Study on Energy Efficiency of Manufacturing Industry in Shandong Province in the Context of Carbon Neutrality

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Abstract. Using the Data Envelopment Analysis (DEA) model, this article establishes an input-output indicator system to study the energy efficiency of 25 subsectors of manufacturing industries in Shandong Province. Subsequently, k-means algorithm is used for cluster analysis to classify the industry into four categories. The article finds that the overall energy use efficiency of manufacturing industries in Shandong Province is not high in 2021. Nearly two-thirds of the manufacturing industries is in the stage of increasing returns to scale, and should increase investment to obtain greater benefits. Most of the manufacturing industries in Shandong Province are of the type of low energy efficiency and low energy consumption. In the future, in order to reduce the amount of energy consumption, realize the efficient use of energy and promote the economic development, the government can take measures to improve the level of technology, optimize the industrial structure and so on.

Keywords: Manufacturing industry; energy efficiency; Data Envelopment Analysis (DEA); K-means clustering algorithm.

1 Introduction

In recent years, along with the introduction of the carbon neutral target, China has attached great importance to improving the efficiency of energy utilization. As a large energy-consuming province, Shandong Province's total energy consumption of manufacturing industry is 302.632 million tons, accounting for 67.84% of the total energy consumption of the province. It can be seen that the study of energy utilization efficiency of manufacturing industry is of great significance to reduce energy consumption, promote the transformation of traditional manufacturing industry in Shandong.

Wang W X (2023) analyses the total factor energy use efficiency of 16 prefecture-level cities in Shandong from 2015 to 2020 using a non-directed SBM model [1]. Liu B et al. (2019) use a centralised energy allocation model to measure industrial energy use efficiency in 17 cities in Shandong from 2005 to 2015 [2]. Wang J B et al. (2017) improve the non-expected SBM model and GMM dynamic regression model to empirically study the energy efficiency and its influencing factors of the industrial sector in 17 cities in Shandong from 2005 to 2015 [3]. Li Y B et al. (2016) measure the total

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factor energy efficiency of each prefecture-level city under environmental constraints using a modified variable scale reward super-efficiency DEA model based on panel data from 17 prefecture-level cities in Shandong from 2007 to 2014 [4]. It can be seen that the research on energy efficiency in Shandong mainly focuses on the study of the energy use efficiency of different cities. The literature on energy efficiency in Shandong from an industrial perspective is scarce. Literature [5]-[7] investigates DEA models. This article innovatively starts from the industrial perspective, takes 25 sub-division industries of manufacturing industry in Shandong as the object to carry out the research, measures the energy efficiency of each industry by using the DEA-BCC model, and classifies different industries by using the k-means model. Based on the results of the calculations, suggestions are made to further realise the efficient, low-carbon and sustainable development of the manufacturing industry in Shandong Province.

2 Materials and Methods

2.1 Indicator Selection and Data Sources

Based on the review of relevant literature, the article establishes the input-output indicator system in Table 1. The data for the article is mainly from the Shandong Statistical Yearbook (2022).

Table 1. System of input-output indicators

	Indicator Setting	Implications of the indicators
Input indicators	Number of laborers	Annual Average of Employed (Unit: 10,000 person)
	capital stock	Composition of Investments in Fixed Assets by Sector (Unit: %)
	Energy consumption	Energy Consumption by Sector (Unit: million tons of standard coal)
Output indicators	Total profits	Total profits of Industrial Enterprises above Designated Size (Unit: 100 million yuan)

This article takes the manufacturing industry of Shandong Province as the research object. According to the classification of manufacturing industry in Shandong Statistical Yearbook, and combining with the availability of data, it is proposed to start the research from the following 25 manufacturing industry segments. Table 2 shows the classification of specific industries in Shandong Province.

Table 2. Shandong Province Manufacturing Industry Segment Classification

Number	Industry
A1	Processing of Food from Agricultural Products
A2	Manufacture of Liquor, Beverages and Refined Tea
A3	Manufacture of Textile
A4	Manufacture of Textile, Wearing Apparel and Accessories
A5	Processing of Timber, Manufacture of Wood, Bamboo, Rattan, Palm, and Straw Products
A6	Manufacture of Paper and Paper Products

Number	Industry
A7	Printing and Reproduction of Recording Media
A8	Manufacture of Articles for Culture, Education, Arts and Crafts, Sport and Entertainment Activities
A9	Processing of Petroleum, Coal and Other Fuels
A10	Manufacture of Raw Chemical Materials and Chemical Products
A11	Manufacture of Medicines
A12	Manufacture of Chemical Fibers
A13	Manufacture of Rubber and Plastics Products
A14	Smelting and Pressing of Ferrous Metals
A15	Smelting and Pressing of Non-ferrous Metals
A16	Manufacture of Metal Products
A17	Manufacture of General Purpose Machinery
A18	Manufacture of Special Purpose Machinery
A19	Manufacture of Automobiles
A20	Manufacture of Railway, Ship, Aerospace and Other Transport Equipments
A21	Manufacture of Electrical Machinery and Apparatus
A22	Manufacture of Computers, Communication and Other Electronic Equipment
A23	Manufacture of Measuring Instruments and Machinery
A24	Other Manufacture
A25	Utilization of Waste Resources

2.2 Research Methods

DEA-BCC Model.

In the process of measuring the energy efficiency of manufacturing industries in Shandong, efficiency can be improved by reducing the amount of inputs under the condition that the amount of outputs remains unchanged. Therefore, the article chooses the input-oriented DEA-BCC model to measure the efficiency value [8].

Assuming that there are n Decision Making Units (DMU), each of which uses m inputs and obtains s outputs. The i-th input and r-th output of any DMU_j can be expressed as x_{ij} and y_{rj}, $i = 1,2,\ldots,m, r = 1,2,\ldots,s, j = 1,2,\ldots,n$. The DEA-BCC model is calculated as shown in (1) and (2).

$$\begin{aligned}
& min\,\theta_d - \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
& s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = \theta_d x_{id}, i = 1,2,......,m. \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} + s_r^+ = y_{rd}, r = 1,2,......,s. \\
& \quad \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1,2,......,n. \\
& \quad s_i^- \geq 0, i = 1,2,......,m. \\
& \quad s_r^+ \geq 0, r = 1,2,......,s.
\end{aligned} \tag{1}$$

$$\begin{aligned}
& min\,\varphi_d + \varepsilon\left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+\right) \\
& s.t.\ \sum_{j=1}^{n} \lambda_j x_{ij} + s_i^- = x_{id}, i = 1,2,......,m. \\
& \quad \sum_{j=1}^{n} \lambda_j y_{rj} + s_r^+ = \varphi_d y_{rd}, r = 1,2,......,s. \\
& \quad \sum_{j=1}^{n} \lambda_j = 1, \lambda_j \geq 0, j = 1,2,......,n. \\
& \quad s_i^- \geq 0, i = 1,2,......,m. \\
& \quad s_r^+ \geq 0, r = 1,2,......,s.
\end{aligned} \tag{2}$$

θ_d: The efficiency value of the d-th DMU; s_i^-: Slack variables for inputs; s_i^+: Slack variables for output; ε: Non Archimedean infinitesimal

Assume $(\theta_d^*, \lambda_j^*, s_i^{-^*}, s_r^{+^*})((\varphi_d^*, \lambda_j^*, s_i^{-^*}, s_r^{+^*}))$ is an optimal solution of the model. If $\theta_d^* < 1$ $(\varphi_d^* > 1)$, DMU_d is inefficient and efficiency needs to be improved by reducing inputs or increasing outputs [9].If $\theta_d^* = 1$ $(\varphi_d^* = 1)$, $s_i^{-^*} = 0$ and $s_{\mathrm{r}}^{+^*} = 0$, the DMU_d is strongly efficient [9].If $\theta_d^* = 1$ $(\varphi_d^* = 1)$, and $s_i^{-^*} \neq 0$ or $s_r^{+^*} \neq 0$, the DMU_d is weakly efficient and there is redundancy in some of the inputs [9].

K-means clustering algorithm.

The article adopts k-means clustering algorithm, selects energy efficiency and energy consumption as independent variables, and classifies different industries of manufacturing industry. For a given dataset $X = \{x_1, x_2, \dots, x_i, \dots, x_n\}$ containing n d-dimensional data points,$x_i \in R^d$. The algorithm organises the data objects into K divisions, $C = \{c_k, i = 1,2, \dots, K\}$, c_k is a class within each division and μ_i is the category centre of each class. The Euclidean distance is chosen as the distance judgment criterion, and alternatelye sum of squares from each category to the center of the category is calculated as shown in (3) [10].

$$J\left(c_k\right) = \sum_{x_i \in C_K}^{n} \| x_i - \mu_k \|^2 \tag{3}$$

The K-means algorithm is an iterative process where the goal of clustering is to minimize the sum of the squares of the total distances $J(C)$ of each category. The center of clustering μ_k is taken as the average of the individual data in c_k. The formula is calculated as shown in (4) [10]. The K-means clustering algorithm starts with an initial classification of categories and then assigns each data point to each category to reduce the total sum of squared distances. Since the $J(C)$is inversely proportional to the number of categories K, $J(C)$ can only be minimized for some definite number of categories K [10].

$$J(C) = \sum_{k=1}^{K} J(c_k) = \sum_{k=1}^{K} \sum_{x_i \in C_k}^{n} \| x_i - \mu_k \|^2 = \sum_{k=1}^{K} \sum_{i \in 1}^{n} d_{ki} \| x_i - \mu_k \|^2$$

$$d_{ki} = \begin{cases} 1, & if \ x_i \in c_i \\ 0, & if \ x_i \notin c_i \end{cases} \tag{4}$$

3 Results and Discussions

3.1 Results of DEA-BCC Model

The article uses the BCC model to develop an energy efficiency analysis of 25 subsectors of manufacturing industries in Shandong. Table 3 shows the calculation results.

In terms of overall energy efficiency, the four categories in which the DEA is effective are A9, A10, A11 and A23. In non-DEA efficient industries, pure technical efficiency efficient rather than combined efficiency efficient industries are A2, A7, A15, A18, A24 and A25. These industries cannot afford to reduce their inputs any further at current outputs. The remaining 15 industries are neither technologically nor scale efficient, and all have redundant inputs or insufficient outputs. In terms of returns to scale, the returns to scale are constant for all four categories of industries for which DEA is effective. Industries with diminishing returns to scale are A15, A18, A21 and A22. If the inputs to these industries are increased, the growth of outputs is lower than the growth of inputs. The remaining 17 categories of industries are all characterized by increasing returns to scale, and these industries would be more profitable if they increased their inputs.

Table 3. Energy Efficiency Evaluation Form

Firm	Crste	Vrste	Scale		Firm	Crste	Vrste	Scale	
A1	0.436	0.467	0.935	irs	A14	0.532	0.541	0.983	irs
A2	0.758	1.000	0.758	irs	A15	0.988	1.000	0.988	drs
A3	0.316	0.387	0.815	irs	A16	0.308	0.337	0.914	irs
A4	0.538	0.814	0.660	irs	A17	0.412	0.424	0.972	irs
A5	0.359	0.510	0.704	irs	A18	0.774	1.000	0.774	drs
A6	0.867	0.927	0.935	irs	A19	0.558	0.588	0.949	irs
A7	0.420	1.000	0.420	irs	A20	0.399	0.518	0.770	irs
A8	0.601	0.674	0.891	irs	A21	0.603	0.614	0.982	drs
A9	1.000	1.000	1.000	-	A22	0.619	0.754	0.821	drs
A10	1.000	1.000	1.000	-	A23	1.000	1.000	1.000	-
A11	1.000	1.000	1.000	-	A24	0.099	1.000	0.099	irs
A12	0.274	0.688	0.398	irs	A25	0.404	1.000	0.404	irs
A13	0.356	0.396	0.900	irs					

3.2 Results of K-Means Clustering

The results of the classification are shown in Table 4. The manufacturing industries are divided into four major categories. There is only one industry in the first category. A14 requires large amounts of energy for smelting metals, but the limited level of technology leads to inefficient energy use. The three industries in the second category are A9, A10 and A15. Most of these industries are traditional high-energy-consuming industries and a relatively mature level of technological development. There are 13 industries in the third category. Such industries are mostly labor-intensive, require less energy inputs. In the future, this type of industry has greater potential for growth. There are eight industries in the fourth category, which have the best energy utilization. Most of such industries are technology-led. As technology advances, it can further promote the efficient use of energy.

Table 4. Classification of manufacturing industries

	Classification basis	Industry
category 1	Low energy efficiency, high energy consumption	A14
category 2	high energy efficiency, high energy consumption	A9, A10, A15
category 3	Low energy efficiency, low energy consumption	A1, A3, A4, A5, A7, A12, A13, A16, A17, A19, A20, A24, A25
category 4	high energy efficiency, low energy consumption	A2, A6, A8, A11, A18, A21, A22, A23

4 Conclusions

Based on the above calculations, the article obtained the following three conclusions.

Firstly, in 2021, the overall energy efficiency of manufacturing industries in Shandong is not high, of which there are only four industries with effective DEA. Nearly two-thirds of industries are in a phase of increasing returns to scale. These enterprises should continue to increase its investment in order to obtain more output benefits and create economies of scale. Secondly, nearly a quarter of industries are of the high energy efficiency and low energy consumption type. Such industries should continue to develop vigorously. Thirdly, that most of the manufacturing industries are of low energy efficiency and low energy consumption type. The government can promote the this kind of industries to realize efficiency development by increasing research on new technologies and introducing excellent talents. The article is important for future dynamic research targeting Shandong's manufacturing industry.

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