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Evaluating energy efficiency of public institutions in China

Tong Xu[a,b], Chunyan Zhu[c], Longyu Shi[a,*], Lijie Gao[a], Miao Zhang[a,b]

[a] Key Lab of Urban Environment and Health, Institute of Urban Environment, Chinese Academy of Sciences, Xiamen 361021, China
[b] University of Chinese Academy of Sciences, Beijing 100049, China
[c] China National Institute of Standardization, Beijing 100191, China

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ABSTRACT

Public institutions play a prominent role in energy conservation efforts, not only by effectively promoting the application of new energy-saving technologies and products, but also by serving as an example to society. In this study, we established a system for evaluating energy management performance based on energy consumption of the People's Bank of China from 2011 to 2014. The decision-making unit was divided into four climatic regions, and the pure technical efficiencies of 336 branches of the People's Bank of China were obtained using data envelopment analysis, which somewhat overcomes the shortcomings of traditional methods for evaluating energy management performance. In addition, we used exploratory spatial analysis to reveal the spatial-temporal evolution, spatial patterns, and spatial agglomeration characteristics of energy consumption. The number of branches with optimal energy efficiency was the highest in the moderate climate region and lowest in cold regions. The performance of each branch was influenced by that of surrounding branches, and branches with high–high agglomeration mainly were located in the northwest and the northeast of China. Based on the evaluation, suggestions for improving the energy management performance of public institutions were provided.

1. Introduction

The energy efficiency of public institutions has become a topic of concern owing to rising awareness of the importance of energy conservation (Santoli et al., 2014; Kavgic et al., 2013; Praznika et al., 2013). Rapid urbanization in China poses challenges to energy security and sustainable development, and public buildings contribute to a large proportion of the nation's total energy consumption (Tang et al., 2016; Berardi, 2016). According to the National Government Offices Administration, there were 1.9 million public institutions in China in 2010, accounting for 6.2% of social energy consumption (Shi et al., 2015). In the same year, social energy consumption, which reflects energy used by industrial, construction, and transport sectors, reached 190 million tons of standard coal. Energy consumption ratio of public institutions in most developed countries is lower than that in China. For example, in France, Germany, and the United States, energy use by public buildings makes up 1.7%, 2.3%, and 4% of corresponding social energy consumption (WB, 2012).

The energy consumption of public institutions per unit area increased by 82% in America from 1959 to 1969, and that in Japan and South Korea increased by 67% (1965–1975) and 97% (1995–2005), respectively. During these periods of rapidly increasing energy consumption, the per capita GDP of China was roughly the same as that of the three countries. Thus, the energy consumption of public institutions in China has potential to develop along the same trajectory. Therefore, public institutions play a prominent role in energy conservation efforts and serve as an example to the whole society. Most countries have promulgated laws, regulations, and standards concerning energy conservation, especially for public institutions (Tronchin and Fabbri, 2008). Public institutions in developed countries such as the United States, European countries, and Japan have been carrying out energy conservation plans for several decades, representing a wealth of experience in this area (Miu et al., 2015). From an amendment of the US National Energy Saving Policy Act in 1988, the United States has administrative orders to oversee energy conservation by federal agencies. In the 1990s, the European Union began requiring member states to develop energy-saving policies for certain public institutions. In 2000, Japan issued the Green Procurement Law, which clarifies the purchasing demands of central and local governments. At the beginning of 2011, the European Union issued a new energy-saving plan and pointed out that the amount of construction devoted to building public institutions represented 12% of the EU's total construction sector.

Prioritizing energy conservation of public institutions is a relatively recent goal in China. Amendments to the Energy Saving Law concerning energy-saving requirements for public institutions were added in 2007. In 2008, the Public Institutions Energy Saving Regulations

* Corresponding author.
E-mail address: lyshi@iue.ac.cn (L. Shi).

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demanded that all levels of public institutions improve their energy efficiency and specified related requirements (Zhu et al., 2016). In 2010, the Bureau of the State Council issued the Public Institutions Energy Consumption Statistic System, which provides data for the national statistical system. In 2013, the State Administration of Quality Supervision and Inspection and the National Standardization Committee promulgated the national standard, "Guideline for the evaluation of energy and resources management performance of public institutions" (30260-2013 GB/T), which provides references and a framework to evaluate the energy efficiency of public institutions.

2. Research on evaluating energy efficiency of public institutions

2.1. Main energy evaluation indices

Typical evaluation index systems classify energy efficiency based on one or multiple input factors. Single factor estimates rely on one type of energy input, whereas total factor estimates reflect energy as well as economic and labor factors (Gong, 2015). Likewise, models for evaluating the energy efficiency of public institutions can be categorized as single (Bosquet et al., 2014; Liu et al., 2012; Liu et al., 2015) or comprehensive (Zhao et al., 2009; Zhang et al., 2015; Wang et al., 2012) index models. For instance, US Energy Star (for buildings) (EPA, 2016) is a single index model that evaluates energy efficiency based on energy use intensity (EUI), but it does not reflect the energy use of personal and official vehicles of public institutions. Multiple regression models are often used to calculate predicted EUI and assess the level of energy efficiency. Such models require a clear functional relationship between energy consumption and impact factors, but determining significant impact factors is usually very difficult.

Commonly used comprehensive index models include China's "Guideline for the evaluation of energy and resources management performance of public institutions", the Canadian Model National Energy Code for Buildings (MNECB), and Sustainable Building Tool (SBTool) proposed by international nonprofit organizations (Saraiva et al., 2015). In the first example, the average value of each indicator in the model is set to an accepted standard and the associated weight is calculated based on correlation coefficients to overcome subjective influence. Even so, this method does not meet the needs of various users. The Canadian administrative department adopted the MNECB (Lee and Yik, 2004) in 1999, but some factories found it difficult to implement. In the same year, Canada also proposed similar energy consumption evaluation requirements, but laws were applicable only to buildings of less than three floors and evaluations required complex calculations. A nonprofit organization comprised of representatives from Australia, Canada, the Czech Republic, Israel, Italy, Malta, Spain, Portugal, and South Korea proposed the SBTool, which can be used to evaluate green and sustainable buildings; however, this model is a half-objective system because some parameters are determined by official departments (Miu et al., 2015).

2.2. DEA model

To evaluate the performance of energy management by public institutions, most scholars use the Delphi method and/or the analytic hierarchy process (AHP). The weights of variables used in each of these methods are assigned based on knowledge, experience, and judgment (Guo, 2007). The AHP employs a mathematical method based on subjective judgment, making it more scientific and reliable than the Delphi method, but it is still limited by personal experience and knowledge (Saranga and Moser, 2010). To mitigate this deficiency, we proposed a non-parameter model, data envelopment analysis (DEA) that includes two types of indicators: energy consumption and institutional scale (Saranga and Moser, 2010).

The DEA model uses variable weights that are determined by numerical calculations and relative efficiency (Wang and Zhang, 2001; Bian et al., 2014). Model parameters are non-dimensional, and there is no need to consider the specific form of a boundary function (Wei, 2014; Lei, 2010). Energy efficiency is predicted from a data envelopment curve (frontier), which does not require a clear functional relationship between energy consumption and impact factors. As a common tool for evaluating energy performance, DEA concentrates mainly on regional and departmental levels. The regional level includes cities and countries. For example, Song et al. (2016) combined DEA and principal component analysis to evaluate the efficiency of material and energy flow in 31 Chinese cities, and Zhou et al. (2006) evaluated the economic-environmental performance of 30 OECD countries using an on-radial DEA method. Ramanathan (2005a) adopted the DEA method to analyze energy consumption and CO_2 emissions of industry and transport sectors in 17 countries throughout the Middle East and North Africa. Schefczyk (1993) first employed DEA to evaluate the performance of industrial departments in 1993, and this method has since been widely used in industry. For example, Honma and Hu (2014) used a DEA method to calculate the total factor energy efficiency (TFEE) of the industrial sectors of 14 developed countries between 1995 and 2005. Considering greenhouse gas emissions and energy consumption, Wu et al. (2016) measured the energy and environmental performance of industrial departments in every province in Mainland China. Yu et al. (2016) used slack-based and network DEA models to evaluate 162 observations of US S & P 500 firms across six industrial sectors in 2012–2013 in terms of operational and climate change mitigation performance. DEA methods have also been used to evaluate the operational performance of transport sectors (Ramanathan, 2005b; Duygun et al., 2015). Few researchers, however, have employed DEA to evaluate the environmental performance of public institutions.

To overcome the limitations of traditional methods, our study employed an input-oriented DEA method, which provides a more objective, fair, and accurate framework for evaluating energy efficiency. In this paper, the energy management performance of public institutions was evaluated on a systematic level. The potential for energy and water conservation was also quantified, providing a scientific basis for energy management planning.

The DEA method includes Charnes Cooper Rhodes (CCR) and Bnaker Charnes Cooper (BCC) models (Charnes et al., 1978; Banker et al., 1984), which differ with respect to assumptions of production possibility sets. The CCR mode assumes "constant returns to scale" (i.e., one unit of investment increase generates one unit of output). In contrast, the BCC model assumes "variable returns to scale", whereby the scale of output varies (Lee, 2009). If there are n units of decision-making units (DMUs) in the CCR model, each DMU has m input types denoted as x_i (i = 1,2…m). The weights of each input are v_i (i = 1,2…m). There are n types of yield denoted as y_j (j = 1,2…n) with weights of u_j (j = 1,2…n). The nonlinear calculation for the CCR model is as follows:

$$\begin{cases} \max \dfrac{\sum_{j=1}^{n} u_j y_{jk}}{\sum_{i=1}^{m} v_i x_{ik}} \\ s.\ t.\ \dfrac{\sum_{j=1}^{n} u_j y_{jt}}{\sum_{i=1}^{m} v_i x_{it}} \le 1 \\ v \ge 0,\ u \ge 0 \end{cases} \tag{1}$$

Through the Charnes-Cooper conversion, we introduced a slack variable s^+/s^- and a dimensionless variable ε. The above calculation is transformed into a linear model as follows: