Scholar Publishing Group
Academic Journal of Energy
https://doi.org/10.38007/RE.2020.010206
ISSN 2790-2714 Vol. 1, Issue 2: 45-53

DEA Model and Energy Efficiency Improvement under Thermal Automatic Control

Ransha Almajend*

American University in the Emirates, UAE

**corresponding author*

Keywords: Automatic Control, DEA Model, Energy Efficiency, SBM Model

Abstract: The issue of energy has always been the focus of the international community, on the one hand, because of the limited and scarce energy, on the other hand, because energy is of great significance to the sustainable development of human society. This paper mainly studies the DEA model under thermal automatic control and the improvement of energy efficiency. This paper first defines the concept of energy, classifies energy, and analyzes the theoretical basis of energy efficiency. The DEA model and SBM model are explained in detail. The Three-stage DEA model is optimized by using the SBM model. The optimized model is used to study the energy efficiency optimization of company A. through the research results, it can be seen that the Three-stage DEA model can be used to optimize the inefficient workshops and key redundant inputs of company a, so as to achieve the effect of optimizing redundant inputs and improving workshop efficiency.

1. Introduction

China has entered the first phalanx of the industrial revolution. The input of resources is increasing. The progress of living standards will bring certain energy demand. The increase of population will also increase the demand for energy, and the degree of energy consumption is increasing. However, the improvement of energy efficiency has been shelved. In recent years, due to the dual impact of environment and energy, Various industries are also paying more and more attention to energy use in order to maximize energy utilization and improve energy efficiency [1-2]. However, despite continuous efforts to reduce energy consumption, the global energy demand is still increasing, and energy efficiency may not be able to give full play to its potential. Therefore, policymakers and stakeholders are increasingly turning their attention to improving energy efficiency by studying different influencing factors, such as technological reform, scale consolidation and other related factors. Environment and resources are the major concerns of the state, as well as the key concerns of every industrial industry. However, at present, the environment and energy are in a state of overload, and the total amount of China's energy consumption continues to rise with the passage of years. With the continuous growth of industrial economy, the supply of energy and natural resources is facing challenges, as well as environmental pressures, such as the increase of carbon, energy, materials and land footprint [3-4]. Energy efficiency is a controversial topic, which helps to achieve China's sustainable development goal of green water and green mountains. Energy efficiency has been analyzed from different perspectives, such as technological change, various renewable energies, industrial waste heat recovery technology, etc. some larger European Union and other countries have tried to identify best practices and case studies for industrial energy efficiency improvement, and some have transferred thinking to a coherent functional energy system to integrate the infrastructure of all sectors.

The economic development, energy consumption, environment and energy efficiency of various countries are closely related. Evaluating and improving energy efficiency is the key way to deal with climate change and global warming. Domestic and foreign experts pay close attention to the hot spot of energy efficiency. In order to better track and detect the level of energy efficiency, some literatures use energy intensity to express it. Energy intensity is a simple and traditional expression of energy efficiency, which is defined as the ratio of energy input to output. Recent literatures use all factor energy efficiency to express energy efficiency, which will be the minimum feasible energy input divided by the actual energy input [5]. Domestic scholars have always attached great importance to the research on energy efficiency in various fields and industries in China. Some scholars calculated the total factor energy efficiency of 35 industrial sub industries in China from 2000 to 2016 by using the index method based on data envelopment analysis, predicted the trend of energy efficiency, and concluded that the development trend of total factor energy efficiency in China's industry is good [6]. Some foreign scholars analyzed the regional energy efficiency of Japan by combining the stochastic frontier model with the meta frontier and the group frontier [7].

The in-depth study of the energy efficiency of China's industrial industries plays a certain role in guiding other industries, has reference significance for other industries, and plays a great role in improving the energy efficiency of other industries.

2. DEA Optimized Energy Efficiency Model

2.1. Theory of Energy Efficiency

(1) Energy and its classification

Cihai has two definitions of "energy": the first is "energy resources, which refers to the transformation of the energy obtained into natural resources such as heat, light, electricity and power, such as fuel, electricity and wind energy, which are necessary for people"; The second is "borrow the energy that people can exert". However, the energy commonly mentioned is mainly energy resources. In a word, energy is a special resource from which we can obtain energy, which can be found everywhere in production and life. Energy has been closely related to modern society and has formed an organic system with the development of social economy [8-9].

There are also various forms of energy, including coal, oil, natural gas, solar energy, wind energy, hydropower, nuclear energy, chemical energy, biomass energy, etc., from one form to another, and the heat and work produced in this process [10]. There are many different ways to classify energy. The more common is to divide energy into primary energy and secondary energy according to the basic form and generation conditions: primary energy is mainly the energy directly obtained from natural resources such as solar radiation, wind, etc., such as coal, oil, natural gas, etc; Secondary energy mainly refers to the primary energy conversion, such as electricity, gas, etc. [11].

(2) Energy efficiency

In view of the lack of unified standards for the concept and content of energy efficiency, there will be some differences in its calculation results. In the 1990s, energy efficiency was recognized as reducing energy input to provide equivalent energy services or useful outputs [12].

The three-level concept of energy system: the first level is the energy unitary structure system, referred to as energy system for short; The second layer is the dual structure system of energy and economy; The third layer is the multidimensional structure system of energy, economy, environment, resources and population. From these three concepts, we can see that energy efficiency matches the binary structure system. The "first fuel" in the global energy system is usually regarded as energy efficiency, which is also one of the key measures adopted by governments to build sustainable energy systems.

Generally speaking, energy efficiency is divided into energy economic efficiency and energy technical efficiency.

Energy economic efficiency refers to the ratio between the useful energy in output and the total energy input. Generally, energy consumption per unit of GDP and energy consumption per unit of product will be selected as its indicators, and the actual value is consistent with the direction of changes in technology and management level.

Energy technical efficiency refers to the ratio between the energy obtained from energy activities and the actual amount of energy. It is mainly composed of the overall energy structure, energy utilization technology and other factors. It is usually shown as a comprehensive index, and its value is usually expressed in percentage.

There are subtle differences between economic efficiency and technical efficiency of energy. The former refers to the ratio between the useful energy in output and the total energy input. The actual value is consistent with the change direction of science and technology and management level. The level of the former is determined by the level of the latter, but the latter is not the only determinant.

Energy efficiency can be divided into single factor energy efficiency and total factor energy efficiency from the perspective of production input. The former is the ratio of energy consumption to actual output. The improvement of energy efficiency will increase with the decrease of this ratio. There is an inverse relationship between them. In the calculation process, the condition that energy is the only input index is generally hidden as a hypothetical condition. By hiding this hypothetical condition, the result is high because the value of other production factors is ignored. Therefore, it will replace the energy intensity to ensure the embodiment of the characteristic attributes of conceptual consistency and integrity.

2.2. DEA Model based on SBM Optimization

(1) DEA model

DEA is a method that does not need to rely on specific functional forms. It was first proposed by Charnes, Cooper, and Rhodes, so the original DEA model is also called the CCR model [13]. The DEA method refers to the measured object as a decision-making unit, and uses a linear programming method to measure the efficiency of the decision-making unit. DEA can measure the efficiency of each evaluated object and evaluate the relative efficiency among multiple evaluation objects of the same type [14]. The DEA method does not need to set a specific production function model. The measurement results of DEA will not change with the unit changes of input variables and output variables, thus ensuring the integrity of the original information and the relative accuracy of the evaluation results. The data of input variables and output variables can be proportional or non-proportional. In the DEA method, there is no need to formulate weights for input variables and output variables, which avoids errors caused by human factors, and is more objective and fair [15]. DEA is applicable in many situations, and it has certain advantages in the analysis of situations with multiple input variables and multiple output variables, so it is widely used in many fields, such as government agencies, power industry, financial institutions, medical care, military , logistics and transportation and other fields, analyze the production and operation efficiency and resource use level of decision-making units to improve the organizational performance of multiple departments. In social production, the evaluation of efficiency has become more and more important, and the results obtained using the DEA method can provide effective guidance and feasible suggestions for departmental decision-makers and leaders [16].

Suppose there are n evaluated objects in the production system, and each evaluated object has input variable X: composed of m input variables; output variable Y: composed of k output variables, the matrix is defined as follows: X= (x1n, x2n,..., xmn), Y=(y1n, y2n,..., ykn), n=1,2...,N. In the DEA method of measuring efficiency, efficiency is defined as the ratio of the weighted sum of output variables to the weighted sum of input variables, as follows:

$$T_n = \frac{\mu y_n}{v X_n} \tag{1}$$

(2) SBM model

The SBM (slacks-based measure) model breaks through the radial change limit, and can intuitively see the degree to which input variables can be simplified, the degree to which undesired output can be reduced, and the degree to which expected output can be increased. In previous literature studies, SBM models with undesired outputs have been widely used to measure environmental efficiency [17-18].

Suppose there are n evaluated objects in the production system, and each evaluated object has an input index x, written as matrix X=(x1,x2,..., xn) ∈ Rm*n>0; expected output index y, written as matrix Y=(y1,y2,...,yn) ∈ Rv1*n>0; Unexpected output indicator z, written as matrix Z=(z1,z2,...,zn) ∈ Rv2*n>0, where m, v1, v2 represent the number of variables x, y, z respectively.

(3) SBM three-stage DEA model

The disadvantage of the SBM model with undesired output is that it cannot effectively distinguish the effects of external environmental conditions, random errors and other issues on the efficiency value. Therefore, in the process of measuring efficiency, it is necessary to strip the impact of external environmental factors and management inefficiency factors to a certain extent on efficiency evaluation.

The three-stage SBM-SFA model used in this paper is as follows:

Stage 1: Build the SBM model to obtain the efficiency value of each decision unit

The second stage: establish m SFA regression models, use the different external environmental variables of each evaluation unit as independent variables, and use the slack value of the input indicators measured in the previous stage as the dependent variable. The regression model can be written as:

$$S_i^k = f_i(Q_i^k, \beta_i, \mu_i^k) \tag{2}$$

Sik represents the slack value of the input variable i of the kth DMU calculated using the SBM model, Qik represents the vector of external environmental variables, i represents the parameter vector, and ik is the random disturbance term. Management inefficiencies can be estimated as:

$$\hat{E}[\mu_i^k \mid v_i^k + \mu_i^k] = \frac{\gamma\sigma}{1+\gamma^2}\left(\frac{\phi(\gamma e_i)}{\varphi(\gamma e_i)} + \gamma e_i\right) \tag{3}$$

φ is the standard normal distribution function, ψ is the density function, and ei is the random error term.

Stage 3: Rebuild the SBM model using the adjusted input variables and initial output variables and calculate the efficiency value θ* for each DMU. Efficiency values are interpreted as if the DMU is in the harshest external environment, the input can be reduced (1-θ*) to reach an effective operating level.

3. Empirical Research on Energy Efficiency Optimization

3.1. DMU Selection

In this paper, the energy consumption of each project workshop of Company A is comprehensively analyzed, and the gear workshop (A), shaft gear workshop (B), assembly workshop (C), and shell workshop (D) are selected as the empirical research objects, and the three-stage DEA of this paper is used quantitatively. The optimization analysis method improves the energy efficiency of company A's workshop.

3.2. Indicator Selection

This paper selects the annual consumption of capital, labor and energy as the input variables of the workshop, and the annual total output value of the workshop as the output variable. The selected input-output indicators are described in detail as follows:

(1) Capital: Plant and equipment are the main objects of capital consumption in the workshop. The total investment in fixed assets is used to represent the amount of capital. It is estimated according to the perpetual inventory method, and the investment in the current year is calculated at constant prices. The depreciation rate of fixed assets is 6%. .

(2) Labor force: The indicator selected in this paper to represent the labor force is employee wages. The number of employees and the average monthly salary of employees are collected by taking into account the basic salary and variable salary of employees.

(3) Energy: According to statistical data, the annual electricity cost of company A’s factories accounts for more than 99% of the total energy consumption cost. In this paper, the total annual electricity consumption represents the energy input. The annual electricity consumption data of each workshop is derived from the monthly energy management system. Summary of energy consumption reports.

(4) Total output value: In order to maintain the correspondence between output elements and input elements, this paper selects the annual total output value of the workshop as the corresponding output element.

3.3. Raw Data

Relevant data were collected from the company's workshop management report through field research. Table 1 shows the original data of manufacturing cost and output value.

Table 1. Raw data of workshop manufacturing cost and output value(ten thousand yuan)

	Manufacturing cost	Output value
A	5021	45162
B	6475	41574
C	5762	42317
D	3995	38107

4. System Test Results Statistics and Analysis

4.1. Energy Efficiency Evaluation

This paper uses DEA Solver Professional 5.0 software to measure the total factor energy efficiency of company A's manufacturing workshop throughout the year. The relative efficiency values of each workshop in the initial period of the year calculated by the model are shown in Table 2.

Table 2. Initial efficiency value

j	DMU	Efficiency value
1	A	0.63
2	B	0.42
3	C	0.95
4	D	0.57

4.2. Optimization of Energy Efficiency Evaluation

In the multi-stage decision-making process, the input values of the non-improved target decision-making units remain unchanged. According to the multi-stage solution process of the above three-stage DEA combination model, the SBM model with the improved slack variable range of each stage is established, and the software Lingo 12.0 is used to solve it, and the stage quantity index corresponding to the decision variable ut of each stage is obtained, that is, the improvement amount of energy input. .

From the multi-stage solution process, there are five strategies that can complete the efficiency improvement of the four workshops with lower than average efficiency.

The abscissa represents the improvement of u1, u2 and u3 decision-making units in the first, second and third stages respectively, and the ordinate represents the total improvement value of the electric energy input in the planning period T under this strategy. The comparison chart of the improvement effect of the strategy is shown in Figure 1.

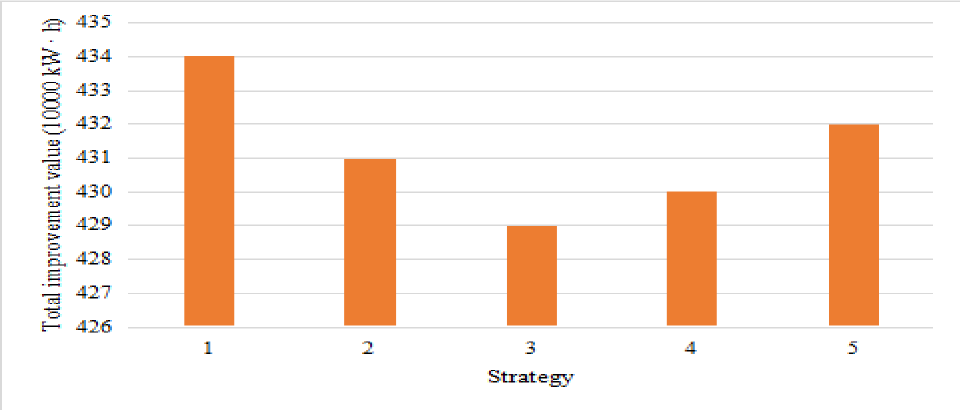

Figure 1. Comparison of improvement effects of various strategies

Table 3 shows the efficiency values of each workshop of Company A after improving the energy efficiency of workshops according to the data selection strategy 1 in Figure 1.

Table 3. Workshop efficiency value under optimal strategy

j	DMU	Efficiency value
1	A	0.74
2	B	0.77
3	C	0.99
4	D	0.72

It can be seen that the average efficiency value of each workshop unit has increased from 0.64 before the improvement to 0.80 after the improvement, and the average efficiency value of the workshop has increased by 25%. The comparison chart of the efficiency of each workshop before and after the improvement is shown in Figure 2.

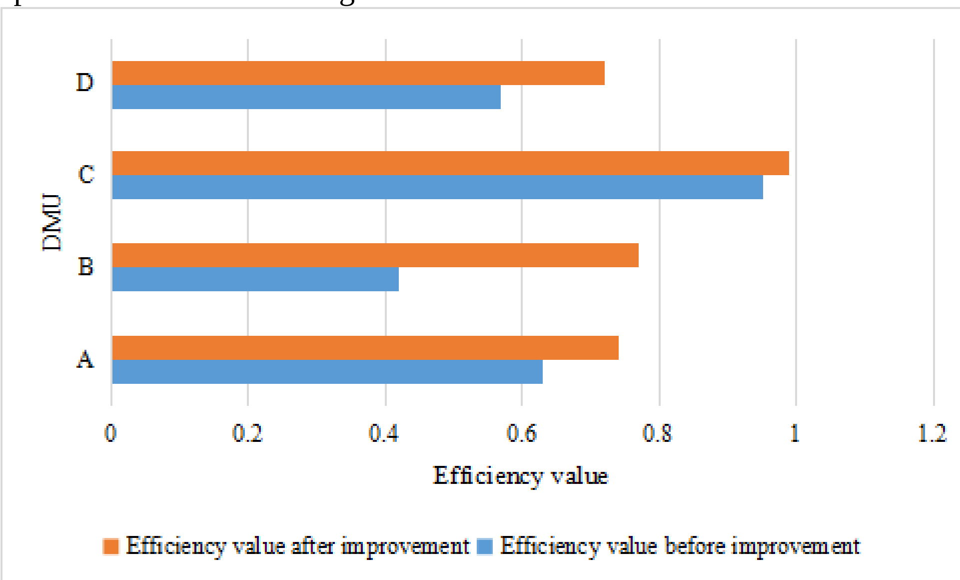

Figure 2. Comparison chart of efficiency of each workshop before and after the improvement of the optimal strategy

5. Conclusion

Based on the evaluation of the total factor energy efficiency of the manufacturing workshop, the three-stage DEA model can be used to optimize the inefficient workshop and key redundant inputs of Company A, so as to achieve the effect of optimizing redundant inputs and improving workshop efficiency. At the same time, in the selection of various optimization strategies, the three-stage DEA model can help identify the optimal efficiency improvement strategy based on the improvement of key redundant inputs, so as to achieve the best effect of improving redundant inputs. Through empirical research, the practicality and effectiveness of the model are demonstrated. It is hoped that the next research will continue to refine the total factor energy efficiency evaluation index system of the manufacturing system, build the third-level index, and further improve the total factor energy efficiency evaluation index system of the manufacturing system.

Funding

This article is not supported by any foundation.

Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

References

[1] *Mallick S P , Dash D P , Mallik S , et al. An empirical approach towards photovoltaic parameter extraction and optimization. Solar Energy, 2017, 153(sep.):360-365. https://doi.org/10.1016/j.solener.2017.05.076*

[2] *Alireza T , Elkafi H . Evaluating Sustainability Performance In Fossil-Fuel Power Plants Using A Two-Stage Data Envelopment Analysis. Energy Economics, 2018, 74(AUG.):154-178. https://doi.org/10.1016/j.eneco.2018.05.032*

[3] *Elmirghani J , Klein T , Hinton K , et al. GreenTouch GreenMeter Core Network Energy-Efficiency Improvement Measures and Optimization. Journal of Optical Communications and Networking, 2018, 10(2):A250. https://doi.org/10.1364/JOCN.10.00A250*

[4] *Sokun H U , Bedeer E , Gohary R H , et al. Optimization of Discrete Power and Resource Block Allocation for Achieving Maximum Energy Efficiency in OFDMA Networks. IEEE Access, 2017, PP(99):8648-8658.*

[5] *Sharma E , Budhiraja R , Vasudevan K , et al. Full-Duplex Massive MIMO Multi-Pair Two-Way AF Relaying: Energy Efficiency Optimization. IEEE Transactions on Communications, 2018, PP(8):1-1. https://doi.org/10.1109/LWC.2018.2847667*

[6] *Torregrossa D , Hansen J , Hernandez-Sancho F , et al. A data-driven methodology to support pump performance analysis and energy efficiency optimization in Waste Water Treatment Plants. Applied Energy, 2017, 208(dec.15):1430-1440.*

[7] *Ortiz J , Poliero T , Cairoli G , et al. Energy Efficiency Analysis and Design Optimization of*

an Actuation System in a Soft Modular Lower Limb Exoskeleton. IEEE Robotics & Automation Letters, 2017, 3(1):484-491. https://doi.org/10.1109/LRA.2017.2768119

[8] Bre F , Fachinotti V D . A computational multi-objective optimization method to improve energy efficiency and thermal comfort in dwellings. Energy and Buildings, 2017, 154(nov.):283-294. https://doi.org/10.1016/j.enbuild.2017.08.002

[9] Galitsky C , Martin N , Worrell E , et al. Energy Efficiency Improvement and Cost Saving Opportunities for Breweries: An ENERGY STAR(R) Guide for Energy and Plant Managers. Lawrence Berkeley National Laboratory, 2019, 32(7-8):e1258, C150.

[10] Zappone A , Lin P H , Jorswieck E . Energy Efficiency of Confidential Multi-Antenna Systems With Artificial Noise and Statistical CSI. IEEE Journal of Selected Topics in Signal Processing, 2017, 10(8):1462-1477.

[11] Eleftheriadis S , Mumovic D , Greening P . Life cycle energy efficiency in building structures: A review of current developments and future outlooks based on BIM capabilities. Renewable and Sustainable Energy Reviews, 2017, 67(jan.):811–825. https://doi.org/10.1016/j.rser.2016.09.028

[12] Gaglia A G , Lykoudis S , Argiriou A A , et al. Energy efficiency of PV panels under real outdoor conditions–An experimental assessment in Athens, Greece. Renewable Energy, 2017, 101(FEB.):236-243.

[13] Escamilla J , Salido M A , Giret A , et al. A metaheuristic technique for energy-efficiency in job-shop scheduling. The Knowledge Engineering Review, 2017, 31(5):1-11.

[14] Rawat D B , Reddy S R . Software Defined Networking Architecture, Security and Energy Efficiency: A Survey. IEEE Communications Surveys & Tutorials, 2017, 19(1):325-346.

[15] M Rkcü, Zsoy V S , HH Rkcü. An Optimistic-Pessimistic DEA Model Based on Game Cross Efficiency Approach. RAIRO - Operations Research, 2020, 54(4):1215-1230. https://doi.org/10.1051/ro/2019052

[16] Mo R , Huang H , Yang L . An Interval Efficiency Measurement in DEA When considering Undesirable Outputs. Complexity, 2020, 2020(1):1-12. https://doi.org/10.1155/2020/7161628

[17] Jha P C , Gupta A , Pachar N . Centralised resource reallocation and reduction with common weight DEA model. International Journal of Business Performance and Supply Chain Modelling, 2020, 12(3):179.

[18] Tsai M C , Cheng C H , Nguyen V T , et al. The Theoretical Relationship between the CCR Model and the Two-Stage DEA Model with an Application in the Efficiency Analysis of the Financial Industry. Symmetry, 2020, 12(5):712. https://doi.org/10.3390/sym12050712