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Analysis on provincial industrial energy efficiency and its influencing factors in China based on DEA-RS-FANN

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A R T I C L E I N F O

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A B S T R A C T

Data envelopment analysis (DEA), rough set theory (RS) and fuzzy artificial neural network (FANN) are combined as DEA-RS-FANN procedure to explore the effects of influencing factors on energy efficiency in China's provincial industry sectors. The analysis begins with the DEA technique to evaluate energy efficiency in provincial industries, followed by fuzzy c-means (FCM) algorithm to classify energy efficiency and the influencing factors to three categories (low-, medium- and high-levels). This process facilitates the construction of the decision table from condition attribute (the influencing factors) to decision attribute (energy efficiency). Then significance analysis of attributes in RS theory is adopted to investigate the significance of the influencing factors and determine the primary factors. Finally, FANN is utilized to further analyze the marginal effect of primary factors on energy efficiency in three specific categories, comprising of those provinces with different levels of energy efficiency. The proposed method takes into consideration non-linear and lag effects between energy efficiency and the influencing factors, as well as the characteristics of the impreciseness and incompleteness of the statistical data, ultimately leading to more precise and reliable results, as compared to conventional methods.

1. Introduction

Global warming resulting from the use of fossil fuels is seen by many observers as a major threat to the environment. Industrial energy efficiency is one of the most important ways to reduce this threat, as industry is the highest energy-using sector on global scale [1,2]. The total amount of industrial energy consumption in China increased considerably from 1.68 billion tons of coal equivalent (tce) in 2005 to 2.52 billion tce in 2012, with an average annual growth rate of 9.6%. In the recent years, industrial energy consumption accounts for over 70% of the total energy usage. Huge disparities are discernible in industrial energy efficiency across China's provinces, with generally higher energy efficiency in eastern provinces, and relatively lower energy efficiency in the western provinces. For example, in 2011, the energy consumption per unit GDP in Guangdong was 0.56 tce per 10,000 Yuan, whereas in Ningxia, it was 2.28 tce per 10,000 Yuan, representing almost a four-fold difference.

Since the industrial sector is recognized as the largest energy consumer in China, industrial energy efficiency will generally have direct effects on total energy utilization efficiency in each provincial region. In recent years, what differences are exists in energy efficiency of industrial sector across China's regions, what are the main factors affecting the changes in the industrial energy efficiency? Answering these issues is of vital importance for the local government to grasp specific energy consumption characteristics of the industrial sector, to develop effective policies to improve energy efficiency of the industrial sectors, and to achieve the goal of energy saving and emission reduction.

Data envelopment analysis (DEA) [3] has been widely employed in efficiency-related studies. As a method for efficiency evaluation, DEA has the capability of measuring the energy efficiency. When deeply analyzing the effect of influencing factors on energy efficiency, generally, econometric methods (such as tobit model) are utilized in the existing literature. But econometric models require that the data must meet several strict assumptions. Actually, the energy economics system is a complex system, the mapping from influencing factors to energy efficiency have non-linear, uncertain, and lag-effect characteristics. The fuzzy c-means (FCM) [4], rough set (RS) [5] and fuzzy artificial neural network (FANN) [6] approaches, that specialize in processing complex systemic problems with non-linear, uncertain, imprecise characteristics, could

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potentially overcome the problems encountered by the econometric models. We therefore combine the DEA, FCM, RS and FANN approaches to explore the effect of influential factors on industrial energy efficiency at the provincial level. First, DEA technique is used to evaluate energy utilization efficiency in the provincial industrial sectors. Second, FCM approach is adopted to identify the indicator value of energy efficiency and its influencing factors, and then RS is employed to analyze the significance of the influencing factors and determine the primary factors. Finally, FANN is used to calculate the marginal effect of the primary factors on energy efficiency.

The rest of the paper is organized as follows. Section 2 gives literature review on the study of industrial energy efficiency. In Section 3, we describe the relevant methods, and proposed the procedure for analyzing the influencing factors of industrial energy efficiency. In Section 4, we conduct the empirical study, and put forwards some policy recommendation. Section 5 concludes the paper.

2. Literature review

DEA techniques, as a non-parametric analysis approach, have been widely used to evaluate industrial energy efficiency, with tobit regressions being employed to further explore the factors driving energy efficiency. For example, using DEA techniques to measure Chinese industrial energy efficiency, Shi et al. (2010) [7] investigated the maximum energy-saving potential in 28 administrative regions in China. Wu et al. (2012) [8] used environmental DEA models to measure industrial energy efficiency performance by constructing both static and dynamic energy efficiency indices. Pan et al. (2013) [9] combined DEA techniques and random effect tobit regressions to analyze the determinants of provincial industrial energy efficiency in China. Zhao et al. (2014) [10] used DEA approach and tobit model to study the changes in total factor energy efficiency (TFEE) at sector and provincial level, and further to illustrate the drivers behind the changes in China. Li and Shi (2014) [11] used the improved super-SBM model to estimate the energy efficiency levels of various industrial sectors in China, and subsequently use tobit regression model to explore the factors influencing such energy efficiency. Wang and Wei (2014) [12] applied DEA techniques to evaluate the regional energy and emission efficiencies, along with the energy saving and emission reduction potential in the industrial sectors of 30 major Chinese cities between 2006 and 2010. Moon and Min (2017) [13] proposed a two-stage DEA model to measure pure energy efficiency and economy efficiency, in order to reach the improvement of total energy efficiency.

In addition to the widespread adoption of DEA with tobit regressions, stochastic frontier analysis (SFA) and index decomposition analysis (IDA) have also been used to quantitatively explore the industrial energy efficiency. For instance, Wu (2015) [14] employed stochastic frontier approach to evaluate the TFEE of the industry sectors in Shandong, and then applied the tobit model to investigate the influencing factors of energy efficiency. Shui et al. (2015) [15] adopted stochastic frontier analysis, and proposed two mathematical models to estimate both the production frontier and energy demand frontier in the evaluation of energy efficiency in the automotive manufacturing sector. Based on index decomposition analysis, Ang and Xu (2013) [16] presented the intensity refactorization(IR) and activity revaluation(AR) approaches to identify the evolving trends of industrial energy efficiency. Using the logarithmic mean divisia index (LMDI) decomposition techniques, Wu and Huo (2014) [17] investigated the effectiveness of the announced or implemented policies over recent decades in the energy intensive manufacturing and transportation sectors. Norman (2017) [18] adopted activity refactorization (AR) approach to measuring the improvement for the United Kingdom industrial sector over the period 1997–2012.

Finally, based on surveys on industrial energy management practices, Palm and Thollander (2010), Tanaka (2011), Lee (2015) and Thollander and Palm (2015) [19–22] used qualitative policy analysis to examine the drivers and barriers to energy efficiency management, to study on how to improve industrial energy efficiency.

Since there are significant differences in the levels of determining factors, such as technological progress, labor productivity, industrial structure, etc. in the industrial sector across various provinces, industrial energy efficiency exhibits obvious disparities across provincial regions in China. However, the existing researches lack comprehensive analysis of the influencing factors on industrial energy utilization efficiency at provincial level. As regards research methods, DEA has been widely and successfully used in macro-level energy efficiency evaluation. However, when quantitatively analyzing the relationship between energy efficiency and the influencing factors, the majority of the studies are based on the econometric models (such as tobit model) or index decomposition methods. However, Econometric models require that the data must meet several assumptions, such as significant linear relationship between the dependent and independent variables, and the models often encounter confounding issues such as multicollinearity, heteroskedasticity and autocorrelation. Furthermore, the index decomposition methods are based on the analysis using univariate analysis, with no consideration of the complementary effects of the non-energy inputs. Therefore, from the prospective of complex energy economic system, the DEA, FCM, RS and FANN approaches are integrated to comprehensively explore the influential factors of industrial energy efficiency in China at the provincial level in this paper.

3. Methodology

3.1. The DEA model for energy efficiency evaluation

Data envelopment analysis (DEA), first proposed by Charnes et al. (1978) [3], has been widely used at the macro-economy level to study the energy and environmental efficiency. It is a non-parametric mathematical programming method used to evaluate a set of homogeneous decision-making units (DMUs). Suppose that there are n DMUs (DMU_j, $j = 1, \ldots n$), each representing one provincial region of China. Each of these DMUs uses energy input e_j along with m other inputs x_{ij} ($i = 1, 2, \cdots m$) to produce the desired output y. Then, the energy utilization performance could be measured as follows.

$$\min \ \theta$$
$$s.t. \quad \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} + s_i = x_{ij_0}, \quad i = 1, \cdots, m \\ \sum_{j=1}^{n} \lambda_j e_j + s_e = \theta e_{j0} \\ \sum_{j=1}^{n} \lambda_j y_j - s_y = y_{j0} \\ \sum_{j=1}^{n} \lambda_j = 1 \\ \lambda_j, s_i, s_e, s_y \geq 0 \end{cases} \tag{1}$$

where λ_j ($j = 1, \cdots n$) is the intensity variable associated with each DMU_j for connecting the inputs and outputs by a convex combination; and s_i ($i = 1, \cdots m$),s_e, s_y are the slack variables associated with the non-energy inputs, energy inputs and desired output. The