Journal of Electronic Research and Application, 2024, Volume 8, Issue 2
http://ojs.bbwpublisher.com/index.php/JERA
ISSN Online: 2208-3510
ISSN Print: 2208-3502

Evaluation of Energy Efficiency and Analysis of Influencing Factors of Company CW's Manufacturing Workshops

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Abstract: In this work, the Slacks-Based Measure (SBM) model within Data Envelopment Analysis was employed to establish a set of indicators for evaluating the energy efficiency of manufacturing workshops. The energy efficiency of 12 Company CW's manufacturing workshops from 2016 to 2022 was assessed. The findings indicated that aside from a few workshops operating at the production frontier, the rest exhibit significant fluctuations in energy efficiency and generally low energy efficiency. Subsequently, a combined GRA-Tobit analysis model was introduced to identify factors influencing the energy efficiency of Company CW's manufacturing workshops. Regression analysis revealed that technological investments, employee quality, workshop production scale, investment in clean energy, and the level of pollution control all significantly impact the energy efficiency of Company CW's manufacturing workshops. By evaluating the energy efficiency of Company CW's manufacturing workshops and studying their influencing factors, this research aids company managers in understanding the energy efficiency of the manufacturing process. It optimizes the combination of various production elements, thereby offering effective guidance for improving the energy efficiency issues of the company's manufacturing workshops, which can contribute to enhancing the corporation's overall energy efficiency.

Keywords: Manufacturing workshop energy efficiency; Energy efficiency evaluation; Data Envelopment Analysis (DEA); GRA-Tobit model

Online publication: March 29, 2024

1. Introduction

Manufacturing workshops serve as the fundamental unit for executing production tasks and assessing energy consumption, where issues related to energy utilization are particularly pronounced. However, the study of energy efficiency in manufacturing systems is relatively challenging due to the diversity of the main components of energy consumption and the dynamic and stochastic nature of energy consumption states and processes. Moreover, the manufacturing system, as a complex entity for product production, spans multiple levels including products, workshops, tasks, and manufacturing units, each with distinct energy consumption characteristics. This complexity renders the energy consumption characteristics at the system level intricate, and research into the energy efficiency of manufacturing workshops, a critical component of the manufacturing system remains underdeveloped. Therefore, establishing an appropriate energy efficiency evaluation system for manufacturing workshops, as a fundamental manufacturing unit, could enhance corporate energy efficiency. This improvement, starting from specific workshops, could promote energy conservation and emissions reduction across industries or even regions.

Company CW, primarily engaged in the production of lead-acid batteries, faces increasingly prominent energy issues with the expansion of workshop production scales. The company's management system lacks the precision to control the complex workshop manufacturing processes, making it difficult for managers to accurately grasp the energy efficiency of each workshop. This lack of control and adjustment over production elements across workshops leads to low energy efficiency and utilization within Company CW. Thus, under the objectives of carbon neutrality and the requirements for energy conservation and emission reduction, it is imperative to establish a comprehensive energy efficiency evaluation model for Company CW's manufacturing workshops. This model should assess and devise corresponding enhancement strategies to guide energy conservation and emissions reduction throughout Company CW's production process.

2. Literature review

The scholarly literature pertaining to this investigation can be broadly classified into two distinct categories:

The first category delves into the measurement of total factor energy efficiency and the exploration of influential factors. Energy efficiency is a crucial metric, measuring the economic benefits derived from each unit's energy consumption during production processes. When it comes to evaluating manufacturing systems' energy efficiency, the Data Envelopment Analysis (DEA) model is most commonly employed by scholars. Current research on energy efficiency's influencing factors is primarily categorized at national, regional, and industrial levels. Using stochastic frontier analysis and translog input distance function, Shen conducted an extensive study investigating China's industrial sector's total factor energy efficiency. He uncovered that technological change, technical efficiency improvement, and input combinations have a significant positive impact on the overall transformation of total factor energy efficiency [1]. Some scholars employed the super-SBM model to assess the renewable energy efficiency of LAC and scrutinized the convergence of this efficiency value. The outcome indicates that technological innovation functions as the paramount catalyst for enhancing the effectiveness of LAC to augment renewable energy proficiency [2]. Ma *et al.* conducted a comprehensive evaluation of the total factor energy efficiency changes of CPTPP's 11 member countries from 2013 to 2017 using the super-efficiency direction distance function. The study emphasized that prioritizing energy policy adjustments, actively exploring new energy utilization, enhancing production technology, minimizing waste, reducing PM2.5, accelerating urban development, and striving for optimal energy efficiency are crucial steps toward achieving sustainable energy progress [3].

The second category delves into the exploration of influential factors. The study on the factors influencing energy efficiency dates back to an earlier era. Scholars have conducted a comprehensive evaluation of various elements' impact on energy efficiency in California, and it has been determined that the escalation of energy prices is conducive to enhancing energy efficiency [4]. Sadorsky's study, which examined the influence of income, industrialization, and urbanization on energy efficiency in 76 developing countries, revealed that income has a profound impact on energy efficiency in these nations, while the effects of urbanization and industrialization are somewhat ambiguous [5]. As Dargasi conducted an empirical analysis of Iran's energy intensity, he discovered that alterations in the economic structure and decreased energy consumption rates have facilitated advancements in Iran's energy proficiency [6]. Pan, through empirical analysis, examines the trajectory of China's energy efficiency development and identifies that the key factors driving this growth are the degree of international integration, financial industry advancements, and technological innovation. The former has a clear positive impact on enhancing energy efficiency, while the latter two have mixed effects on this improvement[7]. By selecting the panel data of energy consumption in Hebei from 2005 to 2009, Wang established that technology investment is the primary driver for enhancing energy efficiency in this region[8].

3. Method and data source

3.1. Method

3.1.1. SUPER-SBM model with undesirable outputs

Compared to traditional Data Envelopment Analysis (DEA) models, the Slacks-Based Measure (SBM) model incorporates slack variables to more accurately assess the efficiency levels of decision-making units under given input and output conditions. The fundamental assumption of the SBM model is that each decision-making unit can achieve maximum efficiency by adjusting the utilization of resources, either by increasing outputs or decreasing inputs. Slack variables are used to represent the quantity of resources that are underutilized under the current resource allocation, including both surplus resources in inputs and insufficient resources in outputs. The mathematical formulation of the SBM model typically takes the form of a linear programming problem, incorporating two objective functions: one to minimize the sum of slack variables and another to maximize the efficiency score. By solving this linear programming problem, the efficiency score of each decision-making unit can be determined, indicating its efficiency level relative to other units. Below is a simplified mathematical expression of the SBM model.

The objective of the SBM model is to minimize the slack variables while maximizing the efficiency value, subject to the constraints on the relationships between inputs and outputs. Assuming there are n decision-making units (DMUs), each with m types of input elements and q types of output elements, the mathematical expression of the SBM model can be represented as the following linear programming problem:

$$min\rho_0 = \frac{1-\frac{1}{m}\left(\sum_{i=1}^{m}\frac{s_{i0}^-}{x_{i0}}\right)}{1-\frac{1}{s}\left(\Sigma_{r=1}^{s}\frac{s_{r0}^+}{y_{r0}}\right)}$$

$$s.t.\begin{cases}\sum_{j=1}^{n} x_{ij}\lambda_j + s_i^- = x_{i0}, i=1,\ldots,m\\ \sum_{j=1}^{n} y_{rj}\lambda_j - s_r^+ = y_{r0}, r=1,\ldots,s\\ \lambda_j, s_r^+, s_i^- \geq 0, j=1,\ldots,n\end{cases} \tag{1}$$

The SBM model with undesired outputs is as follows:

$$\rho^* = min\frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{s_{io}^-}{x_{io}}}{1+\frac{1}{s}\left(\sum_{r=1}^{s_1}\frac{s_r^g}{y_{ro}^g}+\sum_{r=1}^{s_2}\frac{s_r^b}{y_{ro}^b}\right)}$$

$$\begin{gathered}\text{s.t.}\\ x_o = X\lambda + s^-\\ y_o^g = Y\lambda - s^g\\ y_o^b = Y\lambda + s^b\\ s^-, s^g, s^b, \lambda \geq 0.\end{gathered} \tag{2}$$

Among them, ρ is the efficiency value, m, q_1, q_2, are the number of input, expected output, and undesired output, respectively; S_r^{+}, S_i^{-}, S_t^{b-}, are the slack variables of input, expected output, and undesired output respectively, λ_j is the weight.

3.1.2. GRA-Tobit model

This study aimed to explore the influencing factors of Company CW's manufacturing workshops by integrating the Grey Relational Analysis (GRA) model with the Tobit regression model, proposing a combined GRA-Tobit analysis model. The specific process is as follows:

(1) Relevant factors affecting the energy efficiency of manufacturing workshops were identified.

(2) The data to eliminate the dimensions of different measurement units were normalized.

(3) The grey relational degree between each influencing factor and the energy efficiency of the workshops was calculated.

(4) The grey relational degree was determined. If the factor's grey relational degree exceeded 0.5, the factor was included in the Tobit regression model; otherwise, it was discarded.

(5) The regression results were computed and the influencing factors were analyzed.

This approach leverages the GRA model to quantify and preliminarily screen the relevance of various factors to energy efficiency. Factors with a significant grey relational degree are further analyzed using the Tobit regression model, accommodating the censored nature of energy efficiency data. This combined analysis model enhances the precision of identifying and quantifying the impact of various factors on the energy efficiency of manufacturing workshops, offering targeted insights for efficiency improvement initiatives.

3.2. Data source

The energy input, capital investment, and labor input consumed by Company CW's manufacturing workshops from 2016 to 2022 were selected as input variables; the annual total output value of each manufacturing workshop was taken as the expected output; the entropy value method was used to calculate the comprehensive pollution index as the unexpected output. The specific input-output indicators are explained in detail as follows:

(1) Energy input: The production processes in Company CW's manufacturing workshops use mainly electrical energy. Therefore, to ease calculations, the annual electrical energy consumption of each workshop was converted into 10,000 tons of standard coal. The source of the electric energy consumption data was the information collection system of CW Company, which was measured by independent electric energy meters in each workshop and summarized from the monthly and annual energy consumption reports of the workshops.

(2) Capital investment: Company CW's capital investment in workshops includes investment in factory buildings and production equipment. However, these fixed asset investments are often one-time investments. To facilitate calculation, the capital stock of the year estimated by the perpetual inventory method was used to express it. Relevant data were obtained from the financial statements of Company CW.

(3) Human investment: Human investment was measured based on employee wages as the measurement indicator based on the industry-specific and measurable principles of selection of evaluation indicators. Taking into account the basic salary situation and salary fluctuation of employees, the number of employees and the average salary of employees were collected through Company CW's financial statements for calculation.

(4) Workshop output value: As an important expected output indicator, workshop output value information

is obtained from the financial statements of each workshop.

(5) Unexpected output: Unexpected output generated during the production and processing stages in each manufacturing workshop of Company CW was analyzed using the entropy method. This method calculates a comprehensive unexpected output based on specific weights assigned to various factors. The formula used for this calculation was $E_i^t = 0.427\omega_{i1}^t + 0.470\omega_{i2}^t + 0.103\omega_{i3}^t$.

3.3. CW manufacturing shop energy efficiency evaluation

Using the SBM model with input orientation, constant returns to scale, and including undesired output, each indicator data is imported into Dearun software, and the energy efficiency results of CW Company's CW001-CW012 manufacturing workshops can be obtained.

Figure 1 shows the average energy efficiency of each manufacturing workshop from 2016 to 2022. Among them, workshop No. CW007 performed best during the inspection period, reaching the highest average TFEE of 1. This means that among all production workshops, the production input factors of workshop 07 had reached the efficiency frontier. The average TFEE of workshop CW006 was the lowest at 0.5481, indicating that this workshop had redundancy in various input factors in the production process. In addition, the average TFEE of workshops CW002, CW003, and CW008 exceeded 0.8, specifically 0.9083, 0.7969, and 0.8319, indicating high energy efficiency. The average TFEE of workshop CW004 and workshop CW010 ranged from 0.6 to 0.7, 0.6039, and 0.6667, which indicates that the energy efficiency of these workshops is moderate, but there is still room for improvement. The average TFEE of workshops CW009 and CW011 was close to 0.9, which were 0.8984 and 0.8494, respectively, indicating that these workshops had high energy efficiency. Finally, the average TFEE of workshop CW005 was 0.5938. Although it is not as low as the level of workshop CW006, it also indicates the potential for improving efficiency.

Overall, the average TFEE of each workshop of Company CW reflects the heterogeneity of different workshops in terms of energy management and usage efficiency. The energy efficiency of workshop CW007 was optimal, its input factors were on the production frontier, and each input factor was relatively reasonable. However, other workshops showed room for improvement in energy efficiency. These workshops may benefit from conducting detailed analyses on energy usage and other input factors to pinpoint inefficiencies and implement targeted energy-saving measures effectively.

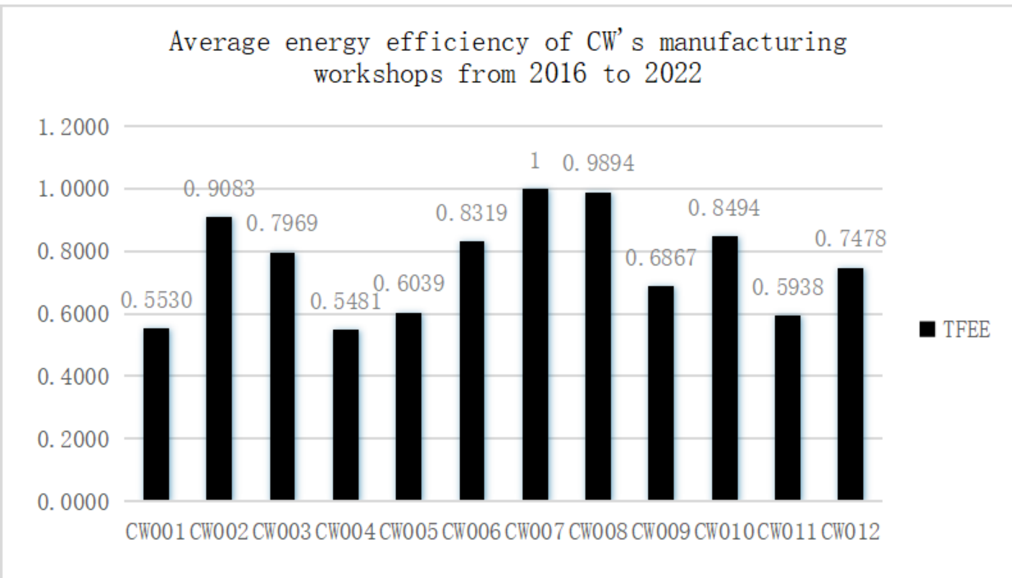

Figure 1. Average energy efficiency of CW's manufacturing workshops from 2016 to 2022

Table 1 reflects the annual actual efficiency values of each manufacturing workshop of Company CW during the inspection period. First of all, from the overall trend, the energy efficiency of workshops CW002, CW007, and CW008 maintained optimal performance during the observation period, reaching the highest energy efficiency value for seven consecutive years. It shows that during this period, the energy efficiency of several workshops was at the forefront of production, and there was no waste of input factors. The energy efficiency of workshop CW010 improved significantly from 2019 through 2020, and the energy efficiency value also reached 1. Furthermore, it sustained relatively high energy efficiency levels in other years, particularly in 2018 and 2021, indicating consistent outstanding performance. These improvements may signify enhancements in shop floor production processes or the successful implementation of technological innovations. In contrast, workshops CW001, CW004, and CW011 showed relatively low energy efficiency values in most years, especially workshop CW001 in 2022 and workshop CW011 in 2017 and 2022. Moreover, the energy efficiency values of most workshops fluctuated between years, indicating that the efficiency values were not static and could be affected by various factors, such as equipment aging, productivity fluctuations, changes in energy costs, and adjustments in production strategies. Lastly, it was observed that the energy efficiency values of workshops CW001 and CW002 dropped significantly in 2022, especially workshop CW002, which had dropped from the highest efficiency value for six consecutive years to 0.358. This was likely due to the COVID-19 pandemic, which had led to a decrease in input factors such as energy and capital, resulting in significant waste. Therefore, it is crucial for the company to conduct in-depth cause analyses and take quick steps to address problems that might lead to reduced efficiency.

Table 1. Energy efficiency of each CW manufacturing workshop

DMUS	Energy efficiency						
	2016	2017	2018	2019	2020	2021	2022
CW001	0.511	0.478	0.657	0.590	0.583	0.601	0.450
CW002	1.000	1.000	1.000	1.000	1.000	1.000	0.358
CW003	0.641	1.000	1.000	0.660	0.620	0.657	1.000
CW004	0.458	0.483	0.569	0.516	0.503	0.649	0.659
CW005	0.641	0.601	0.609	0.597	0.588	0.599	0.592
CW006	0.786	0.861	0.885	0.783	0.757	0.879	0.872
CW007	1.000	1.000	1.000	1.000	1.000	1.000	1.000
CW008	1.000	1.000	1.000	1.000	1.000	1.000	0.926
CW009	0.660	0.667	0.752	0.703	0.688	0.667	0.669
CW010	0.646	0.704	0.870	1.000	1.000	1.000	0.726
CW011	0.571	0.556	0.603	0.519	0.667	0.713	0.526
CW012	0.705	0.702	1.000	0.734	0.727	0.702	0.663

3.4. Analysis of factors affecting energy efficiency in CW's manufacturing workshops

According to the GRA-Tobit combination model proposed in this study, factors related to the energy efficiency of the manufacturing workshop are selected. After consulting relevant literature, combined with the actual production conditions of CW's lead-acid battery manufacturing workshop, and through the gray correlation analysis method, five influencing factors with a gray correlation greater than 0.5 were obtained. The specific values are shown in **Table 2**.

Table 2. Alternative influencing factors

Evaluation items	Correlation	Ranking
Pollution control intensity	0.518	5
Clean energy	0.615	4
The quality of staff	0.707	2
Production scale	0.621	3
Technical investment	0.737	1

Through the above table, this paper selects five indicators of pollution control intensity, clean energy investment, employee quality, workshop production scale, and workshop technology investment to construct independent variables. The energy efficiency of each workshop was used as the dependent variable. In order to eliminate the heteroscedasticity of the data without changing the nature and relationship of the data and performing dimensionless processing on the independent variables, the following Tobit regression model was established:

$$Y_{it} = \alpha + \beta_1 x_1 + \beta_2 x_2 + \cdots\cdots + \beta_n x_n + \varepsilon_i \quad (n = 1,2,3,4,5) \tag{3}$$

x_1 denotes the technological input by CW Company to each workshop, measured by the ratio of the total amount of investment in technology-related activities (in ten thousand yuan) per unit of time (year) to the capital stock (in ten thousand yuan) of the enterprise during the same period. This ratio serves as an indicator of technological input into Company CW's workshops.

x_2 represents the quality of the workforce in the manufacturing workshops. It is measured by the ratio of the wages (in ten thousand yuan) for personnel with an associate degree or higher per unit of time (year) to the total production costs (in ten thousand yuan) incurred by the workshop during the same period, reflecting the labor quality in Company CW's workshops.

x_3 indicates the scale of production in the manufacturing workshops. It is measured by the ratio of the total number of employees in Company CW's workshops to the total output value (in ten thousand yuan) of the workshop, assessing the scale of the workshop.

x_4 denotes the input of clean energy in the manufacturing workshops. It is measured by the ratio of the investment and maintenance costs of solar energy equipment (in ten thousand yuan) to the total production costs (in ten thousand yuan) of the workshop, representing the indicator of clean energy input in Company CW's workshop production.

x_5 signifies the level of pollution control in the manufacturing workshops. This is measured by the ratio of the costs incurred for the treatment of exhaust gases, wastewater, solid waste, etc., to the total production costs of the workshop, serving as an indicator of the pollution control level in Company CW's workshop production.

After preliminary processing of the original data, the respective variables are dimensionally processed and then substituted into the regression model of the above formula. Using stata16.0 to perform Tobit regression analysis, the regression results are shown in **Table 3**.

Table 3. Regression results

	EE
x_1	0.050* -2.353
x_2	-0.047** (-2.580)
x_3	0.037* -2.438
x_4	-0.042* (-2.141)
x_5	-0.050** (-3.031)
log(Sigma)	-2.337** (-25.175)
n	84
Likelihood ratio test	$P = 0.001$
McFadden R^2	-0.256

Note: *$P < 0.05$, **$P < 0.01$

The regression analysis revealed that, based on the production data of Company CW's CW001-CW012 manufacturing workshops from 2016 to 2020, technology investment, production scale, and clean energy investment were statistically significant at the 5% confidence level. Additionally, employee quality and workshop pollution control levels were found to be significant at the 1% level. These results confirm that these five production factors had a significant impact on the energy efficiency of CW's manufacturing workshops.

4. Conclusion

From the perspective of the manufacturing workshop, the fundamental production unit of the manufacturing system, we constructed an energy efficiency evaluation indicator system suitable for manufacturing workshops. A combined GRA-Tobit evaluation model was established, identifying factors influencing the energy efficiency of Company CW's manufacturing workshops. Given the specificity and limitations of workshop data, a combined GRA-Tobit analysis model was proposed. Initially, the Grey Relational Analysis (GRA) method was used to eliminate factors with minimal relation to the energy efficiency of Company CW's manufacturing workshops. Subsequently, factors with a high correlation degree (greater than 0.5) were incorporated into the Tobit regression model. This process yielded influential factors on the energy efficiency of Company CW's manufacturing workshops during the observation period. It was found that technological investment and expansion of production scale could significantly enhance energy efficiency. In contrast, increases in the wages of highly educated employees, clean energy investments, and intensified pollution control efforts would constrain the improvement of energy efficiency at the current production stage. Although the empirical results diverge from those found in domestic and international literature regarding the factors affecting energy efficiency, they align more closely with the actual situation of Company CW at its current development stage, offering more meaningful guidance for its production process.

Disclosure statement

The author declares no conflict of interest.

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