1 \\ u_2 \\ \vdots \\ u_s \end{bmatrix}$$

The structure of DEA problems can be presented as Figure 2.

The efficiency of a DMU is defined as the ratio between the inputs and outputs [66]. Similarly, in DEA model, the efficiency of the DMU<sub>k</sub> can be defined as the ratio between its synthetic inputs and synthetic outputs, as presented in Eq. (7):

$$Z_k = \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}} \quad (7)$$

where  $Z_k$  is the relative efficiency of DMU<sub>k</sub>.

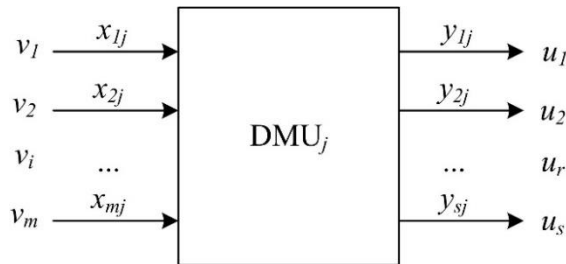


Figure 2. Structure of problems in DEA model

According to the basic DEA model, CCR proposed by Charnes *et al.* (1978) [43], if we need to measure the relative efficiency of DMU<sub>k</sub>, the objective function is to achieve the maximum relative efficiency, with the constraint of efficiency values of all DMUs no greater than one. The CCR model has an assumption of CRS, which is input-oriented, and the model is expressed as presented in Eq. (8) [43]:

$$\begin{aligned} \max Z_{kP} &= \frac{\sum_{r=1}^s u_r y_{rk}}{\sum_{i=1}^m v_i x_{ik}} \\ \text{Subject to :} & \quad (8) \\ & \begin{cases} \frac{\sum_{r=1}^s u_r y_{rj}}{\sum_{i=1}^m v_i x_{ij}} \leq 1 & j = 1, 2, \dots, n \\ v_i \geq \varepsilon & i = 1, 2, \dots, m \\ u_r \geq \varepsilon & r = 1, 2, \dots, s \end{cases} \end{aligned}$$

where  $Z_j$  donates the relative efficiency of DMU<sub>j</sub>, the subscript  $P$  indicates that this is a linear programming problem, and  $\varepsilon$  is a non-Archimedean element.

Since decision makers of energy security usually pay great and nonconstant effort to achieve high efficiency, and they mainly focus on the economic and environmental outputs, so we use the output-oriented BCC or VRS model to evaluate efficiency performance of energy security, and the model is as shown in Eq. (9) [65,67]:

$$\begin{aligned} \max h_k &= \sum_{r=1}^s u_r y_{rk} - u_0 \\ \text{Subject to :} & \quad (9) \\ & \begin{cases} \sum_{r=1}^s u_r y_{rj} - \sum_{i=1}^m v_i x_{ij} - u_0 = 0 & j = 1, 2, \dots, n \\ \sum_{i=1}^m v_i x_{ik} = 1 \\ v_i \geq \varepsilon & i = 1, 2, \dots, m \\ u_r \geq \varepsilon & r = 1, 2, \dots, s \end{cases} \end{aligned}$$

where  $u_0$  is a sign for identifying return to scale aspects of the  $k$ -th DMU.

### 2.3 DEA-AR

No matter for CCR or BCC model, the weight values of the input and output indicators are solely calculated through solving the programming model instead of being determined in advance, and the weight value for the same criterion may vary greatly in different DMUs [54]. To determine the most efficient DMU, it is very likely to weight a single input or output criterion with 1 and the other input and output criteria been weighted 0 [54]. However, energy security in real world is a complex system which involves a lot of elements, and it seems to be unreasonable to give one input or output criterion a very great weight while the rest with very small ones [54]. Besides, when

we talk about energy security, it indicates the state of energy supply and consumption as well as their social and environmental effects, and its connotation may evolve with economic, social and technological development [17,25]. Thus, the extreme weight values derived by linear programming in DEA need to be avoid [68], and man-made criteria weights are essential to be determined in advance. AR developed by Thompson et al. (1986) has provided a feasible solution for allocating reasonable weight to the indicators [56]. By introducing ARs, it adds additional constraints on the comparisons of the weight values to the linear program model of DEA to generate an innovative DEA-AR model. For each pair of input or output criteria, lower and upper bounds for their comparisons are defined as Eqs. (10) and (11).

$$L_{ik} \leq (v_i / v_k) \leq U_{ik} \quad (10)$$

$$L_{rt} \leq (u_r / u_t) \leq U_{rt} \quad (11)$$

where  $v_i / v_k$  is the comparison of the weights in the DEA model for a pair of input criterion  $i$  and  $k$ ,  $u_r / u_t$  is the comparison for a pair of output criterion  $r$  and  $t$ .  $L$  and  $U$  are the lower and upper bounds of the weight comparisons, and are usually determined in advance.

#### 2.4 Malmquist Productivity Index

With the technique of DEA measuring static efficiency, MPI can be used as a useful tool for evaluating energy security performance and the changing trends within a specific period [69-72]. The MPI measures the total factor productivity change between two data points over time, which can be defined as Eq. (12) [73].

$$M_{t,t+1} = \frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)} \times \sqrt{\frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)}} \quad (12)$$

where  $M_{t,t+1}$  donates MPI, which indicates the total factor productivity change from period  $t$  to period  $t+1$ , and  $D(x, y)$  is the distance function.

MPI can be decomposed into two components. The first component,  $\frac{D_{t+1}(x_{t+1}, y_{t+1})}{D_t(x_t, y_t)}$ ,

defines the changes in technical efficiency from period  $t$  to period  $t+1$ , which describes whether a DMU improves or deteriorates its efficiency (Catch-up effect). Further, the technical efficiency change can be decomposed into pure technical efficiency change

and scale efficiency change. The second component,  $\sqrt{\frac{D_t(x_{t+1}, y_{t+1})}{D_{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_t(x_t, y_t)}{D_{t+1}(x_t, y_t)}}$ , is the

technology change which indicates the frontier-shift effect (innovation effect) from period  $t$  to period  $t+1$ .

### 3. Indicators and Data

This study employs Fuzzy BWM-DEA-AR and MPI to assess China's energy security performance with respect to the period of 2008 to 2017. In this section, we developed a group of input and output indicators for measuring energy security with DEA model, and describe the data with respect to these indicators and DMUs.

Totally, we have identified six input indicators in four aspects and five output indicators based on the 4As energy security framework [16], as presented in Figure 3.

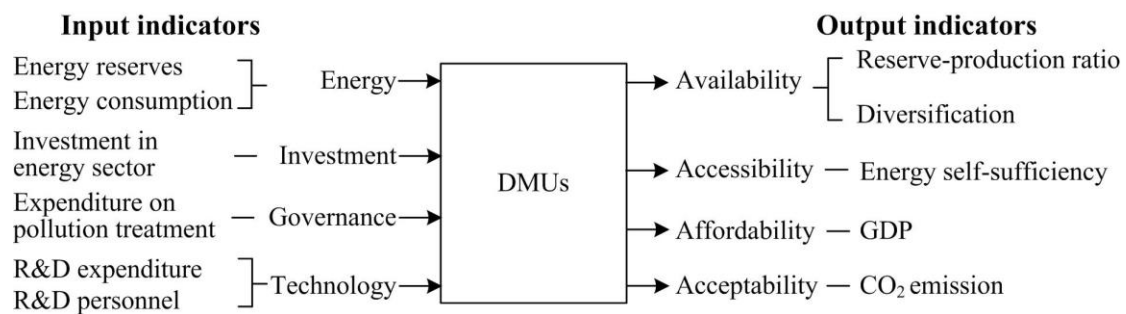


Figure 3. Input and output indicators.

At the end of inputs, we considered six input indicators from four aspects: energy, investment, governance, and technology, as presented in Table 3. To be specific, the energy input involves two indicators: energy reserves ( $I_1$ ) and energy consumption ( $I_2$ ). Energy reserves indicate the geologic existence of fossil fuels, which is the foundation of energy security. Energy consumption defines the annual energy use of each province, which is of great significance to regional energy security. Investment in energy sector ( $I_3$ ) and expenditure on pollution treatment ( $I_4$ ) are selected as input indicators from the aspects of investment and governance, respectively, and these two indicators describes the input for energy security in a broad sense. Besides, the input indicators have also been considered from the prospective of technology and innovation with two indicators: number of R&D personnel ( $I_5$ ) and expenditure on R&D activities ( $I_6$ ).

On the other end, five indicators were identified as outputs from the perspective of 4As framework, as shown in Table 3. Availability is one of the most important dimension of energy security, and we considered the indicators of Reserve-production ratio ( $O_1$ ) and diversification ( $O_2$ ) for this dimension. Reserve-production ratio measures the potential of domestic fossil fuel supply, while diversification describes the characteristics of regional energy mix, which is measured by SWI. The dimension of accessibility is depicted by the indicator of energy self-sufficiency ( $O_3$ ), which refers to the share of energy demand satisfied by domestic supply. In order to present the economic results of energy security, we use the indicator of GDP ( $O_4$ ) to describe the dimension of affordability. As for the last dimension of acceptability, we use CO<sub>2</sub> emissions to indicate the undesirable output, which ensures unbiased results can be obtained [70,74].

In this paper, we have 30 DMUs (30 Chinese provinces, not including Hong Kong, Macao, Taiwan, and Tibet). After determining the input and output indicators, we collected all the data points with respect to 30 Chinese provinces by reviewing Chinese

Energy Statistical Yearbook and the corresponding provincial statistical yearbooks. However, it is worth noting that, among the input and output indicators, investment in energy sector ( $I_3$ ), expenditure on pollution treatment ( $I_4$ ), expenditure on R&D activities ( $I_6$ ), and GDP ( $O_4$ ) are presented in normal terms in the statistical yearbook, which makes data from different years incomparable. Thus, we use CPI to deflate these four indicators to remove the influence of price change. Table 4 gives the descriptive statistics of the inputs and outputs of 30 Chinese provinces within the period of 2008-2017.

Besides, we should also note that CO<sub>2</sub> emission was taken as an undesirable output. There are a variety of techniques, both linear and nonlinear, which can help to deal with undesirable outputs [75]. To facilitate the energy security performance measurement, we take a linear way of subtracting the undesirable values from a large number, as shown in Eq. (13) [76,77]. Also, zero value is not allowed in DEA model, thus we used Eq. (14) to normalize the data with respect to the positive criteria with 0 value.

$$y_r = w - y_r' > 0 \quad (13)$$

where  $y_r'$  and  $y_r$  are the original and positively transformed values of the  $r_{th}$  output criteria, respectively, and  $w$  is a number larger than all values with respect the  $r_{th}$  output criteria.

$$x_{ij} = 0.1 + \frac{x_{ij}' - \min x_j}{\max x_j - \min x_j} \quad (14)$$

where  $x_{ij}'$  and  $x_{ij}$  are the original and normalized values of DMU<sub>*i*</sub> with respect to the  $j_{th}$  criteria, respectively,  $\max x_j$  and  $\min x_j$  are the maximum and minimum values with respect to the  $j_{th}$  criteria, respectively.

Table 3. Description of input and output indicators of energy security.

Components	Criteria	Description
Energy	I <sub>1</sub> : energy reserves	It indicates the geologic existence of fossil fuels.
	I <sub>2</sub> : Energy consumption	it defines the annual energy demand.
Investment	I <sub>3</sub> : Investment in energy sector	It measures the financial inputs of energy sector.
Governance	I <sub>4</sub> : Expenditure on pollution treatment	It describes the efforts of local government on environmental pollution.
Technology	I <sub>5</sub> : R&D expenditure	It measures the financial inputs in improving energy security.
	I <sub>6</sub> : R&D personnel	It describes the human labor input in improving energy security.
Availability	O <sub>1</sub> : Reserve production ratio	It describes the geographic potentials of fossil fuels.
	O <sub>2</sub> : Diversification	It refers to the share of different energy sources in total energy consumption.
Accessibility	O <sub>3</sub> : Self sufficiency	It measures the dependence on imported energy.
Affordability	O <sub>4</sub> : GDP	It deliberates the economic outputs of energy consumption.
Acceptability	O <sub>5</sub> : CO <sub>2</sub> emissions	It describes the environmental output of energy consumption.

Table 4. Descriptive statistics of input and output criteria for provincial energy security in China, 2008-2017.

	Maximum	Minimum	Average	Median	Std. Dev.
I <sub>1</sub> : Energy reserves (mill. tce)	75823.66	0.00	6456.17	1883.83	13661.27
I <sub>2</sub> : Energy consumption/ (mill. tce)	387.23	11.35	134.96	111.81	79.96
I <sub>3</sub> : Investment in energy sector (mill. Yuan RMB)	280.74	3.55	75.21	63.35	50.20
I <sub>4</sub> : Expenditure on pollution treatment (mill. Yuan RMB)	12329.63	35.88	1914.20	1401.25	1757.76
I <sub>5</sub> : R&D expenditure (mill. Yuan RMB)	154776.20	87.68	21900.93	10712.59	29465.56
I <sub>6</sub> : R&D personnel (person)	457342.00	554.00	71477.73	37402.50	96172.16
O <sub>1</sub> : Reserve production ratio (Year)	511.92	0.00	65.05	50.40	71.24
O <sub>2</sub> : Diversification	1.37	0.28	0.94	0.99	0.27
O <sub>3</sub> : Self-sufficiency (%)	784.76	0.52	87.23	53.50	104.48
O <sub>4</sub> : GDP (bill. Yuan RMB)	7444.51	101.86	1742.23	1359.58	1397.30
O <sub>5</sub> : CO <sub>2</sub> emissions (mill. ton)	1424.33	40.63	391.46	296.40	269.41

#### 4. Results

With the Fuzzy BWM-DEA-AR model proposed in this paper, we firstly employed Fuzzy BWM to determine ARs for pairwise comparisons of indicator weights, which were then added as constraints in DEA model to analyze the static annual energy security performance of China's 30 provinces. After that, MPI is utilized to investigate the dynamic change of Chinese provincial energy security performance.

##### 4.1 Fuzzy BWM results

By following the procedure of Fuzzy BWM, we can calculate the weight values for each input and output indicator. In this study, to establish ARs for the weight comparisons, we need to achieve multiple weight values for the indicators. Thus, we invited five experts who have a very good knowledge of energy security, to conduct the identification of the best and worst criteria and preference comparisons. The results of Fuzzy BWM have been displayed in Table 5.

Table 5. Weight values of input and output indicators derived from Fuzzy BWM based on multiple experts' judgement.

	Inputs						CR	Outputs					CR
	$v_1$	$v_2$	$v_3$	$v_4$	$v_5$	$v_6$		$u_1$	$u_2$	$u_3$	$u_4$	$u_5$	
Expert 1	0.2305	0.2597	0.0707	0.1054	0.2296	0.1041	0.0622	0.1261	0.1309	0.2470	0.2400	0.2470	0.0179
Expert 2	0.2730	0.2433	0.0740	0.1569	0.1569	0.0959	0.0372	0.1691	0.0950	0.3014	0.1691	0.2654	0.0312
Expert 3	0.0838	0.2571	0.0973	0.2592	0.1915	0.1111	0.0524	0.1101	0.2970	0.2309	0.1311	0.2309	0.0432
Expert 4	0.1702	0.2732	0.1039	0.1879	0.1879	0.0769	0.0559	0.1456	0.1456	0.3299	0.2565	0.1224	0.0432
Expert 5	0.0868	0.3200	0.0974	0.1483	0.2501	0.0974	0.0372	0.2882	0.0896	0.3306	0.1856	0.1060	0.0372
Mean	0.1688	0.2707	0.0886	0.1715	0.2032	0.0972		0.1679	0.1516	0.2879	0.1983	0.1943	
Maximum	0.2730	0.3200	0.1039	0.2592	0.2501	0.1111		0.2882	0.2970	0.3306	0.2565	0.2654	
Minimum	0.0838	0.2433	0.0707	0.1054	0.1569	0.0769		0.1101	0.0896	0.2309	0.1311	0.1060	

#### 4.2 DEA-AR results

In order to establish the lower and upper bounds in DEA-AR model, the pairwise weight comparisons need to be conducted. The criteria weights in Table 5 derived from Fuzzy BWM based on multiple experts' judgement are served as guidelines for determining the lower and upper bounds.  $v_1-v_6$  are the weight values of input criteria, and  $u_1-u_5$  are the weight values of output criteria. For each pair of  $v_i/v_k$  and  $u_r/u_t$ , the smallest and greatest divisions are calculated as the lower and upper bounds of the weight comparisons, respectively. For instance, for the comparison of  $v_1/v_2$ , the division derived from Fuzzy BWM results of expert 1 takes on a value of  $0.2305/0.2597=0.8875$ . Similarly, the comparison divisions can also be calculated based on the results of other experts, which are 1.1224, 0.3258, 0.6228, and 0.2710. So, we identified the smallest division value, 0.2710, as the lower bound, and the greatest division value, 1.1224, as the upper bound. By taking this method, the lower and upper bounds of each pairwise comparison can be determined, as shown in Table 6.

Table 6. Upper and lower bounds for weight comparisons input and output indicators.

	Lower	Upper		Lower	Upper
$v_1/v_2$	0.2710	1.1224	$u_1/u_2$	0.3711	3.2176
$v_1/v_3$	0.8607	3.6904	$u_1/u_3$	0.4413	0.8719
$v_1/v_4$	0.3230	2.1878	$u_1/u_4$	0.5063	1.5534
$v_1/v_5$	0.3468	1.7403	$u_1/u_5$	0.4774	2.7197
$v_1/v_6$	0.7540	2.8463	$u_2/u_3$	0.2710	1.2864
$v_2/v_3$	2.6297	3.6792	$u_2/u_4$	0.4828	2.2659
$v_2/v_4$	0.9916	2.4650	$u_2/u_5$	0.3581	1.2864
$v_2/v_5$	1.1311	1.5505	$u_3/u_4$	0.9914	1.7821
$v_2/v_6$	2.3146	3.5524	$u_3/u_5$	1.0000	3.1193
$v_3/v_4$	0.3753	0.6700	$u_4/u_5$	0.5677	2.0948
$v_3/v_5$	0.3074	0.5530			
$v_3/v_6$	0.6779	1.3509			
$v_4/v_5$	0.4589	1.3543			
$v_4/v_6$	1.0118	2.4430			
$v_5/v_6$	1.6355	2.5665			

With the determination of lower and upper bound of the input and output weight comparisons, the performance of provincial energy security can be calculated. In order to compare the performance derived from BCC and DEA-AR, we have used both models to conduct evaluation of energy security performance in 30 Chinese provinces, and the results are summarized in Table A1 in the Appendix.

The results of performance derived from BCC model reveal that during the period of 2008-2017, 8 to 15 provinces have achieved performance scores of 1, or rank first that year, indicating they are all efficient DMUs. The average performance score in BCC model varies in the range of 0.5 to 1. By contrast, in the introduced DEA-AR model, only 2 to 7 provinces have gotten performance scores of 1, and the average performance scores fluctuate within the range of 0.17 to 1. In addition, the CV of the performance scores in these two models can also be calculated by dividing the mean



scores by standard deviation. We noticed that the average CV in the BCC model is 0.174, and this coefficient value in the introduced DEA-AR model is as much as 0.311. Besides, the CV in the DEA-AR model is always greater than that in the BCC model during all these years. Therefore, both the performance scores and CV have proved that the DEA-AR model has a better discriminatory power than traditional DEA model, which helps to better understand the situation of energy security performance and improve decision quality.

Although the performance scores in DEA model with respect to different years are not comparable even for the same province, we can still summarize that energy security performance in China has been improved during these years. No matter in the BCC or DEA-AR model, we observed that the number of efficient DMUs (whose efficiency performance score equals 1) has increased. In BCC model, there were 9 provinces have achieved a performance of 1 in 2008, and this number went to 14 in 2017, even reaching 15 in 2014. For comparison, there are only two efficient DMUs with performance scores of 1 in 2008, and 5 efficient DMUs have been observed in 2017, with as much as 7 efficient DMUs in 2013, 2014, and 2015. The increasing numbers of efficient DMUs shows that more and more provinces have improved their performance scores, and this is the evidence indicating that China has kept improving its energy security performance.

We can also make a rank of list for the performance scores of the provinces in each year (see Table A1 in the Appendix), and derived their average ranking positions, which have been presented in Figure 4. We observed that in BCC model, there are as much as seven provinces, including Guangdong, Hainan, Qinghai, Shannxi, Beijing, Shanghai, and Tianjin, were considered as efficient DMUs in every year of this decade. However, only Guangdong province was proved to be efficient DMU in the DEA-AR model. In terms of the average ranking position with respect to each province, the gaps of most provinces between the two models are within 10 positions, and only seven provinces have witnessed great differences of ranking positions between these two models, namely Tianjin, Shandong, Shanghai, Hebei, Chongqing, and Beijing. We believed that this great gap of ranking positions is mainly due to the extreme weights of inputs and outputs in BCC model.

If we divide these 30 provinces into eight economic regions, we can investigate China's energy security performance from a regional perspective by aggregating the performance scores over the period of 2008 to 2017 that derived from the DEA-AR model, and the results is shown in Figure 5. It can be concluded that the coastal regions have achieved higher performance scores than the inland counterparts, and the provinces in the south are more energy secure than the northern parts. To be detailed, we discovered that the southern coastal region has experienced the best energy security performances, with an annual average performance score at the level of 0.8601, followed by the southeast and eastern coastal regions, with annual average performance scores of 0.7743 and 0.7645, respectively. While, the northwest China has shown the worst energy security, with an annual average performance score of mealy 0.5291. In other regions, the northern coastal region has gotten an annual average performance score of 0.7214, ranking fourth among the eight regions. As to the rest three regions,

the middle Yellow River region, the northeast, and the middle Yangtze River region have been given very close average performance scores of 0.6611, 0.6517 and 0.6317, respectively.

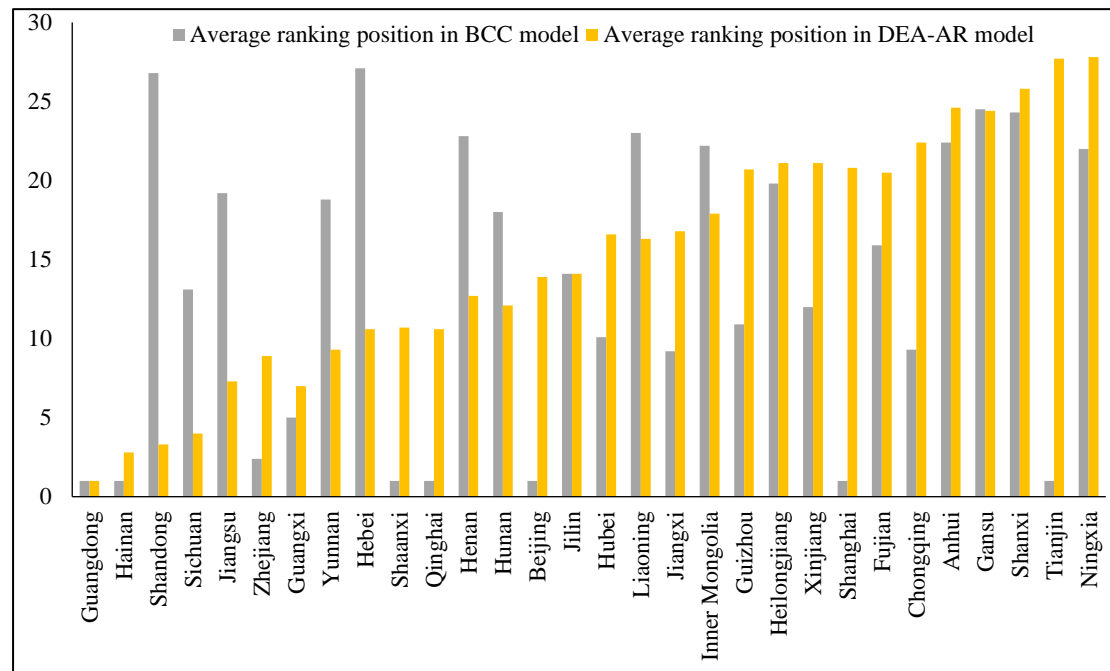


Figure 4. Average ranking positions of energy security performance in 30 Chinese provinces by BCC and DEA-AR model.

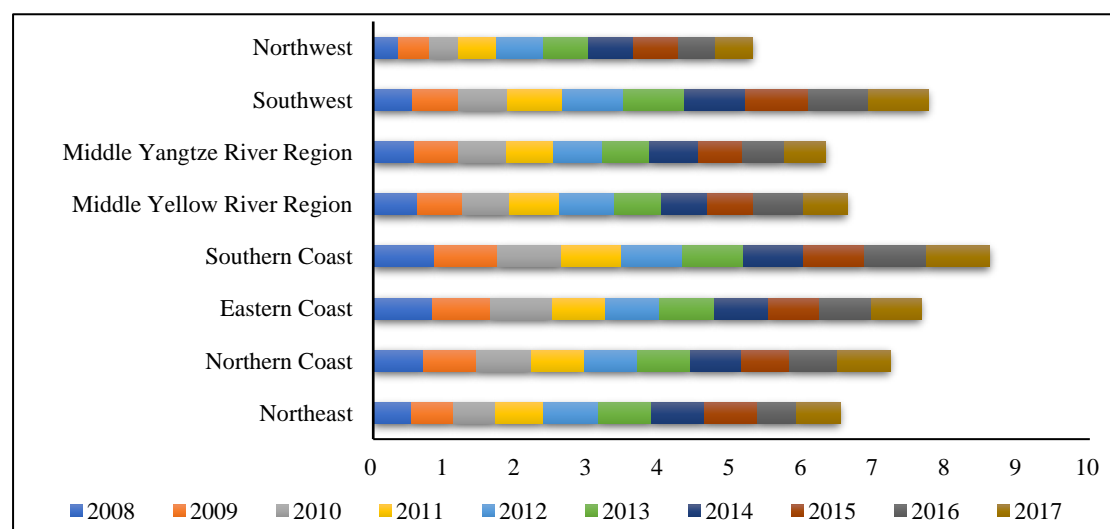


Figure 5. Energy security performance score of eight regions in China derived by DEA-AR, 2008-2017.

We also compared the results of provincial energy security performance from the DEA-AR model with that derived from other MCDM techniques, SWA, TOPSIS, and GRA. We have used the same criteria that have been used in the DEA-based model, and the weight values are derived by averaging the results displayed in Table 5. The

results of provincial energy security performance obtained from three MCDM techniques are shown in Table A4 in the Appendix. It can be noticed that the ranking of each province in term of their energy security performance are quite different from that in DEA-based model. In fact, energy security assessment in DEA model paid more attention on the efficiency between energy security output and input, and technological innovation and economic performance usually play more important roles. By contrast, the general MCDM techniques concentrate on energy supply and consumption, even though they have already taken technology and efficiency factors into consideration in their assessment, and they usually considered the integrated performance, despite that the same criteria and weighting method have been used. Consequently, some provinces that we took for granted as energy secure, like Inner Mongolia, Heilongjiang, Guizhou, Xinjiang, and Shanxi, are not as secure as we thought in DEA-based models. These provinces with abundant energy resources have consumed more primary energy resources, while, achieved less economic outputs and discharged more pollutants. Under the DEA-based models, the efficiency between outputs and inputs would be greatly devalued. On the contrary, the developed provinces can achieve more economic output with less energy consumption by using its advantages in technological innovation and application, as well as their economic scale and strength.

#### *4.3 Dynamic change of energy security performance*

To further explore China's energy security, we used MPI to examine the dynamic change of energy security performance during this period.

According to the results (Table A2 in the Appendix), MPI, also known as TFPch, implies the overall trend of energy security performance within this period. The national average TFPch value is 1.003, which indicating an improving trend of energy security around this country. Specifically, 18 provinces have experienced increasing energy security performance during the past decade, with their TFPch value greater than 1, while the other 12 provinces showing a decreasing situation, as presented in Figure 6.

We can also category the 30 provinces into three groups. Group one is the provinces with a relatively large amplitude of improvement in energy security, including Guangxi, Gansu, Guizhou, Guangdong, Hunan, and Jiangsu. By contrast, Zhejiang, Ningxia, Hainan, Qinghai, Hebei, and Shanghai are selected into group two, which experienced deteriorating energy security situation. The energy security performance has happened small range of changes in the other 10 provinces, and we put them in group three. The TFPch can also be decomposed into technical efficiency TEch and Techch by following the equation of  $TFPch = TEch * Techch$ . Table A3 in the Appendix has also presented the TEch and Techch value, from which we can discover that the average overall TEch is 1.013, indicating the improvement of total technical efficiency of China's energy security. While the average Techch value equals 0.990, which means technology and innovation failed to help improve China's energy security during this period.

The MPI is also available for annual analysis, and Table A3 in the Appendix has given the MPI summary of annual means. By presenting the information as a graph shown in Figure 7, we observed that the TFPch value is greater than one at the early

and late part of this period while less than one in the middle. We also find the trend of TFPch is basically synchronous with Techch, which means the progress of technology and innovation have great significance on energy security. On the other hand, TEch follows an opposite trend, with a decreasing drift at the early and late stage while increasing efficiency in the middle of this period. If we further decompose the TEch into Pech and SEch, we can only notice very slight changes have happened to Pech, who keep a value around one during this period. In addition, the steady trend of Pech lead to the alignment between TEch and SEch.

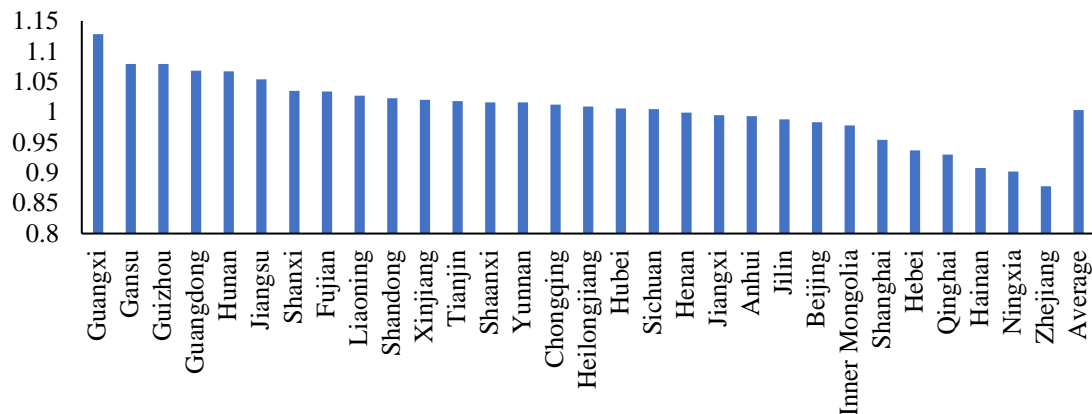


Figure 6. Ranking of Malmquist Productivity Index (TFPch) for 30 Chinese provinces.

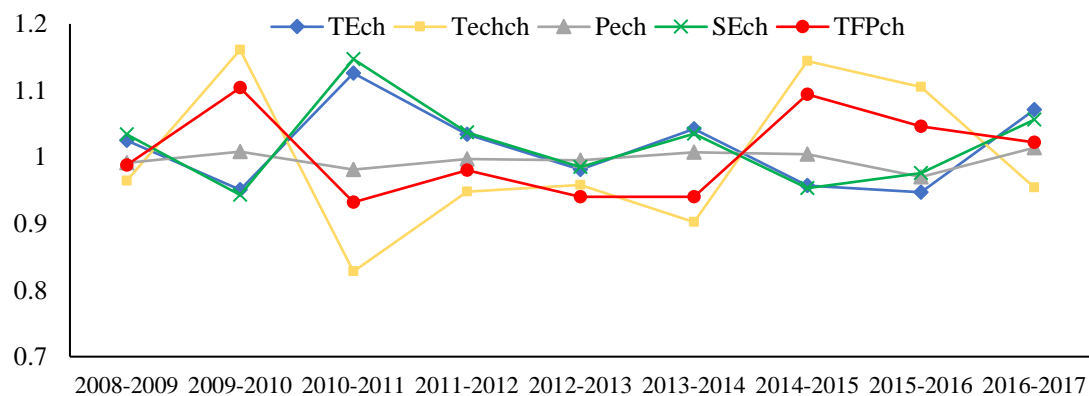


Figure 7. Trends of MPI and its decomposed indices.

## 5. Discussions

Although energy security performance assessment has already been intensively investigated with various methods in previous studies, we tried to probe it with different models and approaches in this paper. This study aimed at developing a methodological framework for measuring energy security performance with an innovative model, Fuzzy BWM-DEA-AR, which can avoid the extreme weight values in traditional DEA by determining ARs for each pair of input or output indicators. The results show that the subjectivity of the predefined ARs have a positive influence on the performance scores in DEA model by avoiding extreme weight values of the indicators, and helps

improve the distinction between different DMUs, which makes it easier to offer a convincing ranking of DMUs and provide insightful understanding of actual energy security performance to policy makers.

We have introduced ARs in the DEA model, which has already been undertaken in some previous works [54,67]. However, they mainly relied on AHP to calculate weight values, while we employed Fuzzy BWM instead in this paper. In fact, BWM is a recently proposed technique that can be used to determine the performance or importance of a group of criteria with less pairwise comparisons and better consistency than AHP [59]. Fuzzy BWM is the improvement of BWM by intruding fuzzy logic, and preferable than AHP and BWM [60]. Here in this study, we introduced this novel Fuzzy BWM to determine weight values for the indicators and make up ARs for the DEA model, and it was proved to be an efficient tool in energy security studies.

We tried to measure China's provincial energy security based on panel data, but the proposed DEA-based models cannot deal with it, which means the efficiency or performance scores in different years are not comparable even for the same province. Thus, we used the Fuzzy BWM-DEA-AR model to compare energy security performance of the 30 provinces in each year, which is to say, we have 30 DMUs to compute the efficiency scores each year, and we need to run this model for 10 times. Since the performance scores in different years are not comparable, we introduced MPI to analyze the changing trends of energy security performance year-by-year. With the models of Fuzzy BWM DEA-AR and MPI, we can analyze China's provincial energy security from both cross-sectional and vertical changing perspectives.

There are also some further works can be undertaken, and one would be considering the opinions of different stakeholders. We have introduced ARs in this study to set constraints for the weight values of the indicators. In order to derive the ARs, every indicator need to be allocated with multiple weight values, so a group of academic experts have been invited to make comparisons separately. In fact, the opinions of other stakeholders can also be considered, for instance, the policy makers and senior managers of energy enterprises. With the wide consideration of different opinions, it can investigate how the importance of input and output indicators of energy security varies among different stakeholders, and even affects energy security performance in different provinces.

We have considered eleven indicators, including six input and five output indicators, for better measuring China's provincial energy security. However, the efficiency of DMUs in DEA model is affected by the numbers of DMUs and indicators. Usually, a high number of variables can increase the number of efficient DMUs, which affects the effectiveness of this method. In order to improve its effectiveness, the further studies could try to conduct a sensitivity analysis to identify a few but important inputs and outputs, to better reflect China's provincial energy security.

## 6. Conclusions

This study aims to establish a methodological framework for measuring energy security performance. In order to differentiate from the energy security index or MCDM methods in previous studies, we measure energy security performance mainly based on

DEA and MPI. Considered the traditional DEA model, no matter which variants, has a great possibility of distributing extreme weight values to the indicators, which may not be in line with reality of energy security. To avoid that, ARs have been introduced as constraints to the weight values. To determine ARs, Fuzzy BWM based on multiple experts' opinions has been employed to derive multiple weight values for the indicators. With the adoption of DEA-AR based on Fuzzy BWM, it can help improve the distinction among different DMUs and provide insightful understandings of energy security to policy makers. Since the DEA model cannot deal with time series data, which leads to the non-comparability of efficiency scores between different years, we introduced MPI to depict the vertical changing trend of energy security performance for each province year by year. In this way, we can make an all-around description to regional energy security.

By adopting the Fuzzy BWM-DEA-AR model and MPI, we investigated the provincial energy security performance for 30 Chinese provinces, and discussed their changing trends over the period of 2008 to 2017. The results showed that China's provincial energy security varies greatly with some obvious regional characteristics. In fact, vast as China is, great divergence exists among different regions, e.g., the heterogeneity in national resources and conditions, economic development, and technology efficiency. These differences lead to notable diversity and bring great challenges to China's energy security. Despite that, we can still summarize some regional characteristics. According to our results, the southern and eastern regions have presented better energy security performance than the northern and western provinces. This is mainly because the DEA technique mainly focuses on efficiency, and the developed provinces seem to have less dependence on energy input to sustain energy security. Instead, the technology and innovation inputs can help to enhance the energy security performance by improving energy efficiency and diversifying energy sources.

Obviously, energy security performance among different Chinese provinces is restricted by various factors. The southern and eastern coastal provinces are enjoying the bonus of Reform and Opening-up, which brings rapid economic development and promotion of advanced technologies. Although they highly depend on imported energy supply, the large scales of economic outputs and less serious pollutant emissions indicate high economic and environmental efficiency. The Middle Yangtze River Region is one of the most economically active regions in recent years with the deployment of national strategy of the Yangtze River Economic Belt, and has been proved to be a follower in technological innovation and economic development after the coastal provinces even though it also relies on external energy supply. The southeast China has the most diversified energy supply, and even achieved energy independence. The northwest China is also one of the main energy producers, but the remoteness and severe natural conditions block local economic development, and lead to inefficient economic outputs. The northeast China confronts the same situation, despite its strong industrial infrastructure and significant economic achievements in the era of planned economy. The northern coastal region is also one of the most developed area in China, while the terrible air pollutions and high external energy dependence dragged down the energy security. The Middle Yellow River Region is gifted with coal and gas

production, and were traditionally seen as regions with high degree of energy security. However, the backward industrial configuration and infrastructure hindered the transformation from resources to economic advantages, resulting in poor energy efficiency.

Technological innovation and renewable energy development are considered as effective way for enhancing energy security in China. The developed coastal provinces faced up with the risk of short energy supply, while have advantages in capital and technological innovation. Thus, the achievement of higher energy efficiency and more diversified energy supply is possible with its technological and economic advantages. The Middle Yangtze River Region and southwest China are home to China's most hydro power and biomass resources, which enable their clean and sustainable energy supply for economic development, while requires larges scales of capital investments and technology introduction. As for the three regions with the worst energy security performance, northern west, northeast and middle reaches of Yellow River, the rich energy resources have provided solid foundation for energy industry, not only traditional fossil fuels, but also wind and solar power. However, the geographical remoteness, backward industrial configuration and technology have impeded the efficient utilization of fossil fuels and renewable energy development. Therefore, clean utilization of fossil fuels, commercial introduction and application of renewable energy technologies are of great significance for enhancing China's regional energy security.

## **Acknowledgement**

The work described in this paper was supported by the Hong Kong Research Grants Council for Early Career Scheme (Grand No. 25208118) and The Start-up Grant of The Hong Kong Polytechnic University for New Employees (1-ZE8W).

## Appendix

Table A1. Efficiency scores of annual energy security performance of China by province.

	2008		2009		2010		2011		2012		2013		2014		2015		2016		2017	
	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR	DEA-BCC	DEA-AR
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Anhui	0.766	16	0.497	22	0.789	15	0.530	23	0.791	14	0.586	20	0.806	21	0.508	25	0.772	25	0.491	25
Beijing	1.000	1	0.626	13	1.000	1	0.704	12	1.000	1	0.830	10	1.000	1	0.746	14	1.000	1	0.780	15
Fujian	0.860	13	0.583	14	0.889	13	0.618	16	0.915	9	0.675	13	0.903	15	0.514	24	0.907	19	0.542	24
Gansu	0.582	27	0.287	29	0.582	28	0.354	28	0.541	29	0.341	29	0.608	30	0.403	28	0.599	30	0.458	29
Guangdong	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Guangxi	0.829	14	0.666	11	0.832	14	0.786	9	0.786	15	0.847	9	1.000	1	0.921	6	1.000	1	1.000	1
Guizhou	0.680	21	0.393	27	0.704	22	0.470	26	0.675	20	0.486	24	0.691	26	0.545	23	0.941	15	0.662	21
Hainan	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1	1.000	1
Hebei	0.501	30	0.901	5	0.737	19	0.888	6	0.544	28	0.913	7	0.757	25	0.788	11	0.774	24	0.861	10
Henan	0.650	24	0.899	6	0.661	25	0.889	5	0.697	18	0.852	8	0.808	20	0.696	17	0.862	21	0.764	16
Heilongjiang	0.689	19	0.532	19	0.656	26	0.525	24	0.636	23	0.476	25	0.811	19	0.573	21	1.000	1	0.665	20
Hubei	1.000	1	0.578	15	0.953	10	0.592	19	0.869	10	0.649	15	0.950	12	0.561	22	0.935	16	0.636	22
Hunan	0.634	25	0.671	10	0.743	18	0.711	10	0.631	24	0.803	11	0.814	18	0.696	16	0.915	17	0.738	18
Jilin	0.681	20	0.502	21	0.709	21	0.613	18	0.671	21	0.614	18	1.000	1	0.793	10	1.000	1	0.855	12
Jiangsu	0.972	10	0.851	7	1.000	1	0.809	7	0.820	13	0.983	5	0.775	22	0.935	5	0.758	26	0.965	7
Jiangxi	0.896	12	0.570	16	0.892	12	0.614	17	0.860	11	0.645	16	1.000	1	0.848	8	1.000	1	0.860	11
Liaoning	0.546	28	0.554	17	0.549	30	0.620	15	0.521	30	0.663	14	0.943	13	0.660	18	0.834	22	0.773	15
Inner Mongolia	0.525	29	0.483	23	0.604	27	0.566	20	0.554	27	0.575	21	0.613	29	0.766	13	0.877	20	0.831	13
Ningxia	0.753	17	0.171	30	0.761	17	0.282	30	0.760	16	0.269	30	0.766	23	0.363	30	0.686	27	0.488	26
Qinghai	1.000	1	0.430	24	1.000	1	0.559	21	1.000	1	0.458	26	1.000	1	0.739	15	1.000	1	1.000	1
Shandong	0.659	23	0.961	3	0.687	23	1.000	1	0.643	22	1.000	1	0.665	27	1.000	1	0.622	28	1.000	1
Shanxi	0.604	26	0.406	26	0.577	29	0.373	27	0.573	26	0.413	27	0.642	28	0.452	27	0.637	29	0.486	28
Shaanxi	1.000	1	0.660	12	1.000	1	0.707	11	1.000	1	0.777	12	1.000	1	0.891	7	1.000	1	0.955	8
Shanghai	1.000	1	0.694	9	1.000	1	0.620	14	1.000	1	0.609	19	1.000	1	0.459	26	1.000	1	0.487	27
Sichuan	0.743	18	0.709	8	0.723	20	0.793	8	0.684	19	0.941	6	0.912	14	1.000	1	0.960	14	1.000	1
Tianjin	1.000	1	0.316	28	1.000	1	0.351	29	1.000	1	0.368	28	1.000	1	0.388	29	1.000	1	0.357	30
Xinjiang	0.777	15	0.509	20	0.763	16	0.534	22	0.722	17	0.561	22	0.902	16	0.619	20	1.000	1	0.668	19
Yunnan	0.678	22	0.547	18	0.681	24	0.680	13	0.630	25	0.640	17	0.759	24	0.782	12	0.816	23	0.911	9
Zhejiang	1.000	1	0.931	4	1.000	1	1.000	1	1.000	1	1.000	1	0.838	9	1.000	1	0.807	14	1.000	1
Chongqing	0.954	11	0.417	25	0.944	11	0.490	25	0.827	12	0.491	23	0.881	17	0.637	19	0.911	18	0.627	23
Average	0.799		0.612		0.815		0.656		0.778		0.682		0.867		0.704		0.895		0.755	
CV	0.217		0.358		0.193		0.309		0.217		0.321		0.155		0.281		0.142		0.263	
No. of efficient DMUs	9		2		9		4		8		4		11		4		13		6	



Table A2. MPI summary for energy security in 30 Chinese provinces, 2008-2017.

Province	TEch	Techch	TFPch
Guangxi	1.021	1.105	1.128
Gansu	1.06	1.017	1.079
Guizhou	1.044	1.034	1.079
Guangdong	1	1.068	1.068
Hunan	1.052	1.015	1.067
Jiangsu	0.994	1.061	1.054
Shanxi	1.058	0.979	1.035
Fujian	1.013	1.021	1.034
Liaoning	1.045	0.983	1.027
Shandong	0.976	1.048	1.023
Xinjiang	1.017	1.003	1.020
Tianjin	1	1.018	1.018
Shaanxi	1	1.016	1.016
Yunnan	1.044	0.973	1.016
Chongqing	1.005	1.007	1.012
Heilongjiang	1.02	0.989	1.009
Hubei	0.993	1.014	1.006
Sichuan	1.034	0.972	1.005
Henan	1	0.999	0.999
Jiangxi	0.995	1.001	0.995
Anhui	0.978	1.016	0.993
Jilin	1.033	0.957	0.988
Beijing	1	0.983	0.983
Inner Mongolia	1.035	0.945	0.978
Shanghai	1	0.954	0.954
Hebei	1.005	0.932	0.937
Qinghai	1	0.93	0.93
Hainan	1	0.908	0.908
Ningxia	0.985	0.916	0.902
Zhejiang	0.999	0.879	0.878
Mean	1.013	0.990	1.003

Table A3. Malmquist Productivity Index summary of annual means between 2008 to 2017.

year	TEch	Techch	Pech	SEch	TFPch
2008-2009	1.025	0.964	0.991	1.034	0.988
2009-2010	0.951	1.161	1.008	0.943	1.104
2010-2011	1.126	0.828	0.981	1.147	0.932
2011-2012	1.034	0.948	0.997	1.037	0.980
2012-2013	0.981	0.958	0.995	0.985	0.940
2013-2014	1.042	0.902	1.007	1.035	0.940
2014-2015	0.957	1.144	1.004	0.953	1.094
2015-2016	0.947	1.105	0.970	0.976	1.046
2016-2017	1.071	0.954	1.014	1.056	1.022
Annual means	1.013	0.990	0.996	1.017	1.003

Table A4. Performance by SWA, TOPSIS, and GRA. (Part One)

Provinces	2008						2009						2010						2011						2012					
	SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Anhui	0.383	17	0.469	13	0.602	20	0.379	1	0.471	11	0.598	21	0.380	20	0.469	12	0.601	20	0.397	19	0.477	11	0.608	20	0.397	14	0.476	11	0.609	15
Beijing	0.467	4	0.484	7	0.666	3	0.446	2	0.477	10	0.650	7	0.439	8	0.477	10	0.647	8	0.463	7	0.494	8	0.663	7	0.461	7	0.495	6	0.660	5
Fujian	0.395	16	0.456	15	0.604	18	0.394	3	0.457	17	0.601	20	0.418	12	0.471	11	0.616	14	0.425	12	0.475	12	0.619	14	0.431	10	0.479	9	0.624	11
Gansu	0.430	9	0.476	11	0.615	13	0.445	4	0.486	8	0.628	9	0.478	6	0.505	5	0.659	5	0.424	13	0.473	16	0.629	11	0.449	8	0.486	8	0.649	9
Guangdong	0.455	7	0.498	5	0.648	5	0.460	5	0.503	4	0.654	6	0.489	4	0.516	3	0.677	2	0.478	5	0.512	4	0.671	4	0.484	4	0.515	3	0.680	2
Guangxi	0.398	14	0.470	12	0.627	10	0.384	6	0.462	15	0.620	10	0.380	19	0.458	18	0.617	13	0.360	25	0.447	21	0.610	17	0.342	23	0.438	22	0.602	17
Guizhou	0.459	6	0.505	4	0.634	8	0.433	7	0.496	5	0.614	13	0.438	9	0.499	6	0.618	12	0.453	9	0.502	6	0.643	9	0.396	16	0.467	14	0.602	19
Hainan	0.350	25	0.441	19	0.611	16	0.336	8	0.433	23	0.604	18	0.347	26	0.439	24	0.610	17	0.399	18	0.464	17	0.629	10	0.402	13	0.465	15	0.630	10
Hebei	0.249	30	0.323	30	0.529	30	0.239	9	0.320	30	0.525	30	0.268	30	0.344	29	0.537	30	0.289	29	0.362	29	0.546	30	0.275	29	0.355	28	0.541	30
Henan	0.343	27	0.428	23	0.573	27	0.345	10	0.434	22	0.575	26	0.367	23	0.450	21	0.587	24	0.376	21	0.453	18	0.592	24	0.354	21	0.439	21	0.588	23
Heilongjiang	0.375	18	0.438	22	0.577	26	0.385	11	0.449	20	0.581	24	0.386	18	0.446	22	0.586	25	0.383	20	0.440	24	0.585	26	0.341	24	0.412	23	0.571	25
Hubei	0.371	19	0.440	20	0.593	22	0.393	12	0.456	18	0.601	19	0.402	15	0.461	17	0.605	19	0.371	23	0.441	23	0.592	25	0.371	19	0.442	19	0.593	21
Hunan	0.363	23	0.442	18	0.592	23	0.367	13	0.448	21	0.593	23	0.377	21	0.453	20	0.600	21	0.375	22	0.452	19	0.600	22	0.377	18	0.455	18	0.602	18
Jilin	0.318	28	0.389	25	0.561	28	0.315	14	0.392	26	0.558	28	0.327	28	0.397	26	0.565	29	0.318	28	0.396	26	0.561	28	0.313	28	0.395	24	0.561	27
Jiangsu	0.438	8	0.478	10	0.634	7	0.450	15	0.486	9	0.648	8	0.449	7	0.482	9	0.643	9	0.470	6	0.499	7	0.657	8	0.469	6	0.498	5	0.660	6
Jiangxi	0.361	24	0.455	16	0.606	17	0.360	16	0.454	19	0.606	15	0.366	24	0.456	19	0.610	16	0.354	26	0.449	20	0.606	21	0.336	25	0.441	20	0.601	20
Liaoning	0.317	29	0.359	28	0.555	29	0.319	17	0.364	27	0.556	29	0.337	27	0.378	27	0.566	28	0.337	27	0.385	28	0.564	27	0.320	26	0.371	27	0.558	28
Inner Mongolia	0.370	20	0.346	29	0.613	14	0.366	18	0.357	28	0.605	16	0.375	22	0.363	28	0.608	18	0.371	24	0.393	27	0.599	23	0.315	27	0.351	29	0.566	26
Ningxia	0.364	22	0.372	27	0.600	21	0.326	19	0.332	29	0.570	27	0.316	29	0.325	30	0.568	27	0.275	30	0.295	30	0.560	29	0.274	30	0.298	30	0.557	29
Qinghai	0.347	26	0.385	26	0.582	24	0.388	20	0.420	24	0.596	22	0.361	25	0.405	25	0.583	26	0.403	17	0.430	25	0.610	18	0.353	22	0.389	25	0.589	22
Shandong	0.369	21	0.420	24	0.579	25	0.362	21	0.420	25	0.577	25	0.405	14	0.462	16	0.600	22	0.433	10	0.483	10	0.613	15	0.413	11	0.470	12	0.606	16
Shanxi	0.535	1	0.517	2	0.690	1	0.547	22	0.529	2	0.693	1	0.513	2	0.521	2	0.659	6	0.550	1	0.532	3	0.698	1	0.516	2	0.510	4	0.668	4
Shaanxi	0.496	2	0.556	1	0.632	9	0.528	23	0.586	1	0.655	5	0.573	1	0.621	1	0.690	1	0.548	2	0.604	1	0.671	5	0.514	3	0.583	1	0.651	7
Shanghai	0.397	15	0.440	21	0.636	6	0.428	24	0.461	16	0.659	4	0.435	11	0.467	14	0.657	7	0.454	8	0.483	9	0.665	6	0.444	9	0.479	10	0.651	8
Sichuan	0.414	12	0.482	8	0.625	11	0.395	25	0.470	12	0.617	11	0.395	17	0.467	13	0.620	11	0.408	16	0.473	15	0.628	12	0.388	17	0.462	17	0.620	12
Tianjin	0.467	5	0.480	9	0.663	4	0.477	26	0.491	6	0.662	3	0.479	5	0.496	7	0.667	3	0.500	4	0.510	5	0.684	3	0.477	5	0.494	7	0.677	3
Xinjiang	0.420	11	0.452	17	0.603	19	0.430	27	0.464	13	0.605	17	0.411	13	0.445	23	0.596	23	0.426	11	0.444	22	0.609	19	0.364	20	0.386	26	0.584	24
Yunnan	0.400	13	0.466	14	0.613	15	0.394	28	0.464	14	0.609	14	0.397	16	0.466	15	0.614	15	0.412	14	0.475	13	0.624	13	0.396	15	0.464	16	0.616	13
Zhejiang	0.493	3	0.507	3	0.672	2	0.509	29	0.519	3	0.680	2	0.491	3	0.508	4	0.666	4	0.534	3	0.535	2	0.694	2	0.538	1	0.539	2	0.698	1
Chongqing	0.429	10	0.491	6	0.621	12	0.421	30	0.487	7	0.617	12	0.435	10	0.493	8	0.624	10	0.410	15	0.474	14	0.613	16	0.403	12	0.469	13	0.614	14

Table A4. Performance by SWA, TOPSIS, and GRA. (Part Two)

Provinces	2013						2014						2015						2016						2017					
	SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA		SWA		TOPSIS		GRA	
	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank	Score	Rank
Anhui	0.395	10	0.473	7	0.607	13	0.375	14	0.462	10	0.602	16	0.393	13	0.474	10	0.609	16	0.394	13	0.469	10	0.614	12	0.448	11	0.504	8	0.635	15
Beijing	0.450	7	0.490	4	0.659	4	0.447	6	0.490	6	0.658	5	0.452	6	0.495	6	0.663	5	0.447	6	0.493	4	0.663	5	0.478	6	0.510	6	0.670	4
Fujian	0.423	8	0.473	8	0.621	9	0.412	8	0.465	8	0.616	9	0.445	9	0.490	7	0.629	8	0.425	7	0.476	7	0.629	8	0.448	10	0.494	11	0.636	14
Gansu	0.382	16	0.441	19	0.604	17	0.361	19	0.430	21	0.593	21	0.348	22	0.427	22	0.587	23	0.352	20	0.428	22	0.594	20	0.398	20	0.462	21	0.611	22
Guangdong	0.474	3	0.510	3	0.672	2	0.472	2	0.510	3	0.672	3	0.479	4	0.517	3	0.676	3	0.476	2	0.512	2	0.678	2	0.488	5	0.520	3	0.682	2
Guangxi	0.339	24	0.436	22	0.600	18	0.332	23	0.434	20	0.601	18	0.359	20	0.448	19	0.612	14	0.338	23	0.437	18	0.608	17	0.352	25	0.444	22	0.612	21
Guizhou	0.384	14	0.461	10	0.599	19	0.369	16	0.453	14	0.594	20	0.379	18	0.459	17	0.597	20	0.349	21	0.430	20	0.591	21	0.404	19	0.472	18	0.610	23
Hainan	0.348	21	0.437	21	0.608	12	0.346	21	0.436	18	0.606	13	0.333	24	0.430	21	0.600	19	0.344	22	0.436	19	0.611	15	0.422	17	0.479	17	0.659	7
Hebei	0.266	29	0.342	28	0.537	30	0.275	29	0.354	27	0.542	30	0.305	28	0.378	26	0.554	29	0.281	28	0.362	25	0.548	29	0.346	27	0.409	26	0.574	27
Henan	0.358	20	0.440	20	0.589	23	0.348	20	0.434	19	0.586	23	0.359	19	0.442	20	0.591	21	0.365	18	0.443	17	0.597	19	0.421	18	0.479	16	0.620	18
Heilongjiang	0.345	22	0.418	23	0.572	25	0.323	24	0.406	23	0.564	26	0.338	23	0.416	23	0.570	27	0.313	26	0.396	24	0.564	27	0.353	24	0.427	24	0.580	26
Hubei	0.383	15	0.454	15	0.604	15	0.382	12	0.455	12	0.605	14	0.391	14	0.462	15	0.611	15	0.400	10	0.465	11	0.616	10	0.437	14	0.489	14	0.631	16
Hunan	0.363	19	0.445	17	0.598	21	0.369	17	0.454	13	0.608	12	0.386	16	0.464	14	0.614	13	0.376	15	0.457	13	0.613	13	0.395	21	0.469	19	0.620	19
Jilin	0.310	27	0.394	25	0.562	27	0.311	26	0.397	24	0.564	27	0.332	25	0.415	24	0.574	25	0.327	24	0.412	23	0.576	25	0.357	23	0.432	23	0.590	25
Jiangsu	0.457	5	0.489	5	0.656	5	0.458	5	0.490	5	0.659	4	0.476	5	0.502	5	0.665	4	0.471	3	0.497	3	0.664	4	0.510	2	0.524	2	0.683	1
Jiangxi	0.345	23	0.444	18	0.604	16	0.337	22	0.441	17	0.602	17	0.356	21	0.450	18	0.608	18	0.356	19	0.448	16	0.610	16	0.391	22	0.467	20	0.622	17
Liaoning	0.321	26	0.374	26	0.559	29	0.311	25	0.367	26	0.555	29	0.294	29	0.357	27	0.548	30	0.288	27	0.356	26	0.547	30	0.335	29	0.394	27	0.567	29
Inner Mongolia	0.388	13	0.407	24	0.596	22	0.373	15	0.392	25	0.591	22	0.380	17	0.393	25	0.590	22	0.397	11	0.430	21	0.615	11	0.440	13	0.423	25	0.618	20
Ningxia	0.248	30	0.295	30	0.559	28	0.248	30	0.295	30	0.562	28	0.246	30	0.294	30	0.564	28	0.248	30	0.292	29	0.573	26	0.256	30	0.279	30	0.560	30
Qinghai	0.305	28	0.348	27	0.572	26	0.294	28	0.336	28	0.568	24	0.317	26	0.356	28	0.582	24	0.316	25	0.350	27	0.591	22	0.346	26	0.380	28	0.602	24
Shandong	0.393	12	0.453	16	0.599	20	0.390	11	0.452	15	0.598	19	0.413	10	0.466	13	0.608	17	0.396	12	0.451	14	0.605	18	0.465	9	0.501	9	0.637	13
Shanxi	0.456	6	0.455	14	0.630	8	0.410	9	0.422	22	0.608	11	0.450	7	0.462	16	0.629	9	0.365	17	0.344	28	0.590	23	0.518	1	0.508	7	0.665	5
Shaanxi	0.497	2	0.569	1	0.642	6	0.471	3	0.552	1	0.630	7	0.494	3	0.569	1	0.638	7	0.404	9	0.469	9	0.587	24	0.506	3	0.573	1	0.646	9
Shanghai	0.419	9	0.461	11	0.639	7	0.435	7	0.473	7	0.648	6	0.447	8	0.481	8	0.653	6	0.449	5	0.480	6	0.654	6	0.472	7	0.499	10	0.661	6
Sichuan	0.382	17	0.459	12	0.620	10	0.378	13	0.459	11	0.620	8	0.388	15	0.466	12	0.627	10	0.388	14	0.463	12	0.631	7	0.431	15	0.491	13	0.645	10
Tianjin	0.465	4	0.488	6	0.672	3	0.470	4	0.490	4	0.674	2	0.506	2	0.517	4	0.691	2	0.461	4	0.486	5	0.669	3	0.444	12	0.482	15	0.641	11
Xinjiang	0.324	25	0.334	29	0.573	24	0.300	27	0.310	29	0.566	25	0.315	27	0.323	29	0.571	26	0.265	29	0.273	30	0.554	28	0.335	28	0.342	29	0.569	28
Yunnan	0.377	18	0.458	13	0.607	14	0.363	18	0.449	16	0.605	15	0.402	12	0.474	9	0.621	11	0.368	16	0.450	15	0.613	14	0.428	16	0.492	12	0.637	12
Zhejiang	0.541	1	0.539	2	0.700	1	0.544	1	0.540	2	0.706	1	0.569	1	0.557	2	0.719	1	0.555	1	0.546	1	0.716	1	0.501	4	0.517	4	0.678	3
Chongqing	0.395	11	0.464	9	0.611	11	0.393	10	0.462	9	0.611	10	0.406	11	0.472	11	0.617	12	0.410	8	0.472	8	0.625	9	0.469	8	0.511	5	0.650	8

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