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The Energy Efficiency of China's Regional Construction Industry Based on the Three-stage DEA Model and the DEA-DA Model

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Abstract

China's construction industry has constantly been confronted with the problems, such as high resource consumption, serious pollution and low energy efficiency. Thus, improving the energy efficiency of the construction industry and reducing its energy consumption can not only promote the sustainable development of the socio-economy and eco-economy, but also enhance the overall development level of the construction industry. In the context, the objectives are to put forward a set of systematic methodologies for measuring the energy efficiency of the regional construction industry and analyzing its change trends. First, the energy efficiency index system of the construction industry and its influencing factors are constructed through the literature review. Second, two research methods (the three-stage Data Envelopment Analysis (DEA) model and the Data Envelopment Analysis-Discriminant Analysis (DEA-DA) model) are applied to analyze the energy efficiency in 30 provinces of China and the change trends from 2003 to 2011. The results indicate that after eliminating the influence of the environment factors and random errors, the energy efficiency values of the construction industry in most of the provinces were improved. The mean of China's energy efficiency of the construction industry in each year was approximately 0.92. Except Shandong with the lowest values, the mean of the other provinces was over 0.8, which reflected that the energy management and utilization levels in the construction industry were relative mature. However, the energy efficiency in most of provinces fluctuated constantly during these nine years, with the peak in 2004 and a downward trend in the overall efficiency after 2004. From the regional aspect, the energy efficiency of the construction industry in the eastern, central and western regions decreased successively; as the development level of the local economy had less significant effects on the energy efficiency, the gaps among the three regions were not obvious.

Keywords: *three-stage DEA model, DEA-DA model, construction industry, energy efficiency*

1. Introduction

With the rapid development of the industrialization and urbanization, China has become the second largest country in the world in terms of energy consumption and carbon dioxide emissions. In the 21st century, China's construction industry has become the fourth pillar industry after manufacturing, agriculture and commerce. In 2011, the total output value of the construction industry reached 11,705.9 billion Yuan, a 21.9% increase over 2010; construction enterprise profits realized 416.8 billion Yuan, growing by 22.3% (National Bureau of Statistics of China, 2012). However, the construction industry is a typical labor-intensive and resource-intensive industry. The extensive operation mode of this industry is at the cost of consuming many resources and much energy, which directly results in a series of problems, such as high resource consumption, serious pollution and low energy efficiency. According to the relevant data, the annual energy consumption of the construction industry (production consumption of building materials, construction consumption and operation consumption) increased from 21.87 million tons of Standard Coal Equivalent (SCE) in 2000 to 62.26 million tons of SCE in 2011, an increase by a factor of 1.86 times (National Bureau of Statistics of China, 2012). Meanwhile, the energy consumption of the construction industry accounts for half of the energy consumption of the entire society, and its carbon dioxide emissions account for approximately 30%-40% of the total; currently, the construction industry, the manufacturing industry and the transportation industry have become the three highest energy-consumption industries in China (National Bureau of Statistics of China, 2012). Therefore, research into energy conservation for the construction industry can not only relieve China's energy supply and demand pressure, but also benefit the sustainable development of the socio-economy and eco-economy.

Although China is a country with vast territory, the develop-

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ment level of the regional economy reflects unbalanced; to large extent, the development of the regional construction industry has correspondingly exhibited significant differences (Liu *et al.*, 2014a). Meanwhile, these differences also influence the energy efficiency of the regional construction industry and its influencing factors. Therefore, how to reasonably narrow the gaps among the regions in the energy efficiency of the construction industry is of critical and practical importance to improve the overall development level of the industry and to effectively allocate the resources. However, the research into the energy efficiency of the construction industry in the academic circles are still at an early stage and there is little relevant literature (Lutzenhiser, 1994; Ryghaug and Soreensen, 2009). In this context, the objectives of this study are as follows: (a) to establish the energy efficiency index system of the construction industry and its influencing factors; (b) to analyze the energy efficiency of the regional construction industry and its development trends; (c) to apply the methodology to other industries and other countries. Based on this, this paper adopts two research methods (the three-stage DEA model and the DEA-DA model) to analyze the energy efficiency of China's regional construction industry and its change trends from the perspectives of industrial economics and sustainable development. The reason why the above methods are selected is that they are well-developed models with some obvious advantages. The three-stage DEA model proposed by Fried *et al.* (2002) combines the strong points of the DEA model (Charnes *et al.*, 1978; 1984) and the Stochastic Frontier Analysis (SFA) model (Timmer, 1971). The new model can not only overcome the shortages of calculating efficiency values with the DEA model (not considering the external environment factors have some effects on a Decision Making Unit (DMU)'s efficiency), but also compensate for the fact that the SFA model ignores the influence of random errors. The DEA-DA model, the combination of the DEA model and the DA model, can provide the discriminant function; moreover, it solves the issue of how to distinguish "overlap" in discriminant analysis, thereby making the DA model more flexible (Sueyoushi, 1999).

The structure of this paper is as follows: section 2 gives the relevant literature review of energy efficiency and its influencing factors; section 3 introduces the mainly research methods, including the three-stage DEA model and the DEA-DA model; in section 4, the energy efficiency of China's regional construction industry is measured with the three-stage DEA model; in section 5, we use the DEA-DA model to analyze the change trends of the energy efficiency of China's regional construction industry; finally, in section 6, conclusions and prospects are provided according to the results of the research.

2. Background Literature

Energy efficiency (the ratio of energy inputs and outputs) can be divided into energy economic efficiency and energy technical efficiency (Shi, 2006). Where, energy economic efficiency is the ratio of energy inputs and the final production results when energy is regarded as fuel and power; energy technical efficiency is the energy input-output ratio when energy is considered to be the energy processed by raw materials (the initial energy). If we calculate energy economic efficiency, final energy consumption should be regarded as energy consumption. Otherwise, if we calculate energy technical efficiency, total energy consumption should be treated as energy consumption. In this paper, energy efficiency refers to energy economic efficiency. Based on this, the literature review is conducted in the following section to form the measurement for energy efficiency and its influencing factors and further to provide a theoretical basis for measuring the energy efficiency of China's regional construction industry with the three-stage DEA model in section 4.

2.1 Review of Energy Efficiency Measurement

The methods of energy efficiency measurement consist of two types, that is, Single Factor Energy Efficiency (SFEE) and Total Factor Energy Efficiency (TFEE) (Hu and Wang, 2006). Where, SFEE measurement generally adopts the thermodynamic index, physical-thermal index, economic-thermal index and economic index (Patterson, 1996). Of them, the economic-thermal index is the most common index, which is known as energy intensity or energy production efficiency. Although the method to calculate SFEE is straightforward, it regards the energy as the only production factor, thereby ignoring the substitution elasticity between other production factors and energy. Meanwhile, Wilson *et al.* (1994) noted that the SFEE measurement is unable to calculate energy technical efficiency (Jenne and Cattell, 1983). By contrast, in the framework of TFEE, Hu and Wang (2006) proposed the TFEE index, which divided the target energy input by the actual energy input. Since TFEE is more practical, it is widely used in academic circles. For example, Hu and Kao (2007) calculated the energy saving ratio and energy savings per capita of 17 countries from Asia-Pacific Economic Cooperation (APEC) between 1991 and 2000 with TFEE; the results showed that China had the highest energy saving ratio and nearly half of energy consumption can be saved by improving energy efficiency. Honma and Hu (2008) obtained the regional TFEE of Japan with the DEA model based on a dataset of 47 prefectures during the period 1993-2003.

In terms of TFEE measurement, it mainly focuses on maximizing outputs with the given inputs or minimizing inputs with the given output level (Lovell, 1993). The rationale for TFEE is to measure the distances between sample points and the production frontier, thereby comparing the relative efficiency. The distance function was proposed from the input-output perspective to measure the distance from the production frontier (Shephard, 1970), and the methods are mainly composed of two, that is the parameter method and the non-parameter method (Farrell, 1957). As the former needs to set the form of the production function in advance and has the strict requirements for efficiency boundary shape, the fitting of the method may result in inconsistencies and non-solution due to non-convergence (Cornwell, 1990). Therefore, the DEA model, which utilizes labor, capital stock and energy consumption as outputs, is the typical non-parametric method

Table 1. Literature Review of the Factors Influencing Energy Efficiency

Time	Author	Objects	Influencing factors of energy efficiency
1983	Jenne and Cattell	UK's industry	Structure change
1994	Lutzenhise	The housing industry in US	Innovation; organization networks
1998	Farla *et al.*	Netherlands's industry	structure change
1998	Edenhofer and Jaeger	A non-linear model with social conflict and induced technical change	Economic growth; business cycles and innovation waves
2000	Henryson *et al.*	Buildings in Swedish	Increasing the knowledge among consumers
2001	Miketa	Manufacturing industry	capital formation
2004	Fish-Vanden *et al.*	The medium-sized industrial enterprises in China	The relative energy prices; research and development expenditures; ownership reform in the enterprise sector; industrial structure; technology development
2006	Fish-Vanden *et al.*	China's industrial sector	
2007	Bert and Kelly	China's industry	structure change
2007	Wei *et al.*	China's iron and steel sector	Technical change (production frontier shifting effect); technical efficiency (catching up effect)
2007	Hang and Tu	China	The relative prices of different energy types
2009	Ryghaug and Sorensen	The building industry	Deficiencies in public policy; limited governmental efforts; a conservative building industry
2010	Shi *et al.*	China's industry	The industrial structure; the pure technical efficiency
2012	Wang *et al.*	China's industrial sector	Technological investment; the scale of manufacture

[a]Note: the influencing factors of energy efficiency in the fourth row are the final factors which were chose through the empirical research.

and is widely used in energy efficiency measurement (Wilson *et al.*, 1994; Boyd and Pang, 2000; Shi, 2006; Hu and Kao, 2007).

In addition to the measurement of the regional energy efficiency, scholars have also extended their research areas to the industrial level. The involved industries include the paper industry (Laurijssen *et al.*, 2010; Fleiter *et al.*, 2012), the textile industry (Pardo Martínez, 2010; Hasanbeigi and Price, 2012), the steel industry (Wei *et al.*, 2007; Johansson and Soderstrom, 2011), the industry (Gielen, and Taylor, 2009; Giacone and Mancò, 2012; Wang *et al.*, 2012), the manufacturing industry (Rohdin and Thollander, 2006; Pardo Martínez, 2009), the electricity industry (Nakano and Managi, 2008), and the construction industry (Lutzenhiser, 1994; Henryson *et al.*, 2000; Ryghaug and Soreensen, 2009), etc.

2.2 Review of the Factors Influencing Energy Efficiency

Currently, decomposition analysis and meterage regression are primarily utilized to analyze the influencing factors of energy efficiency. However, in general, these influencing factors are relatively scattered and not unified. Based on this, we conduct the literature review from four aspects (time, author, objective and the influencing factors of energy efficiency) and the results are clearly presented as Table 1.

From the above table, it can be seen that as for the influencing factors of the industrial energy efficiency, the industry and the manufacturing industry have become the main research objectives (Miketa, 2001; Wei *et al.*, 2007; Shi *et al.*, 2010; Wang *et al.*, 2012), while research into the influencing factors of the construction industry is more scarce (Lutzenhiser, 1994; Henryson *et al.*, 2000; Ryghaug and Soreensen, 2009).

2.3 Comments on the Literature Review

TFEE measurement is the main method to measure energy efficiency currently, and the DEA model, with labor, capital stock and energy consumption as outputs, is most widely used. However, the DEA model ignores that the external environment factors have some effects on DMUs' efficiency and fails to distinguish between DMUs in which the energy efficiency values are one. Although there are many studies into the measurement for industrial energy efficiency, research into the energy efficiency of the construction industry are still at an early stage with few achievements. Moreover, the influencing factors of energy efficiency selected by the scholars are scattered and not unified. However, the construction industry is a typical labor-intensive industry. The influencing factors of energy efficiency of the construction industry can be established according to the literature review and its own characteristics. Based on this, this paper conducts a comprehensive analysis of the energy efficiency of China's regional construction industry and its change trends from the perspectives of industrial economics and sustainable development.

3. Methodology

This paper consists of two main parts: measuring the energy efficiency of China's regional construction industry from 2003 to 2011 with the three-stage DEA and analyzing the change trends of the energy efficiency with the DEA-DA model. The theories of the three-stage DEA model and the DEA-DA model are described in the following two sections, respectively.

3.1 Three-stage DEA Model

The DEA model is a widely used mathematical programming approach for comparing the inputs and outputs of a set of homogenous DMUs by evaluating their relative efficiency. The traditional DEA treats DMUs as black boxes and calculates their efficiencies by considering their initial inputs and their final outputs; therefore, some intermediate measures are lost in the process of changing the inputs to outputs (Ebrahimnejad *et al.*, 2014). Besides, another method to calculate the efficiency (the SFA model) ignores the random errors have the effects on the efficiency value. Under the context, Fried *et al.* (2002) combined the advantages of the above two models and created the three-stage DEA model. Currently, many scholars have constantly applied the new type of measurement model to the research into industrial efficiency and obtained some achievements. For example, the banking industry (Ebrahimnejad *et al.*, 2014; Shyu and Chiang, 2012), the transportation industry (Cui and Li, 2014), the R&D industry (Hsu and Hsueh, 2009).

The three-stage DEA model is composed of two traditional BCC models and one SFA model. The main principles of each model are as follows:

• **The first stage:** traditional BCC model

The BCC model, proposed by Banker, Charnes and Cooper, is the relative efficiency appraisal model based on multi-group input and output data. Under the hypothesis that Variable Returns to Scale (VRS) changes, the BCC model divides the Technical Efficiency (TE) of constant returns to scale into Pure Technical Efficiency (PTE) and Scale Efficiency (SE), that is, TE = PTE × SE. As to the BCC model, the reasons for technical inefficiency are mainly due to the low efficiency on the non-optimal scale or low production technology. However, compared to the TE of the CCR model proposed by Charnes, Cooper and Rhodes, the BCC model eliminates the influences of scale factors and more accurately reflects the operation and management levels of the assessed DMUs. Moreover, the input-oriented and the output-oriented models are available for estimating the efficiency frontier with the DEA model. Where, the input-oriented model is used to measure the decreasing proportion of the inputs when the outputs are constant; the output-oriented model is utilized to measure the increasing proportion of the outputs when the inputs are constant. Lovell (1993) thought that the input-orientated model could be applied to analyze the TE when the DMUs are able to adjust the inputs. In terms of the construction industry, it is much easier to control the inputs than the outputs. Therefore, the input-oriented BCC model is selected to calculate the efficiency values of original input-outputs.

If there are *n* DMUs, and each DMU has *m* inputs and *s* outputs, Formula (1) can be utilized to calculate the efficiency value of one specific DMU.

$$
\begin{aligned}
&\min \theta \\
&s.t \sum_{i=1}^{n} X_i\lambda_i + s^- = \theta X_0 \\
&\sum_{i=1}^{n} Y_i\lambda_i - s^+ = Y_0 \\
&\sum_{i=1}^{n} \lambda_i = 1 \\
&\lambda_i \geq 0,\ i = 1, 2,..., n \\
&s^+ \geq 0,\ s^- \geq 0
\end{aligned}
\tag{1}
$$

where, $X_i = (x_{i1}, x_{i2},..., x_{im})^T$ refers to the input vector of DMU i; $Y_i = (y_{i1}, y_{i2},..., y_{is})^T$ refers to the output vector of DMU j; λ_i represents the weight of DMU i; s^- represents the inputs' slack variable; s^+ indicates outputs' slack variable; $\theta (0 \leq \theta \leq 1)$ indicates the PTE. If the closer the value of θ is to 1, the higher the PTE will be.

In the practical operation, based on the theory of Formula (1), we should provide the data of the inputs and the outputs, use the DEAP 2.1 software and its application guide proposed by Coelli (1996a) and calculate all the values of the variables.

• **The second stage:** the SFA model

In the first stage, the efficiency values and input margins of each DMU are calculated. Among them, the input margin refers to the gap between a DMU's actual input and the input of the optimal efficiency. To eliminate the influences of the external environmental factors and random errors on efficiency values, the SFA model is utilized to analyze the input margin. Assuming that there are *p* environment variables, the SFA regression equation of *n* DMUs with *m* input slack variables is established as follows, according to Battese *et al.* (1989):

$$
s_{ki} = f^k(z_i;\ \beta^k) + \upsilon_{ki} + u_{ki} \tag{2}
$$
$$
i = 1, 2,..., n;\ k = 1, 2,..., m
$$

where, s_{ki} refers to the k^{th} input margin of DMU i; $z_i=(z_{1i}, z_{2i},...,z_{pi})$ refers to the p environment variables; β^k indicates the parameters to be estimated of the environment variables; $f^k(z_i;\ \beta^k)$ indicates how the environment variable affects the input margin s^{ki} and is generally equal to $z_i\beta^i$; $\upsilon_{ki}+u_{ki}$ represents mixed errors. υ^{ki} refers to random interference and $\upsilon_{ki} \sim N(0,\ \delta^2_{k\upsilon})$ is assumed; u^{ki} means management inefficiency and is supposed to obey the truncated normal distribution, that is, $u_{ki} \sim N^+(u^k,\ \delta^2_{u\upsilon})$. υ_{ki} and u^{ki} are mutually independent and irrelevant. In particular, when $\gamma = \delta^2_{uk}/(\delta^2_{uk}+\delta^2_{\upsilon k})$ tends toward one, the influences of management factors play the dominant role; when $\gamma = \delta^2_{uk}/(\delta^2_{uk}+\delta^2_{\upsilon k})$ tends toward zero, the influences of the random errors are in dominant role.

On this basis, the results of the SFA model regression $(\beta^k,\ \delta^2_{\upsilon k},\ u^k,\ \delta^2_{uk})$ are utilized to adjust each DMU's inputs. For example, adding inputs to the DMU in a better environment or with good fortune. Therefore, the influences of the environmental factors and random factors are removed to calculate efficiency values, that is the final results only reflect the DMUs' management level. If the inputs of the DMU with the most efficiency are treated as the baseline, the inputs of the other DMUs can be adjusted as follows:

$$
x^*_{ki} = x_{ki} + [\max_i\{z_i\hat{\beta}^k\} - z_i\hat{\beta}^k] + [\max_i\{\hat{\upsilon}_{ki}\} - \hat{\upsilon}_{ki}] \tag{3}
$$
$$
i = 1, 2,..., n;\ k = 1, 2,..., m
$$

where, x_{ki} and x^*_{ki} represent the input before and after the adjustment, respectively. $\hat{\beta}^k$ refers to the estimation value of the environment variable; $\hat{\upsilon}_{ki}$ indicates the estimation value of the random interference. In the first bracket, all of the DMUs are adjusted into the same environment; in the second bracket, the random errors of all the DMUs are adjusted to the same situation, thereby each DMU having the same external environment and fortune.

In the practical operation, based on the theory of Formula (2), the efficiency values and input margins of each DMU calculated in the first stage, we should provide the data of all the environment variables and use the Frontier 4.1 and its application guide proposed by Coelli (1996b) to conduct the SFA regression, thereby obtaining the value of each β^k. Then, we calculate the adjusted input of each DMU by Formula (3).

• **The third stage:** the adjusted BCC model

Take the adjusted input x_{ki}^* of each DMU and the original outputs into the BCC model of the first stage and calculate the efficiency values of each DMU. After eliminating the environment factors and random factors, the final efficiency values, that is, the PTE, only reflect the operation and management level.

3.2 The DEA-DA Model

When the three-stage DEA model is used to calculate the efficiency, several DMUs' efficiency values may be equal to one. Sueyoshi and Goto (2012) proposed the DEA-DA model to conduct the further comparisons among the efficiency values of these DMUs.

Step1. According to the results by the three-stage DEA model, all of the DMUs are divided into two groups: Efficiency (E) and Inefficiency (IE).

Step 2. The data from the two groups are calculated with the DEA-DA model, as follows:

$$\begin{aligned}
&\min M\sum_{j\in E} z_j + \sum_{j\in IE} z_j\\
&s.t - \sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} w_r y_{rj} + \sigma + M z_j \geq 0, j\in E\\
&\quad - \sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} w_r y_{rj} + \sigma - M z_j \leq -\varepsilon, j\in IE\\
&\sum_{i=1}^{m} v_i + \sum_{r=1}^{s} w_r = 1\\
&v_i \geq \varepsilon\zeta_i,\ i = 1,2,\ldots, m;\ w_r \geq \varepsilon\xi_r,\ r = 1,2,\ldots, s\\
&\sum_{i=1}^{m} \zeta_i = m,\ \sum_{r=1}^{s} \xi_r = s
\end{aligned} \tag{4}$$

σ: unrestricted, $v_i \geq 0$ for all i, $w_r \geq 0$ for all r
z_j: binary for all j, ζ_i: binary for all i, and
ξ_r: binary for all r.

where, x_{ij} and y_{rj} have the same meaning with the ones in Formula (1); M refers to a prescribed large number; ε indicates a prescribed small number; $-\sigma(j \in E)$ and $-\sigma-\varepsilon(j \in IE)$ represent the discriminant values. It is possible to change m and s to numbers that are lower. Such a change depends on the degrees of freedom between the number of observations and the number of weights.

In the practical operation, based on the theory of Formula (4) and the data of the adjusted inputs and outputs, we use Matlab 7.0 to obtain the values of all the variables.

Step 3. The model provides an optimal solution and calculates the following value of DMU j:

$$\rho_j = -\sum_{i=1}^{m} v_i^* x_{ij} + \sum_{r=1}^{s} w_r^* y_{rj} + \sigma^*, j = 1,2,\ldots, n \tag{5}$$

Step 4. According to the value of ρ_j, efficiency values are obtained.

(i) The maximum and minimum values of ρ are $\max_j \rho_j$ and $\min_j \rho_j$.

(ii) The adjusted efficiency value of DMU j can be obtained:

(ii-1) Efficiency = $[\rho_j - \min_j \rho_j] / [\max_j \rho_j - \min_j \rho_j]$ if $\min_j \rho_j$ is non-negative.

(ii-2) Efficiency = $[\rho_j + |\min_j \rho_j|] / [\max_j \rho_j + |\min_j \rho_j|]$ if $\min_j \rho_j$ if is negative.

Based on the above formulas, the efficiency values calculated belong to [0,1], which satisfies the efficiency requirement. Then, all DMUs can be sorted in accordance with the efficiency values.

4. The Measurement for the Energy Efficiency of China's Regional Construction Industry with the Three-stage DEA Model

4.1 The Energy Efficiency Index System of the Construction Industry and its Influencing Factors

4.1.1 Selections of the Input And Output Indicators

According to the literature review of energy efficiency measurement, TFEE is the method which is most widely used. However, two key issues of total factor inputs need to be resolved: how to determine input factors and how to gather all the inputs with different attributes, which is the basis of establishing the reliable energy efficiency index system. Currently, the production function with energy, labor and capital as factors, proposed by Rashe and Tatom (1977), is accepted and applied for the assessment of energy efficiency by most scholars. As to the construction industry, construction activities are completed by workers on-site, and most of the processes are manual or accomplished by simple tools; on the whole, the construction industry is a typical labor-intensive industry with a low technological level (Liu *et al.*, 2014a; 2014b). Meanwhile, the construction industry obtains a certain amount of income by producing building products and providing relevant services within a certain period. Therefore, labor, capital and construction equipment are the most basic factors in the operation process of the construction industry. Besides, a certain amount of energy is consumed in the construction process, including material production, construction work and operation of the machinery and equipment. In fact, the various types of energy are consumed in the construction industry, and the proportions of each type of the consumption are very different and change annually (National Bureau of statistics of China, 2012). Thus, we selected energy, labor, capital and construction machinery and equipment as the input factors.

Energy input. Considering different types of energy have distinctive dimensions and various unit energy heating values, we converted the energy consumption of the construction industry into ten thousand tons of SCE to calculate the total energy consumption of each region in the current period.

Labor input. As the construction industry is a labor-intensive industry, the development level and the competitiveness of this kind of industry depend largely on the quality and quantity of labor. According to some research achievement, such as Hu and Wang (2006) and Honma and Hu (2008), we selected the total number of employees in the construction industry as the labor input indicator. The formula is as follows:

$$\text{The total number of employees in the current period} = \frac{\text{the number at end of the current period} + \text{the number at the end of the previous period}}{2} \tag{6}$$

Capital input. Epitaxial expanding reproduction is the main growth mode of China's construction industry. This is mainly because capital input is a driving force for the economic growth of the construction industry. At present, most scholars selected capital stock as an indicator for measuring capital input (Hu and Wang, 2006; Honma and Hu, 2008). However, the methods to measure capital stock, for example the perpetual inventory method, may involve the utilization rate of capital or the depreciation rate of fixed assets, which are unavailable for the construction industry of each region. Due to the above reasons, we selected fixed assets for the construction industry as the capital input indicator. The formula is as follows:

$$\text{The fixed assets in the current period} = \frac{\text{the fixed assets at the end of the current period} + \text{the fixed assets at the end of the previous period}}{2} \tag{7}$$

Construction machinery and equipment input. The construction enterprises in China that depend on manual and semi-manual operations account for a significant proportion of the whole construction enterprises; in this way, construction equipment inputs can improve the productivity of the construction industry. The total power of the machinery and equipment owned is the total power of the machinery and equipment directly used by the enterprises involved in the construction and can be used to measure the construction machinery and equipment input of the construction industry.

Energy-utilization outputs. Currently, most scholars consider the economic index and the physical index to be energy-utilization outputs. Where, the economic index measures the services provided by energy utilization with market prices; the physical index measures the services provided by energy utilization with physical units. Based on the features of the construction industry and its energy consumption, two economic indexes (total output and total profits of the construction industry) were selected as the energy-utilization output indicators of the construction industry.

4.1.2 Selection of the Environmental Variables

In general, environmental variables are the factors that influence the energy efficiency of the construction industry and are out of the control of objective samples. Based on the literature review of the influencing factors of energy efficiency and combining the development features of the construction industry, four aspects of environment variables are considered: energy consumption structure, industrial development degree, organization structure and technological level (See Table 2).

Energy consumption structure. The energy consumption structure has a significant influence on energy efficiency (Shi, 2006). At present, energy consumption in the construction industry mainly depends on raw coal, petroleum, diesel and electrical power. However, there are some differences in the energy consumption structure of different regions. Compared with coal, electrical power is high-efficiency energy, and increasing electricity power consumption is beneficial to improve the overall energy efficiency (Shi, 2006).

Industrial development degree. In the regions with the developed construction industry, the construction market is relatively standard and effective competition can be fully realized , thereby stimulating each enterprise to improve their own productivity.

Table 2. Environmental Variables Influencing Energy Efficiency of the Construction industry

The first-order variable	The second-order variable	Definition
Energy consumption structure (A_1)	Energy consumption structure (A_{11})	Electrical power consumption / total energy consumption
Industrial development degree (A_2)	Industrial development level (A_{21})	Total output of the construction industry / GDP
	Industrial open degree (A_{22})	Total output of foreign-funded construction enterprises / total output of the construction industry
Organization structure (A_3)	Industrial scale structure (A_{31})	Total output of the construction industry / total number of construction enterprises
	Market ownership structure (A_{32})	Total output of state-owned construction enterprises / total output of the construction industry
	Market industry structure (A_{33})	Total output of house building and civil engineering / total output of the construction industry
	Market specialization-division structure (A_{34})	Total number of construction enterprises of general contractors / total number of construction enterprises of professional contractors
Technological level (A_4)	Technological innovation (A_{41})	R&D expenditure / GDP

[b] GDP refers to gross domestic product; R&D represents research and development.

Besides, the well-developed construction industry can make production resource allocation more reasonable and the agglomeration and scale effects stronger. In this paper, the development degree of the construction industry is considered to consist of industrial development level and industrial open degree. Where, more developed the construction industry is in a region, the higher the efficiency of the construction industry will be (Dai and Chen, 2010). The industrial open degree is mainly reflected by foreign investment. Advanced technologies and managerial experience brought in by foreign investment can not only stimulate market competition, but also transfer technology and demonstration effects to domestic enterprises, which has a positive influence on the regional production efficiency (Wang and Tao, 2010).

Industrial organization structure. Industrial market structure is the centralized or decentralized level of the enterprises in the same industry, as well as the competition, labor division and cooperation relationships among large-sized, medium-sized and micro-sized enterprises. As to China's construction industry, from the perspective of market structure, current academic circles describe the organizational characteristics of the construction industry as scale structure, ownership structure, industry structure and specialization division (Fan, 2010). Where, market scale structure described by market concentration is an important basis for positioning market structure and the direction of policies. The higher the market concentration is, the fiercer the competition of the construction industry will be; market ownership structure reflects the coexistence of construction enterprises with multiple types of ownerships, which has a direct impact on the competitive market establishment and promotes the sustainable development of the construction industry; market industry structure can be viewed as the market composed of several sub-markets in the construction industry, where the enterprises produce different products. As the competition levels of various industries are distinctive, market industry structure directly reflects the competition patterns of the construction industry; the market specialization-division structure demonstrates the production specialization level, which can not only improve production efficiency, but also reflects the level of internal labor division and cooperation.

Technological level. Cohen and Levinthal (1989) proposed

Table 3. Comparison of the Energy Efficiency of China's Regional Construction Industry

Region	2003	2004	2005	2006	2007	2008	2009	2010	2011	mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Tianjin	1.000	0.995	1.000	1.000	0.927	0.947	0.668	0.659	0.746	0.882
Hebei	0.378	0.384	0.400	0.417	0.370	0.430	0.357	0.306	0.304	0.372
Shanxi	0.544	0.682	0.973	0.688	0.488	0.486	0.505	0.508	0.813	0.632
Inner Mongolia	0.557	0.540	0.682	0.855	0.764	0.897	1.000	0.898	0.857	0.783
Liaoning	0.580	0.555	0.718	0.630	0.659	0.740	0.648	0.656	0.670	0.651
Jilin	0.556	0.532	0.538	0.674	0.926	0.890	0.829	0.713	0.770	0.714
Heilongjiang	0.851	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.983
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.985	0.765	0.972
Jiangsu	1.000	0.959	0.862	1.000	1.000	1.000	1.000	1.000	1.000	0.980
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Anhui	0.467	0.487	0.631	0.622	0.656	0.676	0.663	0.571	0.575	0.594
Fujian	0.727	0.710	0.801	0.794	0.827	0.611	0.564	0.541	0.527	0.678
Jiangxi	1.000	1.000	1.000	0.934	0.971	1.000	0.967	0.944	0.880	0.966
Shandong	0.477	0.370	0.568	0.439	0.485	0.767	0.574	0.664	0.558	0.545
Henan	0.600	0.721	0.662	0.795	0.973	1.000	1.000	0.965	0.921	0.849
Hubei	0.495	0.455	0.444	0.443	0.406	0.589	0.443	0.377	0.509	0.462
Hunan	0.575	0.569	0.488	0.469	0.481	0.717	0.435	0.314	0.291	0.482
Guangdong	0.908	0.918	0.741	0.682	0.971	0.872	0.746	0.545	0.675	0.784
Guangxi	1.000	0.687	0.743	0.621	0.596	0.737	0.751	1.000	1.000	0.793
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Chongqing	0.572	0.637	0.744	0.772	0.760	1.000	0.860	0.918	0.844	0.790
Sichuan	0.516	0.465	0.499	0.535	0.456	0.607	0.644	0.509	0.448	0.520
Guizhou	0.862	1.000	1.000	0.825	0.739	0.645	0.813	0.831	0.968	0.854
Yunnan	1.000	0.729	0.678	0.546	0.687	0.430	0.511	0.741	0.434	0.640
Shaanxi	0.490	0.437	0.643	0.603	0.710	0.563	0.600	0.527	0.464	0.560
Gansu	0.348	0.342	0.424	0.453	0.385	0.361	0.381	0.415	0.407	0.391
Qinghai	0.788	0.737	0.908	0.884	1.000	0.878	1.000	1.000	0.986	0.909
Ningxia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Xinjiang	0.737	0.694	0.729	0.738	0.741	0.724	0.702	0.714	0.679	0.718
mean	0.734	0.720	0.763	0.747	0.766	0.786	0.755	0.743	0.736	0.750

that R&D investment can strengthen the ability to absorb information and knowledge, promote the transfer of knowledge and technology and improve innovation and absorption. Keller (2002) noted that greater number of R&D inputs and effective research activities promoted technological advance more effectively. Therefore, R&D activity is the key factor in increasing technological progress, thereby improving the overall technical level of the industry.

4.2 The Analysis of the Energy Efficiency of China's Regional Construction Industry

According to the input and output indicators as well as the environmental variables and considering the accessibility and integrity of the data, we selected the data of China's construction industry of 30 provinces (except Tibet) from 2003 to 2011 to be the samples. Then, we conducted an empirical analysis of the energy efficiency of China's regional construction industry with the three-stage DEA model with the data from *China Statistical Yearbook* (2004-2012), *China Construction industry Statistical Yearbook* (2004-2012) and *China Energy Statistical Yearbook* (2004-2012) (National Bureau of statistics of China, 2004-2012).

4.2.1 The Empirical Results of the DEA Model at the First Stage

Based on the theory of Formula (1), all the values of the variables in the formula can be calculated with DEAP 2.1 software. The Table 3 only listed the results for the energy efficiency of China's regional construction industry from 2003 to 2011.

Without considering the external environment factors and random errors, the representative regions with the higher energy efficiency in the construction industry included Beijing, Heilongjiang, Shanghai, Jiangsu, Jiangxi, Hainan and Ningxia. In particular, the energy efficiency values of Beijing, Zhejiang, Hainan and Ningxia possessed the value of one during the 9-year period. Besides, from the longitudinal perspective of the table, although the means of the energy efficiency of China's regional construction industry in each year was approximately 0.74, the largest mean of all the regions was 1.0 and the smallest was 0.372. Moreover, the last entry in the last column was 0.750, which reflected that there was some difference in the energy efficiency of China's regional construction industry.

4.2.2 The SFA Regression Analysis at the Second Stage

Based on the four input slack variables of the 30 DMUs calculated at the first stage, we chose them as independent variables and eight environmental variables as dependent variables. Then, according to the theory of Formula (2), we applied Frontier 4.1 to the SFA regression analysis. Considering the time series of all the samples were long, the regression results of 2007 were took as an example (See Table 4).

According to the above table, some variables failed to pass the significance test, such as the energy consumption structure on the total power of machinery and equipment owned as well as the market specialization-division on fixed asset investment. The other variables all passed the significance test at least at the level of 10%, which reflected that the external environment factors

Table 4. The SFA Regression Results of 2007

	Number of employees		Fixed asset investment		Energy consumption		Total power of machinery and equipment owned	
	value	t value	value	t value	value	t value	value	t value
Constant term	9.14E+01	2.53E+01 (***)	2.05E+02	7.82E+00 (***)	5.62E+01	2.22E+00 (**)	8.25E+02	1.23E+01 (***)
A_{11}	5.01E+00	2.38E+00 (**)	-7.50E+01	-4.04E+00 (***)	-9.11E+01	-4.87E+00 (***)	-1.19E+00	-2.18E-02
A_{21}	6.12E+01	5.05E+01 (***)	-1.04E+02	-8.49E+00 (***)	-3.00E+02	-2.24E+01 (***)	-2.46E+02	-1.96E+01 (***)
A_{21}	-5.66E+02	-5.66E+02 (***)	-6.68E+01	-1.83E+01 (***)	-2.30E+02	-5.94E+01 (***)	-3.31E+03	-7.48E+02 (***)
A_{31}	-1.64E+01	-2.12E+00 (**)	-1.91E+01	-9.62E-01	-8.37E+00	-4.27E-01	7.24E+01	1.42E+00 (*)
A_{32}	-1.62E+01	-6.58E+00 (***)	-4.77E+01	-2.02E+00 (***)	-8.84E+01	-2.76E+00 (***)	8.12E+00	1.03E-01
A_{33}	-9.18E+01	-3.23E+01 (***)	-1.57E+02	-7.33E+00 (***)	4.61E+01	1.91E+00 (**)	-8.30E+02	-1.95E+01 (***)
A_{34}	3.17E+00	1.50E+00 (*)	3.51E+00	6.71E-01	2.07E+00	3.29E-01	-2.41E+01	-1.53E+00 (*)
A_{41}	-9.97E+01	-9.95E+01 (***)	2.57E+02	1.01E+02 (***)	1.15E+03	3.98E+02 (***)	-2.19E+03	-8.09E+02 (***)
Sigma squared	1.54E+02	1.99E+01 (***)	7.92E+02	4.66E+00 (***)	7.25E+02	3.95E+00 (***)	5.06E+03	5.89E+01 (***)
Gamma	1.00E-08	1.72E-05	1.00E-08	2.29E-04	1.00E-08	1.67E-04	3.11E-03	2.25E-02
Log likelihood	-1.18E+02		-1.43E+02		-1.41E+02		-1.70E+02	

[d]***significant at 1%, **significant at 5%, *significant at 10%.

Table 5. The Comparison of the Adjusted Energy Efficiency of China's Regional Construction

Region	2003	2004	2005	2006	2007	2008	2009	2010	2011	mean
Beijing	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Tianjin	1.000	0.998	1.000	1.000	0.993	0.993	0.942	1.000	0.949	0.986
Hebei	0.688	0.703	0.717	0.846	0.885	0.935	0.913	0.714	0.851	0.806
Shanxi	0.960	0.984	0.994	0.974	0.963	0.965	0.929	0.926	0.979	0.964
Inner Mongolia	0.954	0.898	0.938	0.963	0.974	0.987	1.000	1.000	0.973	0.965
Liaoning	0.885	0.781	0.900	0.832	0.877	0.918	0.877	0.867	0.857	0.866
Jilin	0.837	0.887	0.883	0.945	0.993	0.983	0.971	1.000	0.957	0.940
Heilongjiang	0.969	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.997
Shanghai	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	0.977	0.997
Jiangsu	1.000	0.982	0.933	1.000	1.000	1.000	1.000	1.000	1.000	0.991
Zhejiang	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Anhui	0.652	0.806	0.895	0.874	0.892	0.899	0.894	0.873	0.855	0.849
Fujian	0.908	0.912	0.944	0.938	0.967	0.953	0.917	0.897	0.919	0.928
Jiangxi	1.000	1.000	1.000	0.988	0.998	1.000	0.996	1.000	0.979	0.996
Shandong	0.584	0.508	0.659	0.531	0.610	0.816	0.642	0.769	0.704	0.647
Henan	0.938	0.959	0.913	0.948	0.995	1.000	0.978	0.996	0.980	0.967
Hubei	0.779	0.721	0.740	0.776	0.935	0.923	0.879	0.681	0.914	0.816
Hunan	0.891	0.818	0.786	0.820	0.867	0.916	0.805	0.649	0.702	0.806
Guangdong	0.920	0.935	0.893	0.836	0.988	0.951	0.894	0.722	0.923	0.896
Guangxi	1.000	0.962	0.968	0.953	0.950	0.975	0.970	1.000	1.000	0.975
Hainan	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Chongqing	0.770	0.909	0.935	0.942	0.960	1.000	0.964	0.987	0.953	0.936
Sichuan	0.853	0.786	1.000	0.894	0.902	0.930	0.881	0.781	0.835	0.874
Guizhou	0.994	1.000	0.992	0.989	0.996	0.993	0.986	0.958	1.000	0.990
Yunnan	1.000	0.974	0.934	0.975	0.994	0.965	0.946	0.871	0.902	0.951
Shaanxi	0.859	0.849	0.897	0.910	0.945	0.935	0.900	0.846	0.800	0.882
Gansu	0.764	0.807	0.850	0.806	0.851	0.864	0.860	0.878	0.866	0.838
Qinghai	0.951	0.965	0.994	0.992	1.000	0.995	1.000	1.000	0.999	0.988
Ningxia	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	**1.000**
Xinjiang	0.913	0.950	0.935	0.940	0.975	0.976	0.953	0.959	0.953	0.950
mean	0.902	0.903	0.923	0.922	0.950	0.962	0.937	0.912	0.928	0.927

had the significant influence on the inputs of energy efficiency in China's construction industry.

4.2.3 The Empirical Results of the DEA Model with the Adjusted Inputs at the Third Stage

We adjusted the inputs of the energy efficiency of China's regional construction industry from 2003 to 2011 with Formula (3). Then, DEAP 2.1 was again used to conduct the analysis with the DEA model for the second time. The adjusted results are shown in Table 5.

Compared with the DEA model results at the first stage, the energy efficiency of the construction industry in each region reflected some relatively substantial change after removing the influence of the external environment factors and random errors. The mean of the energy efficiencies of China's regional construction industry in each year improved from approximately 0.75 at the first stage to 0.92 at the third stage, which showed that energy efficiency was underestimated without before removing influencing factors. Besides, from the horizontal perspective of the table, the regions where the energy efficiency of the construction industry during nine years was 1.0 after the adjustment remained the same. Moreover, the order for the means of energy efficiency of the construction industry in part of the regions from 2003 to 2011 had changed. The energy efficiency in Beijing, Zhejiang, Hainan, Ningxia, Heilongjiang, Shanghai, Jiangsu and Jiangxi, were still in the dominant roles. The order of energy efficiency of some provinces, including Guizhou, Inner Mongolia, Shanxi, Yunnan, Shaanxi, Sichuan, Gansu and Hebei, showed some progress, whereas the order of energy efficiency of some provinces, such as Jiangsu, Chongqing, Guangdong, Liaoning, Anhui, Hunan and Shandong, declined. The above results demonstrated that the energy efficiency of the regional construction industry was affected by local environmental factors or fortune.

According to the DEA model results at the third stage, the energy efficiency of the construction industry in Shandong was lowest at 0.647, but the energy efficiency of all of the other provinces exceeded 0.8. This showed that the operation and management of the construction industry energy in most of China's regions were relatively mature and showed little difference. However, considering China's construction industry has

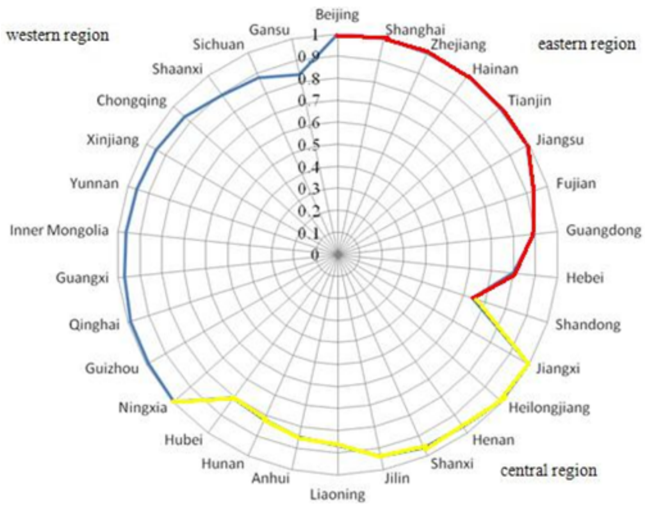

Fig. 1. Energy Efficiency of the Construction Industry of China's Three Main Regions

always adopted the extensive operation mode for a long time, insufficient technological innovation and labor with low-quality lead to the shortage of the whole competitiveness. Therefore, the management level for the energy of the regional construction industry needs to be further improved.

Moreover, as the energy efficiency of the construction industry was affected by the development level of the local economy, we can further analyze the results from the regional perspective. According to the different development levels of the local economy, all the provinces of China are divided into three main regions, that is the eastern, the central and the western regions. Besides, the development levels decrease successively as the above order. The provinces involved in each region and their energy efficiencies of the construction industry can be seen in Fig. 1.

The eastern region: the energy efficiency of the construction industry in ten provinces can be divided into three types.

- excellent (energy efficiency value was greater than 0.93): Beijing, Shanghai, Zhejiang, Hainan, Tianjin and Jiangsu;
- good (energy efficiency value was between 0.8 and 0.93): Fujian, Guangdong and Hebei;
- poor (energy efficiency value was equal to 0.647): Shandong.

Therefore, the energy efficiency of the construction industry in most eastern regions was satisfactory, except in Shandong, which should be regarded as a key subject to be improved. Besides, all of the other provinces should maintain their existing advantages and improve themselves according to their own features.

The central region: the energy efficiencies of the construction industry in nine provinces can be divided into two types:

- excellent (energy efficiency value was equal to or more than 0.94): Jiangxi, Heilongjiang, Henan, Shanxi and Jilin;
- good (energy efficiency value was between 0.8 and 0.87): Liaoning, Anhui, Hunan and Hubei.

Totally speaking, the energy efficiency of the construction industry in the central region consist of the excellent and the good efficiency. The influence between the two types of the provinces is necessary to improve the energy efficiency of the construction industry.

The western region: the energy efficiency of the construction industry of eleven provinces (except Tibet) can be divided into two types:

- excellent (energy efficiency was greater than 0.93): Ningxia, Guizhou, Qinghai, Guangxi, Inner Mongolia, Yunnan, Xinjiang and Chongqing;
- good (energy efficiency was between 0.83 and 0.9): Shaanxi, Sichuan and Gansu.

According to the results, we can see that the energy efficiency of the construction industry was relatively good. To large extent, the superior provinces should drive the weaker ones to further develop the energy efficiency of the construction industry.

5. Change Trend Analysis of the Energy Efficiency of China's Regional Construction Industry with the DEA-DA Model

From the data in Table 4, it can be seen that the energy efficiency of the construction industry in some regions during the nine years was effective. For example, in Beijing, Tianjin, Shanghai, Jiangsu, Zhejiang, Jiangxi, Guangxi, Hainan, Yunnan and Ningxia in the year 2003. To distinguish the energy efficiency values of the construction industry of these regions, we divided them into two groups according to the principal that whether their energy efficiency values were one. Then, the DEA-DA model was utilized to sort the regions based on the adjusted data of the inputs and the outputs of the construction industry. Based on the Matlab 7.0, the results for the variables in the model and the sorting results of the energy efficiency of the construction

Table 6. Variable Results of the DEA-DA Model

	2003	2004	2005	2006	2007	2008	2009	2010	2011
v_1	0.021	0.211	0.185	0.253	0.329	0.001	0.148	0.001	0.001
v_2	0.674	0.016	0.429	0.167	0.001	0.280	0.192	0.180	0.185
v_3	0.077	0.209	0.286	0.259	0.458	0.410	0.158	0.802	0.599
v_4	0.001	0.001	0.001	0.001	0.016	0.029	0.031	0.001	0.001
w_1	0.001	0.001	0.025	0.017	0.030	0.007	0.001	0.015	0.005
w_2	0.226	0.562	0.074	0.303	0.167	0.273	0.471	0.001	0.209
σ	26.826	24.194	106.861	61.531	122.396	216.946	111.212	316.443	197.280

industry were shown in Table 6 and Table 7, respectively.

Comparing the results in Table 5 with in Table 7, we can find that there were some differences between them. For example, the energy efficiency value of Guangdong in 2000 with the three-stage DEA model was the fourth from the bottom, whereas it came in last with the DEA-DA model. The energy efficiency values of Beijing from 2003 to 2011 calculated with the three-stage DEA model were one, while the values with the DEA-DA model were 0.874, 0.973 and 0.981 in the years 2003, 2004 and 2005. The evaluation difference is caused by the measurement method with the DEA-DA model, which has an industry-wide evaluation; thus, a scale merit directly influences its efficiency measurement as part of the industry-wide evaluation; meanwhile, the conventional use of DEA does not have such an important analytical capability (Hu and Wang, 2006). Therefore, energy efficiency values with the DEA-DA model can overcome the methodological limit of the DEA model.

According to the results in Table 7, some conclusions can be obtained as follows:

From the regional perspective, in accordance with the fluctuation of energy efficiency of the construction industry over the nine years, the values of Shandong were the most stable and constantly came in last. In fact, the heavy industries, such as coal power and steel, are the dominant industries of Shandong, and its resources are limited. Therefore, improving its energy efficiency of the construction industry has great significance for its sustainable development. The energy efficiency of the construction industry in Guangdong and Hunan fluctuated most substantially, which can also be reflected by sorting the changes in the annual efficiency values. Meanwhile, the other provinces can be separated into two types according to the fluctuation degree of the energy efficiency: (a) the great fluctuation: Hubei, Gansu, Hebei, Anhui, Zhejiang, Henan and Sichuan; (b) the little fluctuation: the remaining provinces. Besides, with respect to the energy efficiency values only, Shandong was the lowest with constant values of 0. The values of Beijing in 2006, 2007 and 2009 were effective;

Table 7. Sorting of the Energy Efficiency of China's Regional Construction Industry

Region	2003		2004		2005		2006		2007		2008		2009		2010		2011	
	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.	Efficiency value	No.
Beijing	0.874	6	0.973	3	0.981	2	1.000	1	1.000	1	0.899	8	1.000	1	0.833	4	0.822	2
Tianjin	0.854	7	0.970	4	0.867	8	0.845	4	0.884	4	0.870	14	0.549	15	0.716	13	0.634	16
Hebei	0.240	29	0.589	28	0.524	29	0.520	29	0.472	29	0.233	29	0.260	28	0.144	26	0.145	29
Shanxi	0.647	21	0.735	25	0.867	13	0.739	20	0.723	24	0.685	23	0.415	25	0.691	14	0.579	20
Inner Mongolia	0.766	16	0.867	17	0.783	21	0.813	6	0.766	21	0.832	17	0.550	14	0.691	15	0.623	17
Liaoning	0.648	20	0.789	24	0.777	22	0.788	15	0.777	20	0.713	21	0.509	19	0.665	21	0.617	18
Jilin	0.615	22	0.839	20	0.773	24	0.731	23	0.792	17	0.924	6	0.629	5	0.779	8	0.697	12
Heilongjiang	0.832	12	0.926	11	0.869	7	0.813	9	0.869	5	0.974	3	0.616	7	0.912	2	0.698	10
Shanghai	0.843	10	0.964	6	0.867	9	0.911	2	0.822	9	0.885	11	0.783	2	0.827	5	0.678	14
Jiangsu	0.843	9	0.865	18	0.867	12	0.813	10	0.822	12	0.885	10	0.550	13	1.000	1	1.000	1
Zhejiang	1.000	1	0.960	7	1.000	1	0.898	3	0.902	2	0.955	5	0.550	12	0.755	11	0.698	9
Anhui	0.336	28	0.794	23	0.775	23	0.716	24	0.747	22	0.714	20	0.429	23	0.675	19	0.523	21
Fujian	0.805	13	0.926	12	0.858	15	0.800	12	0.822	13	0.722	19	0.494	21	0.677	18	0.615	19
Jiangxi	0.894	3	0.926	10	0.891	3	0.813	7	0.842	6	0.997	2	0.603	8	0.885	3	0.748	5
Shandong	0.000	30	0.000	30	0.000	30	0.000	30	0.000	30	0.000	30	0.000	30	0.051	29	0.000	30
Henan	0.738	18	0.838	22	0.812	19	0.773	18	0.897	3	0.885	9	0.420	24	0.760	10	0.789	3
Hubei	0.555	27	0.723	27	0.590	28	0.633	27	0.570	27	0.527	27	0.357	26	0.089	27	0.377	26
Hunan	0.759	17	0.839	21	0.670	27	0.658	26	0.636	26	0.600	26	0.323	27	0.073	28	0.164	28
Guangdong	0.790	15	0.922	13	0.759	25	0.771	19	0.790	18	0.764	18	0.724	3	0.000	30	0.364	27
Guangxi	0.893	4	0.932	8	0.867	11	0.776	17	0.777	19	0.885	13	0.511	18	0.821	6	0.784	4
Hainan	0.843	8	1.000	1	0.878	5	0.813	8	0.822	11	1.000	1	0.621	6	0.779	7	0.743	7
Chongqing	0.573	24	0.894	16	0.826	17	0.785	16	0.820	14	0.885	12	0.719	4	0.691	16	0.680	13
Sichuan	0.573	23	0.548	29	0.867	10	0.613	28	0.553	28	0.669	24	0.490	22	0.381	25	0.419	25
Guizhou	0.883	5	0.926	9	0.860	14	0.794	13	0.802	16	0.860	15	0.558	11	0.675	20	0.747	6
Yunnan	0.843	11	0.902	14	0.814	18	0.738	21	0.742	23	0.707	22	0.514	17	0.580	22	0.485	22
Shaanxi	0.572	25	0.730	26	0.800	20	0.733	22	0.822	10	0.612	25	0.509	20	0.532	24	0.459	23
Gansu	0.570	26	0.853	19	0.748	26	0.707	25	0.708	25	0.435	28	0.252	29	0.534	23	0.444	24
Qinghai	0.801	14	0.969	5	0.874	6	0.809	11	0.823	8	0.962	4	0.597	10	0.763	9	0.742	8
Ningxia	0.911	2	0.990	2	0.891	4	0.820	5	0.828	7	0.918	7	0.599	9	0.718	12	0.697	11
Xinjiang	0.711	19	0.898	15	0.847	16	0.789	14	0.805	15	0.847	16	0.545	16	0.681	17	0.671	15
mean	0.707		0.836		0.793		0.747		0.755		0.761		0.523		0.613		0.588	

although the values of Beijing in other years were not 1, there was little difference among them. The energy efficiency values Jiangsu, Zhejiang and Hainan in some years were effective, while there were relatively great differences between the values and those of the adjacent years. To large extent, it showed that the energy efficiency values of these provinces were not stable.

From the time dimension, the mean of the energy efficiency values of the construction industry during the nine years was largest (0.836) in 2004, which reflected that the whole energy efficiency in this year was higher. Although the energy efficiency values in 2010 saw some increase, the overall energy efficiency of the construction industry showed a downward trend after 2004. Besides, from the sorting of the annual energy efficiency values, it can be seen that the ranks of all the regions changed, except Hebei, Hubei and Xinjiang. However, the effective energy efficiency values of the construction industry always belonged to the leading provinces, including Beijing, Zhejiang, Hainan and Jiangsu.

From the perspective of the three main regions, the energy efficiency ranks of the east during the nine years were in the top ten (Grade one), which was similar to the energy efficiency values calculated with the three-stage DEA model. Of these provinces, Shandong was rated last, Hebei came to Grade 3 and Fujian and Guangdong came to Grade 2. To large degree, due to the rate change of the above provinces, the whole energy efficiency of the construction industry in the eastern region had declined, thereby narrowing of the gaps between itself and the central and western regions, respectively. Besides, the higher development level of the local economies had little significant influence on improving the energy efficiency of the construction industry. As for the central region, most of the provinces came to Grade two, except Heilongjiang and Jiangxi (in the top ten) as well as Anhui, Hubei and Hunan (in Grade three). In terms of the western region, the energy efficiency of the construction industry fluctuated most during these nine years. Among these provinces, the values of Qinghai and Ningxia were in the top ten; the values of Sichuan, Shaanxi and Gansu came to Grade 3; and the values of the other provinces came to Grade 2. Therefore, the energy efficiency distribution of the inner provinces had improved the whole energy efficiency of the construction industry in the western region. Meanwhile, similar to the results of the eastern region, it proved the relationship between the energy efficiency of the construction industry and the development level of the local economy was weak.

6. Conclusions

The energy efficiency of the construction industry has a direct connection with its sustainable development. Based on the literature review of energy efficiency and the feature of the construction industry, this paper chose energy, labor, capital as well as construction machinery and equipment as energy-utilization inputs of the construction industry, total output and total profits of the construction industry as the energy-utilization output indicators of the construction industry, energy consumption structure, industrial development degree, organization structure and technological level as the factors influencing its energy efficiency. Afterwards, the research method (three-stage DEA model and DEA-DA model) was adopted to conduct an analysis on the energy efficiency and its change trend of China's regional construction industry. The results show that before eliminating the influence of the environment factors and random errors, the energy efficiency values of the construction industry in most of the provinces were under-estimated. The mean of China's energy efficiency of the construction industry in each year was approximately 0.92. Shandong was the province with the lowest values (0.647), while the mean of the other provinces was over 0.8, which reflected that there were small differences in the energy efficiency of the construction industry. However, the energy efficiency in the majority of provinces constantly fluctuated during these nine years, with the peak in 2004 and a downward trend in the overall efficiency after 2004. From the regional aspect, the energy efficiency of the construction industry in the eastern, central and western regions decreased successively. Besides, the energy efficiency in the three main regions did not have the similar difference to their development level of the local economy.

In terms of the methodology, that is the combination of three-stage DEA model and DEA-DA model, it not only overcomes the deficiencies of calculating the efficiency with the DEA model, but distinguishes among several DMUs with the same energy efficiency of one. Meanwhile, the research method presented in this study can be not only applied to measuring the energy efficiency of the construction industry in other countries, but also to the other industries for measuring the energy efficiency from the regional perspective.

Currently, research into the energy efficiency of the construction industry is still at an early stage. This paper only conducted the research from the perspectives of descriptive statistics. In the future, the differentiation in the energy efficiency of the regional construction industry and its formation mechanisms, as well as the policy incentive systems of energy-saving and emission-reduction, will become the key issues for the construction industry.

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