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Energy efficiency of China's industry sector: An adjusted network DEA-based decomposition analysis

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Abstract: The process of energy conservation and emission reduction in China requires the specific and accurate evaluation of the energy efficiency of the industry sector because this sector accounts for 70 percent of China's total energy consumption. Previous studies have used a "black box" data envelopment analysis (DEA) model to obtain the energy efficiency without considering the inner structure of the industry sector. However, differences in the properties of energy utilization (final consumption or intermediate conversion) in different industry departments may lead to bias in energy efficiency measures under such "black box" evaluation structures. Using the network DEA model and efficiency decomposition technique, this study proposes an adjusted energy efficiency evaluation model that can characterize the inner structure and associated energy utilization properties of the industry sector so as to avoid evaluation bias. By separating the energy-producing department and energy-consuming department, this adjusted evaluation model was then applied to evaluate the energy efficiency of China's provincial industry sector.

Key words: Energy consumption; Energy conversion; Structure decomposition

1 Introduction

Accounting for more than one fourth of global total primary energy consumption [1], China's efforts towards energy conservation and greenhouse gas emission reduction play an important role in global warming mitigation. Within the country, the Chinese industry sector is the primary energy consumer and comprises up to 70 percent of the national total energy consumption [2]. Evaluating and improving the energy utilization efficiency of the industry sector in China has been given high priority in the policy-making processes of governments [23, 24] and has attracted increasing interest from researchers [4, 5, 26]. Data envelopment analysis (DEA) is a widely utilized approach to evaluate energy economic efficiency and was first proposed by Charnes et al. [3]. This approach measures the relative efficiencies of decision-making units (DMUs) based on multiple inputs and outputs. One of the characteristics of traditional DEA models is that it treats each DMU as a "black box" and identifies the efficiency in the absence of internal activities of a DMU [29, 30]. Therefore, when utilizing DEA for industrial energy efficiency evaluation, only the initial energy input and final economic output data are needed, whereas the data on energy production or energy conversion related to the internal activities in each industry department are usually omitted.

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Several traditional DEA models have been applied to evaluate China's regional energy efficiency. For instance, Hu and Wang [4] applied a standard DEA model to obtain the regional total-factor energy efficiency, and Wang et al. [5] evaluated the regional energy performance while considering undesirable outputs and broadening the energy efficiency study to multi-directional analyses. Li and Lin [28] estimated the total-factor energy efficiency of China's regions using a combined model based on a superior efficiency DEA and sequential frontier model to improve the discriminating power and avoid the technical regression of traditional DEA approaches. Furthermore, utilizing a traditional DEA model, Zhao et al. [31] evaluated the total factor energy efficiency of provincial industrial sectors in China. In these cases, the "black box" DMU structure was applied for modeling, and thus, the energy efficiency as measured using total energy consumption (or primary energy consumption) as the input and gross domestic product (GDP) or gross value added as the economic output. However, in the "black box", the conversion from primary energy (e.g., coal, oil and natural gas) to secondary energy (e.g., coke, liquefied petroleum gas, thermal electricity) is omitted, and the gross value added from an energy conversion process and a final energy consumption process cannot be separated. In other words, the energy production or energy conversion department and the energy utilization department in the industry sector are not distinguished from each other. To provide a more specific evaluation of the energy efficiency of industry based on the above differences, the traditional "black box" DEA model may lack discriminating power [6] and consequently cannot provide process-specific guidance to separately improve energy efficiency in the energy production department and energy utilization department.

Furthermore, unlike general producing and consuming processes in manufacturing industries, energy inputs in some industry sectors are not only combusted as fuel to produce economic outputs but part of the energy inputs (both primary energy and secondary energy) are consumed within the "black box" for the production process. In other words, energy inputs can be divided into two parts. The first part is used for general producing and consuming processes, and the other part is the raw material for the "black box" itself. The traditional DEA model assumes that all energy inputs are directly consumed for producing outputs because the traditional "black box" modeling structure cannot distinguish these two parts before the energy inputs flow into the "black box". Thus, differences in the energy properties in different departments of industry sectors may result in evaluation bias in the traditional model.

Regarding the properties of different energy consumption processes, a two-stage network structure will be more appropriate to evaluate energy efficiency in industry. In this network structure, the first stage is the energy-producing or conversion department, whose input is primary energy and whose output is secondary energy. The second stage is the energy-consuming department, where energy (including both primary and secondary energy) is an input and part of the energy input (secondary energy) is the output of the first stage. In other words, within the network structure, some energy outputs that flow from the first stage become inputs in the second stage and can be considered intermediate inputs/outputs. Ignoring these intermediate measures in the traditional DEA model decreases the accuracy of industrial energy efficiency evaluation for different energy-using departments.

This network structure requires more appropriate approaches that consider intermediate measures. To tackle this issue, a network DEA model should be applied. Färe and Grosskopf [7] as well as Seiford and Zhu [14] first develop a network DEA model that addresses links between different industrial departments. For more general situations, an extension of the network DEA model introduced by Tone and Tsutsui [8, 9] can be applied via the slacks-based measure (SBM) technique. Furthermore, Fukuyama and Weber [10] extended the SBM network DEA model for cases involving undesirable outputs. These network DEA models have been successfully applied to various industries. For example, Fukuyama and Matousek [11] evaluated the efficiency of Turkish banking systems, which have an inherent network structure. Yu and Lin [12] obtained the railway effectiveness in 20 countries using a multi-activity network DEA model. Hsieh and Lin [13] used a relational network DEA to test the performance of international tourist hotels in Taiwan. However, to the best of our knowledge, few studies have considered differences in energy utilization properties and applied the network DEA structure to evaluate energy efficiency in China's industry sector. In this paper, we developed an adjusted network DEA model based on the approach described by Fukuyama and Weber [10] so as to improve industrial energy efficiency evaluation. We then applied this model to China's industry sector.

Although network DEA models can be applied to multi-stage network structures, early network DEA models cannot easily address conflicts between intermediate measures. For example, the links between stages may reduce inputs for some stages to ensure that the entire DMU is efficient [15]. To resolve conflicts between stages, efficiency decomposition techniques have been developed. The approaches developed by Kao and Hwang [17], Liang et al [16, 18] and Chen et al [19] are several good examples of reasonable models for intermediate measures within DMU to evaluate financial institution or supply chain efficiency.

Nevertheless, these existing extensions of DEA models cannot address additional inputs and outputs in intermediate measures, which are very common in regional energy efficiency evaluations. For instance, large amounts of intermediate energy products are transferred between different regions during evaluation, and these transfers break the integrality of traditional DEA models and network DEA models. These transfers arise because energy-producing and energy-consuming processes are not necessarily completed within a single DMU, i.e., part of one DMU's intermediate outputs from its energy-producing department may become the intermediate inputs of another DMU's energy-consuming department instead of the energy-consuming department itself. Previous network DEA models describe the DMU as closed-system in which no additional inputs are involved in intermediate measures. Therefore, these models cannot be directly utilized in regional energy efficiency evaluation, in which regions are not independent from each other. Although problems related to intermediate outputs can be solved with methods for undesirable outputs (may also increase error) [27], intermediate inputs remain unconsidered. Therefore, an improved approach is needed for open-systems. To model a network structure in which all stages are open, we extended the efficiency decomposition methods by evaluating each stage individually in this study.

The newly developed efficiency decomposition method divides each DMU into sub-DMUs and combines the performance of sub-DMUs by different weights. Although this adjusted efficiency decomposition approach partially mathematically reverts to the traditional DEA model, both structures and intermediate transferred are better addressed. The approach proposed in this study was further applied to evaluate the regional energy efficiency of China's industry sector. As shown in Figure 1, three DEA models were applied. The results from a traditional DEA model, a network DEA model and an efficiency decomposition approach are compared and analyzed to observe improvements associated with the new approach. Additionally, the specific situations in the energy-producing department were evaluated for multi-stage structures.

[Insert Figure 1 here]

2 Network DEA models for energy efficiency evaluation

2.1 Traditional DEA model

The traditional DEA model introduced by Charnes et al [3] treats DMU as a "black box". Without considering intermediate measures, it obtains a maximum ratio of weighted outputs and weighted inputs of one DMU under the condition that similar ratios in every DMU do not exceed unity. Recently, Fukuyama and Weber [20] developed a slacks-based measure for the network DEA model. In this paper, we first applied the slacks-based measure within the traditional “black box” DEA model to obtain an intuitive energy efficiency measure.

Suppose there are n DMU_j (j=1,…n), each representing the industry sector of a province in China. Let x_k (k=1,…L) be an L-dimensional input representing multiple inputs, including the original energy input, labor input and capital input. Y_h (h=1,…,R) is an R-dimensional output representing the GDP output. The energy efficiency can then be measured in the traditional DEA model as follows:

$$\begin{aligned}
&\max \frac{1}{2}\cdot\frac{1}{L}\cdot\sum_{k=1}^{L}\frac{s_k^{x-}}{x_{kj_0}}+\frac{1}{2}\cdot\frac{1}{R}\cdot\sum_{h=1}^{R}\frac{s_h^{y+}}{y_{hj_0}}\\
&s.t.\ \sum_{j=1}^{n}\lambda_j x_{kj}+s_k^{x-}=x_{kj_0},k=1,\dots,L\\
&\quad\ \sum_{j=1}^{n}\lambda_j y_{hj}-s_h^{y+}=y_{hj_0},h=1,\dots,R\\
&\quad\ \sum_{j=1}^{n}\lambda_j=1,s_h^{y+}\ge 0,s_k^{x-}\ge 0,k=1,\dots,L,h=1,\dots,R
\end{aligned}\tag{1}$$

Here, $\lambda_j(j=1,\dots,n)$ are the intensive variables associated with DMU_j. $s_k^{x-}(k=1,\dots,\mathrm{L})$ and $s_h^{y+}(h=1,\dots,R)$ are slack variables associated with $x_{kj}(k=1,\dots,L)$ and $\mathrm{y}_{hj}(h=1,\dots,R)$, respectively. The model returns only inefficiencies; thus, we define the energy efficiency from Model (1) as follows: Black box energy efficiency (*BBE*) $=1-\frac{s_k^{x-}}{x_k}$, k for the energy input. Each DMU reaches efficiency when *BBE* equals 1 and is considered inefficient if *BBE* is less than 1.

Within DMUs, the properties of energy utilization depend on the industrial department. Specifically, energy inputs in the energy-producing department can be divided into two parts: energy for final consumption and energy as raw material for conversion. Figure 2 shows the energy flow in the industry sector. To describe the entire industry as a “black box”, we utilized all energies that flow into stage 1 as energy inputs, the total number of employee and capital stock of the industry sector as labor inputs and capital inputs, and the gross industrial output values as outputs.

[Insert Figure 2 here]

At the national level, if we ignore the intermediate energy input/output and omit the difference between two departments as shown in Figure 2, the “black box” is appropriate because horizontal comparisons are neglected and provinces can be treated as sub-DMUs within the entirety. However, this model yields bias in horizontal comparisons between provinces because provincial industry sectors are not independent. Different natural conditions and different economic development statuses result in different industrial structures. In general, the energy-consuming department tends to yield higher economic returns than the energy-producing department. Because the gross industrial output values are the outputs in this “black box” model, the energy efficiency of well-developed provinces with lower proportions of energy-producing departments may be overestimated. The energy utilization property is an important factor in the evaluation of industrial energy efficiency, and the network DEA model is an existing model that can describe the industry structure. Thus, we next applied this technique to improve provincial industrial energy efficiency evaluation.

2.2 Network DEA model

A multi-stage DEA or Network DEA model has been applied to evaluate the efficiency of various structures in industry and business sectors since Seiford and Zhu [14] first applied it to US commercial banks. These models have also been applied to, for example, the Turkish banking system [20], Taiwanese hotel industry [13] and Brazilian port system [21]. These systems share a common two-stage structure within the industry sector evaluated in this study. The two-stage structure divides the DMU into two sub-DMUs in which each sub-DMU consumes inputs to yield outputs. In addition, the first sub-DMU consumes exogenous inputs, and the second sub-DMU consumes outputs originate from the first sub-DMU. Thus, the performances of both sub-DMUs can first be separately evaluated before evaluating the comprehensive performance of the entire system (whole DMU) based on adjusting the importance of its sub-DMUs. In the industry sector examined herein, the sub-stages (sub-DMUs) were defined due to energy properties as shown in Figure 3. The energy-producing department and energy-consuming department were identified as sub-stage 1 and sub-stage 2, respectively.

[Insert Figure 3 here]

The network DEA model to measure energy efficiency is then represented as follows:

$$
\begin{aligned}
&\max \frac{1}{2}\cdot\frac{1}{L}\cdot\sum_{k=1}^{L}\frac{s_k^{x-}}{x_{kj_0}}+\frac{1}{2}\cdot\frac{1}{R}\cdot\sum_{h=1}^{R}\frac{s_h^{y+}}{y_{hj_0}} \\
&s.t.\ \left.\begin{aligned}
&\sum_{j=1}^{n}\lambda_j^1 x_{kj}+s_k^{x-}=x_{kj_0},\quad k=1,\ldots,L \\
&\sum_{j=1}^{n}\lambda_j^1 z_{tj}-s_t^{1z+}=z_{tj_0},\quad t=1,\ldots,M
\end{aligned}\right\}\text{for stage 1} \\
&\qquad \left.\begin{aligned}
&\sum_{j=1}^{n}\lambda_j^2 z_{tj}+s_t^{2z-}=z_{tj_0},\quad t=1,\ldots,M \\
&\sum_{j=1}^{n}\lambda_j^2 y_{hj}-s_h^{y+}=y_{hj_0},\quad h=1,\ldots,R
\end{aligned}\right\}\text{for stage 2} \qquad\qquad (2) \\
&\qquad \sum_{j=1}^{n}\lambda_j^1=1,\ \sum_{j=1}^{n}\lambda_j^2=1, \\
&\qquad \lambda_j^1\ge 0,\ \lambda_j^2\ge 0,\ s_k^{x-}\ge 0,\ s_t^{1z+}\ge 0,\ s_t^{2z-}\ge 0,\ s_h^{y+}\ge 0, \\
&\qquad k=1,\ldots,L,\ t=1,\ldots,M,\ h=1,\ldots,R
\end{aligned}
$$

In Model (2), z_{tj} (t=1,…,M) is an M-dimensional vector that represents the intermediate products (energy consumed in stage 2), including secondary energy and primary energy (this part of primary energy is not converted into secondary energy in stage 1 but directly consumed in stage 2). In this study, M equals 1 because all energy terms are converted into standard units (coal equivalent) and combined. λ_j^1 and λ_j^2 (j=1,…,n) are intensity variables associated with stage 1 and stage 2, respectively. The energy efficiency measured by the network model is unchanged compared with the black box model: Network energy efficiency (NEE) = $1-\frac{s_k^{x-}}{x_k}$, k for energy input.

By introducing restrictions on intermediate activities shown in Model (2), the network DEA model improves the process-specific guidance to manage DMUs provided by the traditional "black box" model. However, conflicts may arise between stages from intermediate measures when assessing full-scale efficiencies is easier but access to specific data is lacking. For instance, for a province with low efficiency in sub-stage 1 and high efficiency in sub-stage 2, the network DEA model needs to balance the performance of sub-DMUs to ensure the overall efficiency of the DMU. Thus, it may require sub-stage 1 to reduce its inputs to increase the efficiency. Therefore, changes in the outputs from sub stage 1 may decrease the efficiency of sub-stage 2. In other words, provinces with equal or similar efficiencies in sub-stage 1 and sub-stage 2 may have higher network energy efficiencies than provinces with large different efficiencies in sub-stage 1 and sub-stage 2.

Intermediate measure conflicts between sub-DMUs are not the only disadvantage of the original network DEA model. The original network model places a strict requirement on the system: the second sub-stage should not have independent inputs (i.e., inputs that are not from the first sub-stage itself but are from other DMU). Such closed systems only exist if the inputs for the first stage represent all inputs for the entire system. However, industry sectors are usually open systems, and the second sub-stages of these systems have unique independent inputs. Thus, the original network model may introduce bias to the evaluation of regional industrial energy efficiency. For instance, the electricity production from one province may be the primary supplement of a large area. In other words, as shown in Figure 4, the electricity supplier's outputs (secondary electricity generation) from stage 1 become inputs for stage 2 of other provinces in the intermediate measure. If the original network model is applied to such a system, the supplier's performance of stage 1 will be underestimated because large inputs flow into stage 1 and few outputs flow out to its own stage 2. On the contrary, the performance of stage 2 in the other provinces will be overestimated when few inputs flow from its own stage 1 and large outputs flow out.

[Insert Figure 4 here]

Interactions between DMUs and conflicts between sub-DMUs are common in industrial energy-producing and energy-consuming processes. Thus, a specific energy efficiency decomposition approach was introduced to improve traditional "black box" DEA model and original network DEA model and avoid large biases due to these two aspects.

2.3 Adjusted efficiency decomposition approach

The efficiency decomposition approach was first introduced by Kao and Hwang [17]. The difference between previous DEA models and the efficiency decomposition approach is that the sub-DMUs are treated independently in the latter, which allows each sub-DMU to have exogenous inputs and to produce final outputs. Therefore, energy outputs in sub-stage 1 that are exported to other provinces can be defined as part of the final outputs of the entire industry. In addition, Golany et al. [22] demonstrated the availability for systems in which sub-DMUs share resources. Thus, energy flow in each provincial industry sector can be well described by the efficiency decomposition approach, as shown in Figure 5. The exogenous inputs of sub-stage 2, including unprocessed primary energy inputs and secondary energy inputs from other provinces, can be distinguished from the total energy inputs of sub-stage 2. The intermediate outputs of stage 1 that are exported to other provinces can be eliminated in the evaluation of sub-stage 2.

[Insert Figure 5 here]

In Kao and Hwang's model [17], the weights of intermediate measures are assumed to be same for sub-DMUs. However, to evaluate the industry sector, the energy utilization processes in different departments differ among China's 30 provinces from the perspective of multi-stage energy efficiency evaluation. If the weight associated with the intermediate measure is the same as that in Kao and Hwang's model, the independent application of a traditional "black box" model to each sub-DMU and the application of a network DEA model will produce the same results [19]. Thus, we directly applied a slacks-based traditional "black box" model to sub-stage 1 and sub-stage 2 and then assembled the efficiencies by selecting appropriate weights. The weight of a specific sub-stage is the proportions of its energy inputs in the total energy consumption of the entire industry sector. Labor inputs and capital inputs are divided into 2 parts each according to the consumptions in the energy-producing and energy-consuming departments. The following equation shows the adjusting energy efficiency measure of the efficiency decomposition approach: Adjusted energy efficiency (*AEE*) = $1-\frac{s_k^{x^1-}}{x_k^1}\frac{x_k^1}{x_k^1+x_k^2}-\frac{s_k^{x^2-}}{x_k^2}\frac{x_k^2}{x_k^1+x_k^2}$, k for energy input, in which x_k^1 and x_k^2 (k=1,…,L) are energy inputs of sub-stage 1 and sub-stage 2, respectively.

To obtain more specific energy efficiency evaluation results for different departments within the industry sector, the efficiency decomposition for a specific sub-stage is needed. Due to the limited availability of accurate data, we applied the proposed method only to sub-stage 1 to demonstrate the effectiveness of the adjusted efficiency decomposition in this study. The energy flow in this sub-stage can be additionally separated into three parts: exploitation, processing and electricity generation, which are named sub-stage 1.1, sub-stage 1.2 and sub-stage 1.3 in this study, respectively.

The inner structure in sub-stage 1 is described by a more complicated relationship, which is further illustrated in Figure 6. The net energy inputs of the 3 sub-stages are the same as the total energy inputs of stage 1 in the network model. The energy inputs of stage 1.1 are consistent with the local primary energy and imported primary energy from other provinces. The energy outputs of stage 1.1 provide parts of the secondary energy outputs of stage 1 as well as the secondary energy inputs of stage 1.2 and stage 1.3. For stage 1.2, the energy inputs are the local primary energy inputs, imported primary energy inputs and secondary energy inputs from stage 1.1; energy outputs are the secondary energy for stage 1.3 and energy outputs of stage 1. The energy inputs of stage 1.3 originate from all previous energy resources, including the local and imported primary energy and secondary energy from stage 1.1 and stage 1.2. The energy outputs from stage 1.3 directly flow out of stage 1. The net energy outputs from the 3 sub-stages (sum of their total output minus the parts that have been consumed in stage 1) become the intermediate output of stage 1 in the network model.

[Insert Figure 6 here]

The energy efficiency of sub-stage 1 is defined similarly to the defined energy efficiency of the entire industry sector, and the weights associated with sub-stages 1.1 to 1.3 are calculated based on the the ratio of its energy inputs to the sum of the energy inputs of all three sub-stages, as shown in the following equation, which is additionally defined as the adjusted energy efficiency of sub stage 1: $1-\frac{s_{1k}^{x^1-}}{x_{1k}^1}\frac{x_{1k}^1}{x_{1k}^1+x_{1k}^2+x_{1k}^3}-\frac{s_{1k}^{x^2-}}{x_{1k}^2}\frac{x_{1k}^2}{x_{1k}^1+x_{1k}^2+x_{1k}^3}-\frac{s_{1k}^{x^3-}}{x_{1k}^1}\frac{x_{1k}^3}{x_{1k}^1+x_{1k}^2+x_{1k}^3}$.

At last, we define the difference between the adjusted energy efficiency measure and the traditional "black box" efficiency measure as the evaluation bias (efficiency overestimation or underestimation) caused by not considering the inner structure of the energy utilization process.

3 Empirical result and comparison

3.1 Input and output data

The models and approach proposed in this study were further applied to evaluate the regional energy efficiency of the industry sectors of China's 30 provinces. Because specific data on the energy consumption and economic output of energy-producing and energy-consuming departments are only available for the year 2008 from the second National Economic Census, the empirical analysis in this study was restricted to this year. The third National Economic Census was conducted in 2014, which is more recent, but the specific date that we need for multi-stage industrial energy efficiency evaluations has not yet been released. Furthermore, this study primarily aimed to propose a more appropriate network DEA-based evaluation model for energy efficiency evaluation and decomposition while considering different energy properties in different energy utilization department. Therefore, we expect that the empirical analysis of one year will be acceptable to demonstrate the effectiveness of this model given the current lack of recent data. Tibet, Hong Kong, Macau and Taiwan are excluded from the calculation because a lack of data.

In this section, we use the phrase "energy input" to represent the local primary and secondary energy input plus the secondary energy import from other provinces, and we use the phrase "energy output" to represent the local secondary energy outputs plus the secondary energy export to other provinces. The DEA model for each province contains three inputs, including non-energy inputs and energy inputs. We used labor and capital as two-dimensional non-energy inputs in units of ten thousand employees and billions of Yuan (Chinese currency), respectively. Energy inputs in ten thousand tons of coal equivalent are used as one-dimensional energy inputs. The gross industrial output value is utilized as one-dimensional output, which is also given in billions of Yuan.

In the traditional "black box" model, we set the energy inputs for the energy-producing department to be the initial energy input for the entire industry sector. The total labor and capital inputs for both sub-stages 1 and 2 are utilized as non-energy inputs. In the network model, the intermediate product is the energy consumption of stage 2. We ignore the intermediate effects of non-energy factors and set z_{tj} to be a one-dimensional vector that only includes energy. In the adjusted efficiency decomposition approach, local primary and secondary energy input plus the secondary energy import are utilized as energy inputs of sub-stages 1 and 2 (note that their sum does not equal the energy input in the black box model); labor and capital inputs are divided into two parts for stages 1 and 2; and the separated gross industrial output of stage 1 and stage 2 were utilized as output of each stage. In addition, three DEA models that measure the efficiencies of sub stages 1.1 to 1.3 are relatively uncorrelated to the models of the whole industry sector. The data are the joint subsets of the data we used above. We excluded the relevance of industry processes to determine the development potentials in manufacturing processes. Input vectors between sub-stages as well as output vectors between sub-stages are relatively independent. We used the actual energy inputs, non-energy inputs and outputs from the statistical data of each sub-stage.

3.2 Results

We first applied the traditional "black box" model, the network model, and the adjusted efficiency decomposition approach to evaluate China's provincial industrial energy efficiency and obtained three sets of efficiency results, as shown in Table 1. The adjusted efficiency decomposition approach was then additionally applied to evaluate the efficiency of sub-stage 1.

[Insert Table 1 here]

The traditional "black box" model is first considered. The regional differences are obvious, as shown in Figure 7. In China's northern provinces, the industrial energy efficiencies tend to be very low (below 0.5), whereas the energy efficiencies in China's eastern provinces are much closer to 1 (efficient). This efficiency distribution appears to be a projection of China's economic development. Well-developed provinces have higher industrial energy efficiency and vice versa. However, in actuality, the productions of fossil fuel exceed the consumptions of it in China's northern provinces, while the consumptions of fossil fuel exceed the productions of it in China's eastern provinces. The energy efficiency is higher in provinces that have smaller proportions of energy-producing departments (stage 1) and larger proportions of energy-consuming departments (stage 2).

[Insert Figure 7 here]

We then applied the original network model. As shown in Figure 8, the efficiencies obtained by the network model significantly differed from those illustrated in Figure 7. Although the industrial structure is considered, some of the results are clearly inaccurate. For example, Shanxi is one of China's most well-developed regions and the largest energy-importing region, however its energy efficiency score is only 0.222 based on the traditional "black box" model and 0.291 based on the network model. Beijing is the capital city and features advanced technology and more efficient industry structure than its surrounding regions. However, the network model assigns a low efficiency score of 0.320 to this city.

[Insert Figure 8 here]

To better evaluate regional energy efficiency with the consideration of industry structures, energy transfer between provinces and intermediate processes, we used the adjusted efficiency decomposition approach to independently evaluate each sub-stage in the industry sector and then combined the results according to the energy consumption proportion of each stage. The evaluation results of previous models are generally modified and updated using this decomposition analysis. For the obviously underestimated province, Shanxi, the adjusted energy efficiency is 0.647, which is much higher than the previously obtained efficiency. For energy-importing provinces or cities such as Beijing, Tianjin, Shanghai and Guangdong, the low efficiencies proposed by the network model increase to more reasonable ranges. For energy-exporting provinces such as Ningxia, Qinghai and Inner Mongolia, the energy efficiencies reflect a compromise between the "black box" energy efficiencies and network energy efficiencies.

For sub-stage 1, Table 2 lists the specific energy efficiencies of the energy exploitation department, the energy process department, and electricity generation department. The overall energy efficiency of the entire energy-producing department is also listed in Table 2. The overall energy efficiencies are lower than the previously identified adjusted efficiencies from the decomposition method. This finding may be due to the smaller subdivisions, which make the result more relevant to manufacturing processes. For example, the energy exploitation department in Beijing continued to reduce its outputs in the last decade. However, some expenses, such as electricity consumption, were not reduced as much as the outputs in this department, moreover, the equipment (capital input) in this department could not be reduced in the short term. Thus, the energy efficiency of manufacturing process in Beijing should be relatively lower than the province that still has high speed growth on manufacturing industry. The process-specific evaluation proposed in this study effectively captured this phenomenon. Therefore, the inclusion of the inner structure of sub-stage 1 in the model provides insight into the energy efficiencies in sub-industry departments, which could provide more specific guidance for further energy efficiency improvement.

[Insert Table 2 here]

3.3 Adjusted efficiency decomposition approach vs. "black box" and network models

Both the traditional "black box" model and network model evaluate the energy efficiency of industry sectors by simplifying its inner structure and omitting intermediate energy inputs and outputs. On the contrary, the adjusted efficiency decomposition approach modifies the overall efficiency as a weighted average of the process-specific energy utilization efficiencies of sub-stages. Therefore, differences between the results of the three models directly depend on how similar the modeling system is to the real industry system and how the weights are selected in the adjusted efficiency decomposition approach. For China's industrial energy efficiency evaluation, the adjusted efficiency decomposition approach helps to address the interprovincial energy import and export and the different energy properties associated with energy-producing and energy-consuming processes in the industry sector.

The traditional "black box" model ignores both of the above issues. It treats every provincial industry sector as a closed system, and the difference in energy properties of different sub-industry departments may consequently lead to efficiency evaluation bias. The above evaluation results clearly show that provinces with well-developed energy-consuming departments have higher energy efficiencies. Most of these provinces rely on importing large amounts of secondary energy from other provinces. In other words, based on the "black box" modeling perspective, these provinces consume fewer inputs but produce higher outputs compared than other provinces because they mainly consume secondary energy imported from other provinces. In addition, because the "black box" model also treats industries as closed systems, the imported secondary energy is ignored, which leads the "black box" energy efficiency evaluation is more likely to be an evaluation of the energy-consuming department.

Although the network model was developed to improve the traditional "black box" model by considering industrial structure, its evaluation results continue to have some disadvantages. Specifically, the network model provides more reasonable results than the traditional "black box" model for some provinces while giving unreasonable results for other provinces. This shortage may be because the network model was also originally designed to describe a closed system. Energy import and export activities markedly differ between provinces in China, and the original network model consequently cannot provide more appropriate evaluation results when given that the provincial industry sector is an open system and both intermediate energy inputs/outputs and independent energy inputs should be considered.

Considering the above modeling shortages, the adjusted efficiency decomposition approach may be a more appropriate choice. The separated sub-DMUs in the adjusted efficiency decomposition address the problem of intermediate energy import and export between provinces. For each sub-DMU, the inputs and outputs are exactly equal to the energy consumption and energy production in the corresponding real industry department, respectively. Moreover, all intermediate measures are considered. However, if we apply the original efficiency decomposition method to a situation in which all sub-DMUs share the same weight, the bias introduced by different energy properties may remain. Thus, different weights are assigned to different sub-DMUs in the adjusted efficiency decomposition method. Weights are determined according to the amount of energy that is consumed or converted by sub-DMUs. Note that these weights also avoid increases in bias due to energy "import and export" between provinces. For example, if a province strongly depends on the energy-producing department, the original DEA model and the network DEA model will underestimate efficiency because the province is an "energy exporter" with a high energy input for stage 1 and low output in stage 2. In addition, the overall efficiency obtained by the adjusted efficiency decomposition provides more objective results because it combines a higher weighted energy efficiency in stage 1 and a lower weighted energy efficiency in stage 2. In other words, the adjusted efficiency decomposition gives more objective results via the process-specific evaluation for both "energy exporters" and "energy importers". Note that the adjusted efficiency decomposition approach also tends to produce high efficiencies for well-developed provinces in which the black box energy efficiencies are also high. The difference between these two efficiency measures is that the traditional "black box" model obtains these high efficiencies because it ignores the energy imports consumed in stage 2, whereas the adjusted efficiency decomposition yields high efficiencies for both stage 1 and stage 2. This finding demonstrates that although well-developed provinces do not satisfy their own energy demands, more advanced techniques and management of these provinces maintain the energy efficiency of their energy-producing departments.

[Insert Figure 9 here]

The bias shown in Table 1 reflects the differences between the "black box" energy efficiency and the adjusted energy efficiency. For the first aspect of improvements, energy transfer between provinces, the bias shows the correction of energy efficiencies of "energy exporters". As shown in Figure 9, the traditional "black box" model underestimates the energy efficiency for primary "energy exporters" (provinces with negative net energy transfer between provinces), while the adjusted efficiency decomposition model provided a correction for seven "energy exporters". The second improvement is for different energy properties and different relying on industrial departments. Table 3 lists 10 provinces that are highly reliant on energy-producing departments. Specifically, highly relying on stage 1 may lead to high bias in the traditional "black box" model.

[Insert Table 3 here]

4 Conclusion

The traditional "black box" DEA model has been applied to evaluate the energy efficiency of Chinese industry in previous studies. This paper aimed to improve the evaluation by eliminating the impact of different energy properties, the conflicts between stages, and the previously neglected intermediate energy inputs and outputs in the industry sector. Considering the structure of the industry sector and the energy intermediate transfer in it, this study proposes a more appropriate model, the adjusted efficiency decomposition approach, for industrial energy efficiency evaluation. The evaluation relies on the separation of industry departments based on the properties and functions of their energy utilization processes. The energy efficiency of Chinese industry in 2008 was evaluated using the proposed model as an example. The difference between the evaluation results of the traditional “black box” DEA and the adjusted efficiency decomposition approach demonstrates the improvement provided by our new approach. In the traditional model, differences in energy properties in different energy departments give rise to large bias when the inner structure of the industry sector is ignored. In our adjusted efficiency decomposition approach, the efficiency evaluation result is more objective because it considers differences in energy utilization properties (final consumption or intermediate conversion) in different industry departments and energy transfers between different regions. The empirical analysis shows that the adjusted efficiency decomposition approach assigns more reasonable energy efficiencies to both of the “energy exporter” regions in China, i.e., Shanxi and Xinjiang. In addition, the adjusted efficiency decomposition approach was demonstrated to be applicable for evaluating the energy efficiency of specific sub-industry sectors and can consequently provide more process-specific guidance for further efficiency improvement.

Acknowledgement

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Tables and Figures

Table 1 Provincial industrial energy efficiency obtained by three models and bias between *BBE* and *AEE*

Provinces	Black box energy efficiency	Network energy efficiency	Adjusted energy efficiency from efficiency decomposition approach	Bias
Beijing	0.967	0.320	1.000	0.033
Tianjin	1.000	0.416	1.000	0.000
Hebei	0.467	1.000	0.886	0.419
Shanxi	0.222	0.291	0.647	0.425
Inner Mongolia	0.163	1.000	0.509	0.346
Liaoning	0.499	0.641	0.631	0.132
Jilin	0.613	0.636	0.627	0.014
Heilongjiang	0.322	0.307	0.789	0.466
Shanghai	1.000	0.252	1.000	0.000
Jiangsu	1.000	0.839	0.905	-0.095
Zhejiang	0.978	0.497	0.965	-0.014
Anhui	0.584	0.622	0.670	0.085
Fujian	0.915	0.380	0.816	-0.099
Jiangxi	0.857	0.402	0.811	-0.046
Shandong	1.000	1.000	1.000	0.000
Henan	0.466	0.688	0.883	0.417
Hubei	1.000	0.878	0.688	-0.312
Hunan	0.801	0.784	0.598	-0.202
Guangdong	1.000	0.496	1.000	0.000
Guangxi	1.000	1.000	0.515	-0.485
Hainan	1.000	1.000	1.000	0.000
Chongqing	0.882	0.537	0.727	-0.155
Sichuan	0.796	1.000	0.551	-0.245
Guizhou	0.332	0.624	0.475	0.143
Yunnan	0.683	1.000	0.511	-0.172
Shaanxi	0.442	0.309	0.818	0.376
Gansu	0.426	0.461	0.531	0.106
Qinghai	0.913	1.000	1.000	0.087
Ningxia	0.328	1.000	0.757	0.429
Xinjiang	0.275	0.516	0.693	0.418

Table 2 Energy efficiency of sub stage 1 obtained by efficiency decomposition approach

Provinces	Stage 1.1 Efficiency of energy exploitation department	Stage 1.2 Efficiency of energy processing department	Stage 1.3 Efficiency of electricity generation department	Overall efficiency of stage 1
Beijing	0.188	0.365	0.531	0.436
Tianjin	1.000	0.596	0.571	0.615
Hebei	0.374	0.939	0.411	0.468
Shanxi	1.000	1.000	0.419	0.760
Inner Mongolia	1.000	1.000	0.738	0.811
Liaoning	0.295	1.000	0.620	0.649
Jilin	0.465	1.000	0.603	0.588
Heilongjiang	0.506	0.779	0.603	0.608
Shanghai	1.000	0.327	0.882	0.630
Jiangsu	0.468	1.000	1.000	0.981
Zhejiang	0.593	1.000	0.488	0.534
Anhui	0.992	1.000	0.693	0.756
Fujian	1.000	1.000	0.900	0.903
Jiangxi	0.414	0.747	0.930	0.801
Shandong	0.454	0.724	0.870	0.764
Henan	0.595	1.000	0.535	0.582
Hubei	0.181	0.977	1.000	0.969
Hunan	0.842	0.952	1.000	0.974
Guangdong	1.000	0.336	1.000	0.876
Guangxi	1.000	1.000	0.952	0.954
Hainan	1.000	1.000	0.783	0.852
Chongqing	0.676	1.000	1.000	0.908
Sichuan	0.542	0.653	1.000	0.768
Guizhou	1.000	1.000	0.816	0.843
Yunnan	1.000	0.894	0.934	0.935
Shaanxi	1.000	0.809	0.732	0.792
Gansu	1.000	0.559	1.000	0.854
Qinghai	0.462	1.000	1.000	0.715
Ningxia	0.701	0.897	0.794	0.783
Xinjiang	0.734	0.657	0.758	0.723

Table 3 Bias of provinces with high relying on stage 1

Provinces	Bias	Energy utilization percentage of stage 1
Hainan	0.000	44%
Qinghai	0.087	31%
Gansu	0.106	38%
Guizhou	0.143	33%
Inner Mongolia	0.346	30%
Shaanxi	0.376	42%
Xinjiang	0.418	59%
Shanxi	0.425	54%
Ningxia	0.429	37%
Heilongjiang	0.466	50%

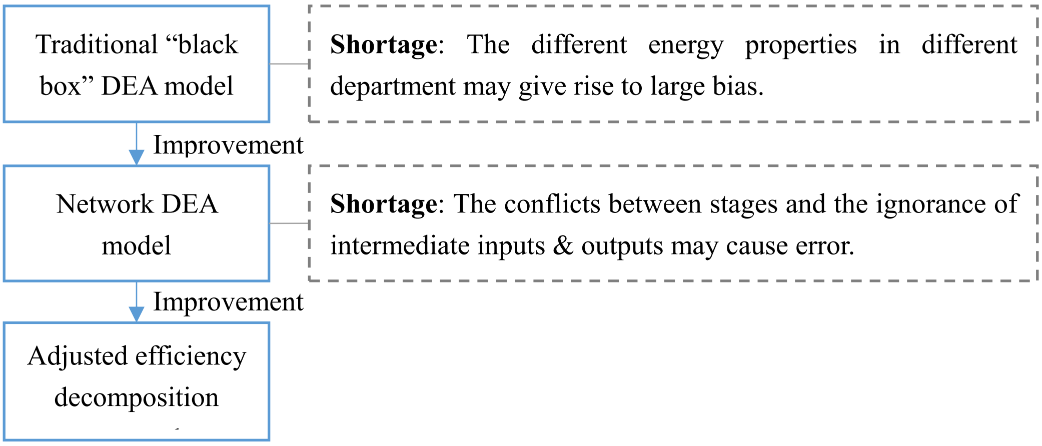

Figure 1 Three approaches for energy efficiency evaluation

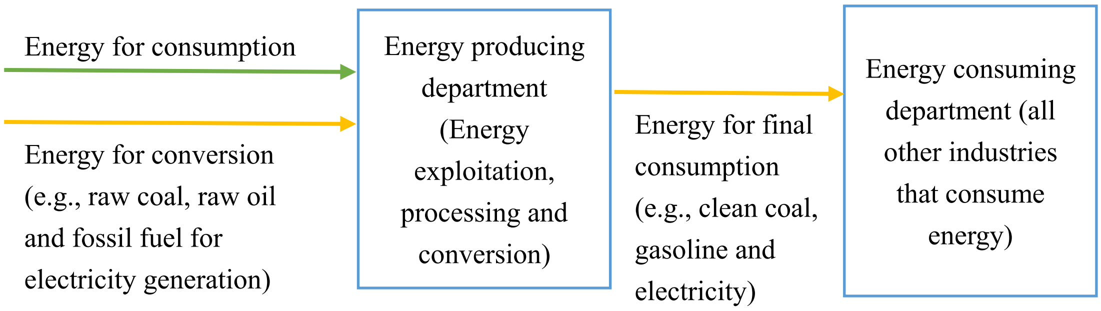

Figure 2 Energy flow in industry sector

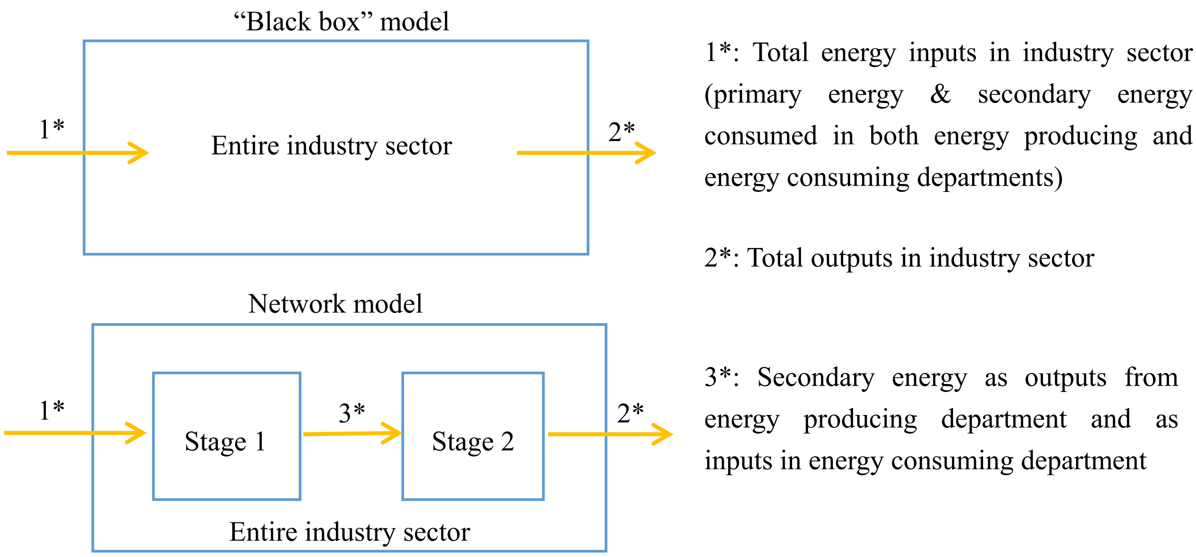

Figure 3 Structures of energy flow in "black box" model and network model

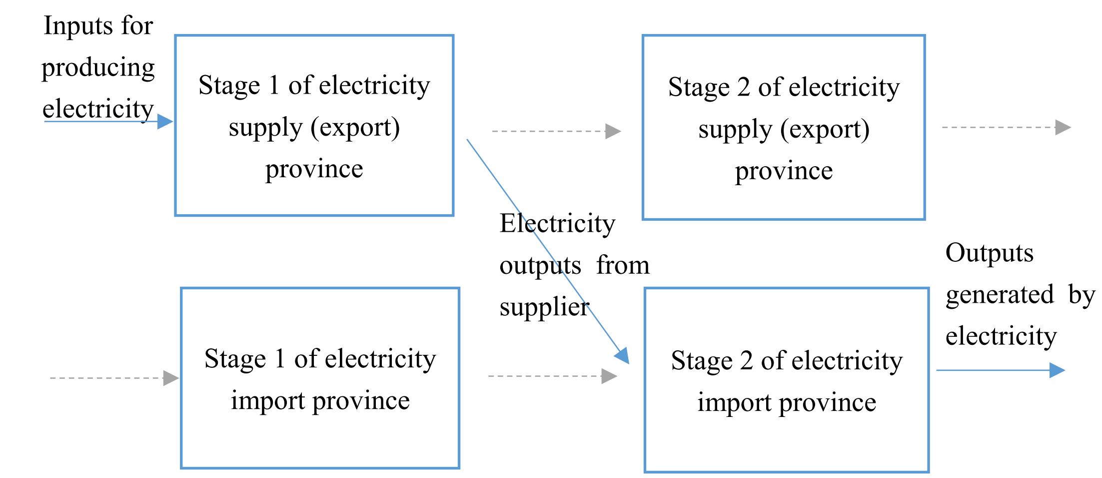

Figure 4 Example of intermediate measure of electricity flow

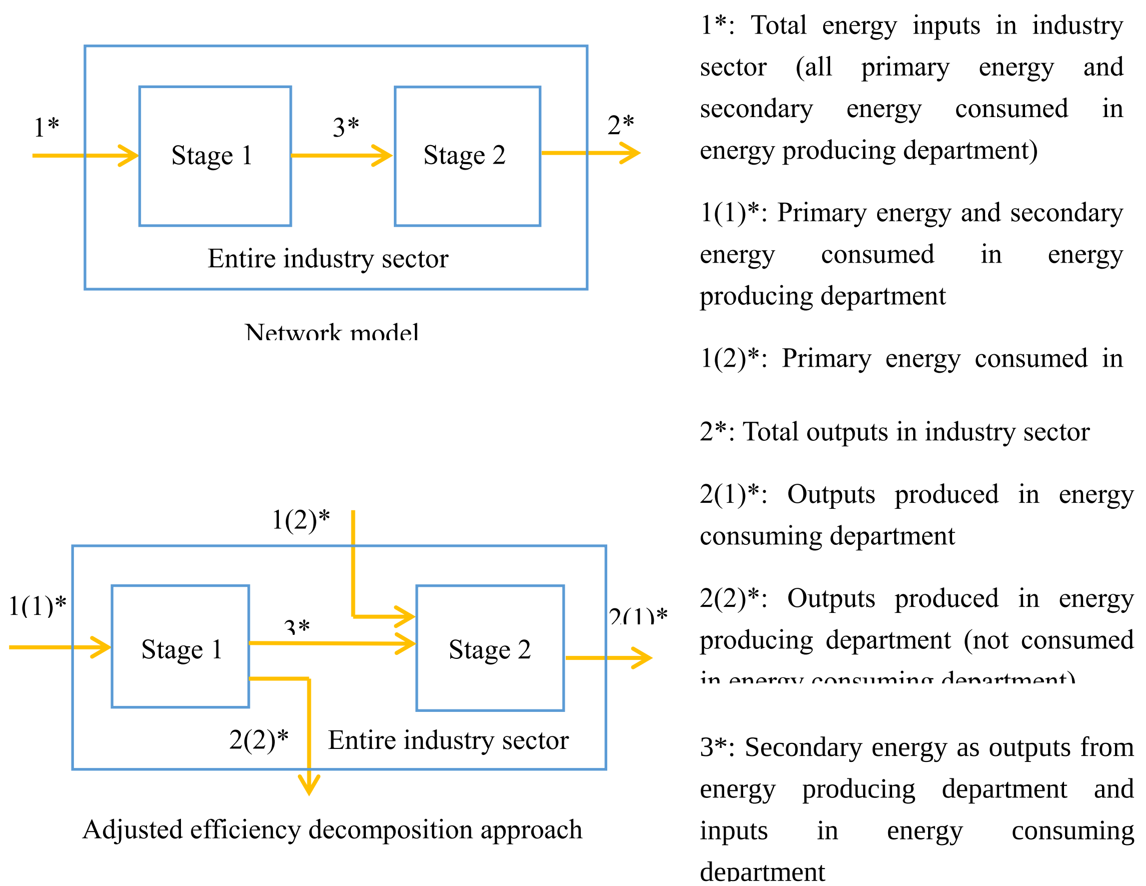

Figure 5 Structures of energy flow in network model and adjusted efficiency composition approach

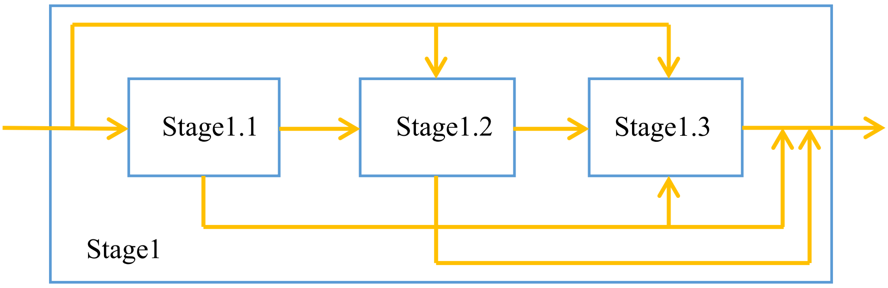

Figure 6 Inner energy flow of sub stage 1

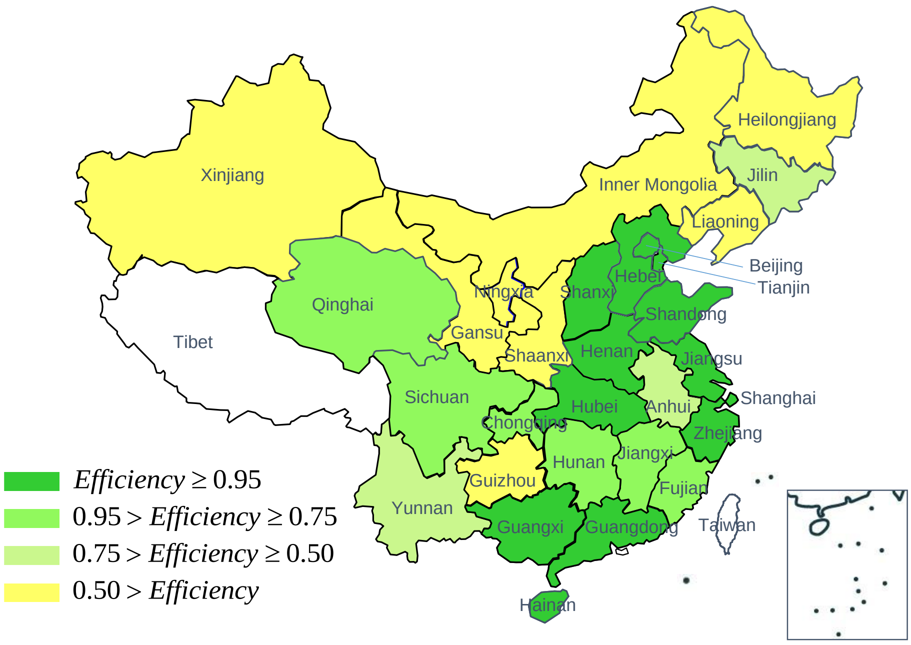

Figure 7 Regional energy efficiency obtained from "black box" model

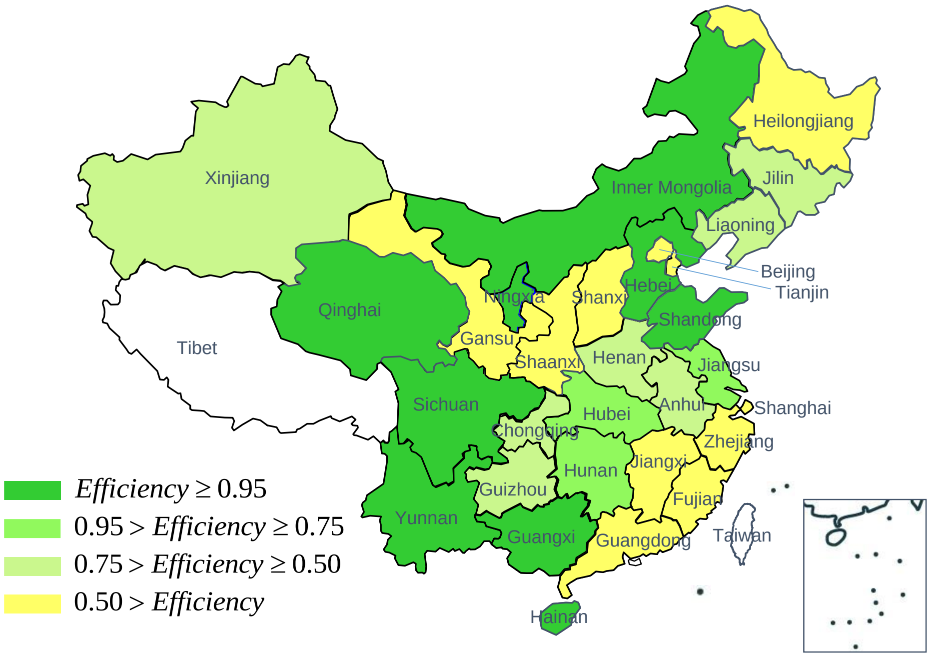

Figure 8 Regional energy efficiency obtained from network model

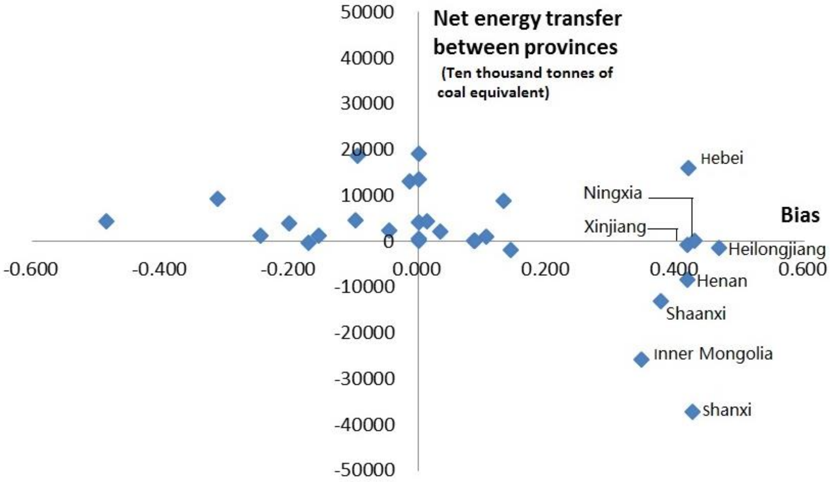

Figure 9 Net energy transfers between provinces (in 10^4 tons of coal equivalent) and bias between *BBE* and *AEE*