Analysis of China’s Regional Energy Utilization and Environment Protection Efficiency Based on the DEA-SBM Model

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ABSTRACT

Energy saving and emission reduction are increasingly important. This paper studies a two-stage network based on the DEA-SBM model to study the two aspects. This study evaluates their efficiency, including benchmarks for improvement, of 27 regions in China from 2009 to 2013. First, the efficiency of each DMU in each stage can be obtained by the proposed model. Second, by combining the two stages, the integrated efficiency of each region can be calculated. The regions are also grouped geographically. The empirical results show that: (i) Beijing and Tianjin are the best in terms of energy system, while Gansu and Ningxia perform best in terms of environment system. (ii) From the perspective of geographical area in China, the eastern area are the best for stage one, while the western area is the best for stage two. (iii) In terms of integrated efficiency, the western area performs worst.

KEYWORDS

DEA-SBM, Emission Reduction, Energy Saving

1. INTRODUCTION

Since mainland China’s economic reform and opening policy started in 1978, China’s economy has developed rapidly, and in 2010 it became the world’s second largest economy (Bi, 2012). According to the National Bureau of Statistics of China (NBSC) in 2014, the year of 2013 of China’s real GDP has grown to about 56,884,500 million Yuan, which is about two times more than Japan. With such astonishing economic expansion, China’s energy consumption is growing rapidly. In 2007, China overtook the United States to become the world’s largest energy consumer (Wang, 2010). With the appearance of energy price increases and energy resource scarcity, the government of China is concerned about energy utilization efficiency. Rapid economic development also causes environmental problems. Hu (2008) proposed that China has become the third largest SO₂ emission producer. For these reasons, it is imperative to carry out a policy of energy saving and emission reduction. Many scholars have set out to study the energy and environmental (E&E) issues. For example, Huang (1995) presented the findings of a literature survey on decision analysis in E&E modeling. Since then, many new studies and several new decomposition methods have been reported and the methodology has been increasingly used in energy-related environmental analysis. Ang (2000) surveyed index decomposition analysis in E&E studies.
DEA, as a non-parametric programming technique, has proven to be effective in identifying best practice frontiers and ranking decision making units (DMUs), and does not require a priori assumptions on the weights of inputs and outputs (Seiford, 1996; Ahn, 2015; Cherchye, 2015). The method often is combined with other theories, like stochastic theory and TOPSIS method (Dharmapala, 2014). It is often applied in benchmarking and efficiency evaluation of schools, bank branches, energy utilization, environment protection, and so on (Charnes, 1978; Cook, 2009; Karagiannis, 2015). When considering energy utilization efficiency, many studies used gross domestic product (GDP) as the output (Hu, 2007; Hu, 2006). Hu (2006) and Hu (2007) developed a total-factor energy efficiency index based on DEA. However, one weakness is that their index treated energy consumption as one input and GDP was the single output in their research. Lee (2008) and Wei (2009) utilized DEA and regression methods to analyze and evaluate the energy efficiency of Taiwan government office buildings and that of Chinese provinces, respectively. All of these studies did not consider any undesirable output. Obviously, this is unreasonable in the real world, because energy utilization is always accompanied by emission of pollutants.

Considering environmental efficiency, the most common consideration is pollutants produced, which are called undesirable outputs in various models. Koopmans (1951) firstly proposed a method to account for a production process’s undesirable outputs. Since then, a variety of approaches have been proposed to deal with undesirable outputs including the “undesirable output as input” model (Hailu, 2001), the SZ model (Seiford, 2002), and the hyperbolic model (Färe, 1989). A point has been made that without considering the undesirable outputs, the results of the measurement of energy efficiency do not provide an appropriate score for energy efficiency benchmarking and comparison (Zhou 2008). Yeh (2010) incorporated undesirable outputs into calculating the technical efficiency of energy utilization in the Chinese mainland and Taiwan during the period 2002-2007 through employing the traditional BCC model. Using the time series of 2002-2007, Time series analysis consists of methods for analyzing time series data to extract meaningful information (Hebert, 2014). Then Watanabe (2007) considered undesirable outputs in examining the efficiency of Chinese industries. Zhou (2007, 2008b) developed several DEA models to evaluate DMUs’ environment efficiencies incorporating all possible factors, i.e., energy inputs, non-energy inputs (e.g. labor), desirable outputs, and undesirable outputs. Lozano (2008) introduced several DEA models to study the relationships among population, GDP, energy consumption, and CO₂ emissions by modeling GDP, energy input, and CO₂ emissions, separately. Zhang (2008) used DEA to measure the eco-efficiency of the industrial system in China. (Song, 2012) tell us that environmental efficiency can comprehensively reflect the operational situation of industry because it considers both economic and environmental factors in the efficiency evaluation system.

Obviously, previous research generally focused on either energy efficiency or environmental efficiency, omitting the integration of energy and environmental measures. Zhou, Levine, and Price (2010) provided a detailed overview of energy and environmental-related policies in China. Shi (2010) used three extended DEA models to investigate the energy and environmental overall technical efficiency, pure technical efficiency, and scale efficiency of industry sectors in 28 regions of China during 2000-2006, with the undesirable output of industrial waste gas being treated as an input in the energy and environmental efficiency analysis. Wu (2015) applied a two-stage network DEA framework to evaluate the efficiency of energy saving and emission reduction in China during the period of the eleventh five-year plan, which was in effect from 2006 to 2010.

This paper takes undesirable outputs into consideration to study a two-stage network based on the DEA-SBM model. This study is intended to evaluate energy saving and emission reduction efficiency, and offer benchmarks for 27 regions in China using data from 2009 to 2013. To analyze the efficiency of the network structure, we use two steps. Firstly, the efficiency of each DMU at each stage can be obtained by the proposed model, enabling comparisons among all DMUs. Secondly, the
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