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Review of methodologies and polices for evaluation of energy efficiency in high energy-consuming industry

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HIGHLIGHTS

- The classification of the industrial energy efficiency index has been summarized.
- The factors of energy efficiency and their implement in industries are discussed.
- Four main evaluation methodologies of energy efficiency in industries are concluded.
- Utilization of the methodologies in energy efficiency evaluations are illustrated.
- Related polices and suggestions based on energy efficiency evaluations are provided.

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ABSTRACT

Energy efficiency of high energy-consuming industries plays a significant role in social sustainability, economic performance and environmental protection of any nation. In order to evaluate the energy efficiency and guide the sustainability development, various methodologies have been proposed for energy demand management and to measure the energy efficiency performance accurately in the past decades. A systematical review of these methodologies are conducted in the present paper. First, the classification of the industrial energy efficiency index has been summarized to track the previous application studies. The single measurement indicator and the composite index benchmarking are highly recognized as the modeling tools for power industries and policy-making in worldwide countries. They are the pivotal figures to convey the fundamental information in energy systems for improving the performance in fields such as economy, environment and technology. Second, the six factors that influence the energy efficiency in industry are discussed. Third, four major evaluation methodologies of energy efficiency are explained in detail, including stochastic frontier analysis, data envelopment analysis, exergy analysis and benchmarking comparison. The basic models and the developments of these methodologies are introduced. The recent utilization of these methodologies in the energy efficiency evaluations are illustrated. Some drawbacks of these methodologies are also discussed. Other related methods or influential indicators for measuring energy efficiency performance have also been presented. Finally, the related polices and suggestions based on the energy efficiency evaluations are provided.

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1. Introduction

The world is witnessing a major transition from fossil energy to clean energy during the recent decades. However, fossil fuel in the form of coal, natural gas and oil are still possesses 80% of the worldwide energy usage. About half of the electricity generated is still produced in coal-fired power plants. Increasingly, the general public, researches and governments are paying more concern to energy efficiency, especially in developing countries.

Understanding the actual physical definition of energy efficiency is crucial to develop and apply different methodologies in worldwide countries. Particularly to the industries, the competition between firms can be evaluated by some kinds of energy efficiency indicators. The improvement of energy efficiency is a vital strategy, which is to maximize outputs and to decrease operational costs. Patterson who is the earlier scholar presented that energy efficiency is a generic issue and there is no quantitative measure, and it should be estimated by a series of indicators [1]. In the aspect of high energy-consuming industries, energy efficiency of performance tends to the less energy usage for more outputs. Moreover, the importance of energy efficiency in power industries is heavily linked to commercial and energy security, as well as to environmental benefits such as less greenhouse gas (hereinafter presented as the GHG) emissions. Therefore, the evaluation of energy efficiency of high energy-consuming industries plays an important role in different countries. In order to confirm the optimization of power systems, the modeling of energy efficiency should be implemented constantly and regularly to capture the pattern trend of energy usage. In recent years, more scholars proposed various quantitative models to solve the comprehensive problems of energy efficiency. Some of them adopted economic analysis depending on engineering assumptions, and the benchmarking influential factors. The others employed different kinds of methodological models to investigate the overall economic impact.

All the above mentioned are the reasons why the review paper pays attention on the methodologies and polices for the measurement of energy efficiency in high energy-consuming industries with international perspectives. It is necessary to summarize the recent trends in the energy efficiency research, the latest trends of methodologies of energy efficiency evaluation, and the classification of different approaches. Moreover, it is essential to propose the further needed and to point out the valuable topics for improving energy efficiency issues of high-consuming industries. Thus this paper, as a beneficial complement, is necessary and timely.

The reminder of the paper is structured as below. Section 2 summarizes the classification of energy efficiency in industries, and the definition of energy efficiency indicators. Section 3 discusses the major factors, which directly and indirectly affect the performance of energy efficiency in high energy-consuming industries. It will contain capital investment, environmental indicators, structural indicators (including energy consumption of plant-levels), Gross Domestic Product (hereinafter presented as the GDP), energy price and labor. Section 4 provides different types of energy modeling on evaluating the energy efficiency. It describes how and where these models can be adopted based upon manufacturing processes. Section 5 gives related policy and recommendations. Finally, conclusion is presented in Section 6.

2. Classification and definition of energy efficiency in industry

The objectives of this section involve the definition of boundaries for measuring the energy efficiency indicators at plant-level in industries. It provides different scholars' opinions with international perspectives.

2.1. Definition

The definition of energy efficiency is a complex question. Martin et al. first defined energy efficiency as that which presents the amount of human activities, such as manufacturing industry, transportation and electricity industry, provided per unit of energy used [2]. For the industrial energy efficiency, it is a quality of a system of industrial sectors. Martin et al. primarily pointed out that industrial sectors can be measured in economic terms or physical terms, such as market value, weight of products, and number of outputs [2]. It is related to costs of energy source, technological efficiency, capital investment and labor, etc. Moreover, the energy efficiency of economic procedure can't be easily evaluated precisely because it is a comprehensive activity. Hence the energy efficiency indicator of industries is a ratio of service output to energy input defined by Eq. (1)

$$\frac{\text{Useful output of a process}}{\text{Engery input into a process}} \tag{1}$$

For manufacturing industries, the issue then becomes how to precisely state the useful output and energy input. A number of indicators can be adopted to represent changes in energy efficiency. Energy efficiency can be used to evaluate industrial activities, and energy usage efficiency, especially on a macro-level. It is harder to estimate the energy efficiency variation with time [3].

2.2. Classification

Energy efficiency indicators can be divided into four main groups as below.

(1) Thermodynamic indicators. This kind of indicator displays some sort of second law efficiency, and it depends upon the sophisticated methods that can be used to estimate actual energy usage in a producing process [4]. It is the most traditional method to evaluate energy efficiency through the scientific reaction processes. The first-law energy efficiency has been early applied in macro-level energy efficiency studies,

such as Sioshansi [5], Jenne and Cattell [6]. This is because the first-law energy efficiency treated different energy inputs as the same measure units of heat content, which is measured in terms of change values of enthalpy (ΔH). The formula is as below [1].

$$E_{\Delta H} = \frac{\Delta H_{output}}{\Delta H_{input}} \quad (2)$$

where $E_{\Delta H}$ is enthalpic efficiency, ΔH_{output} represents the total output in a process, and ΔH_{input} means the total energy inputs in a process. They mainly estimated the efficiency indicators from the industrial level and the sector level [6]. The second law analysis has been developed over past decades. It became popular in different communities, and can be categorized as below: exergy, exergy-consumption, physical-exergy, negentropy and entropy [7]. It is well known that the energy efficiency in the second law of thermodynamics is more restrictive than the first law. It has been widely used as measures of effectiveness compared with the first law. The idea of the second-law energy efficiency was adopted to elaborate the application in heat transfer [8], alternative indicators of the energy conversion system [7], and a transfer of chemical energy in the chemical process [9]. The ratio is as below [1].

$$\rho = \frac{E_{\Delta H(actual)}}{E_{\Delta H(ideal)}} \quad (3)$$

where ρ represents the second-law efficiency of a process, $E_{\Delta H(actual)}$ is the actual enthalpic efficiency of a process, and $E_{\Delta H(ideal)}$ means the ideal enthalpic efficiency of a perfect manufacturing process.

With the improvement of technology in comprehensive procedures, the calculation of the thermodynamic indicators becomes more complex, and the results are needed to contain more information. The disadvantage of mere thermodynamic indicators is that above studies only treat inputs as being homogeneous in quality measures, not in terms of other units that taking account of different end use service. The numerator of energy efficiency ratios should contain either heat equivalent or some work potential [1]. Therefore, the thermo-physical indicators have been developed that containing the physical measure units rather than merely thermodynamic measures, and it can reflect the consumers' requirement.

(2) Thermo-physical indicators. These are hybrid indicators that the numerator is thermal units, and the denominator is measured in physical units. It describes how much energy consumption is needed for producing each output. For example, these indicators have been applied in passenger transport by Collins [10], the input can be kilometers of distances.

(3) Thermo-economic indicators. These indicators measure the change in secondary energy consumption led by the energy intensity differences between the computation year and the base year. The formula is as below [1].

$$E = \frac{A_t \sum S_{it}(I_{i0} - I_{it})}{E_t} \quad (4)$$

where A_t means the net output of activity (the real GDP) in the tth year, S_{it} is the shares of outputs i, I_{it} represents the economic energy intensity of output i in the tth year, I_{i0} represents the economic energy intensity of output i in the base year, E_t means the energy consumption in the tth year. The Joint Economic Committee of the Congress of the United States has extended these indicators to an energy intensity ratio of the energy input to GDP in 1981. This ratio has become an unit of energy intensity of economy [1]. However, there is a problem with this method that has been pointed by Wilson et al. The authors stated that the energy efficiency ratio did not measure the change of technical energy efficiency, especially the effect on structural changes at the plant-levels. This situation will lead to the underestimated outputs in energy efficiency [11]. Some papers argued that the technological change can be demonstrated by the capital investment, which is useful insight into energy inputs [12]. With the further requirement of inputs, factors have become diversified such as changes in labor [13] and the mixed sector in economy [6]. Some papers allow changes in energy inputs to be decomposed into four components [14]. With the faster speed of economic development, questions were raised as to how the thermo-economic indicators can change with time when a country has economic development constantly. Therefore, some studies are inclined to the economic indicators.

(4) Economic indicators. These indicators are in terms of total dollar output of a sector, which means both the input and production output are enumerated in monetary terms. Economic indicators are normally adopted in benchmarking studies of various countries. In the 1970s and early 1980s, the comparisons are usually made between primary energy consumption and the real GDP. Some economic scholars such as Turvey and Norbay [15], Bullard and Herendeen [16], argued that, due to the economic circumstance, both inputs and outputs should be measured in terms of currency value. They presented that energy price should be adopted instead of thermodynamic units for the energy inputs.

The changes of energy efficiency are normally affected by the changes of energy intensity and other factors related to efficiency. The indicators mentioned above, especially the thermodynamic indicators, can be adopted merely at the device level and specific analysis, such as turbine, and boiler. The thermo-economic indicators are the most popular indicators in the evaluation of industrial energy efficiency nowadays. These are intuitive and inclusive terms that can be conveniently understood and applied by policy makers. Until now, the thermo-economic indicators are widely adopted by international agencies and by many countries in the world.

Within the energy industry, the measurement indicators are employed at different computational situations. They are commonly affected by other activity levels. Therefore, in practice, it is necessary to consider all related factors that would be useful to build a comprehensive methodology of energy efficiency.

3. Factors influencing the performance of energy efficiency in industry

Energy demand is increasing steeply in developing countries because of the fast development. Until now, most of the energy productions are dominated by fossil energy, and energy usage is still dominated by industries. Therefore, to improving the energy efficiency of industries is an indispensable issue. There are studies try to compare various indicator factors in energy efficiency across industries at the macro-economic level. This section gives an overview of the factors that have been found to affect technology in industries. It can be summarized that the following 5 factors affect the energy efficiency technology: (1) capital investment, (2) environmental indicators, (3) structural indicators (including energy consumption of plant-levels), (4) GDP, (5) energy price, (6) labor.

Capital investment: Comin and Hobijin [17] examined the factors of more than 20 technologies in 23 world's leading industrial economies. They adopted the regression analysis to demonstrate that the higher GDP per capita is positively linked to both human capital indicators and technologies. They further demonstrated an important issue called "technology locking". It means that the new technologies of industries need to spend more time compare with the old ones, and the inter-correlation of capital investment and labor affect energy efficiency obviously [17]. Benhabib and Spiegel concluded that human capital is a positive factor of technological factors [18].

Environmental factors: Environmental factors of industries have been found as a rough proxy for energy consumption [19]. Environmental quality can be an important indicator for industries to measure energy efficiency. For example, capital cost per unit and energy consumption are involved in a model, and environmental indicators are the proxy. The higher energy efficiency needs, the more rigorous environmental factors should be. The purposes of environmental indicators are comprehensive, such as highlighting the energy efficiency potential of optimization, evaluating cost potential reduction, proving the opportunity to identify weak points and potential improvements, and benchmarking performance between industries or even making technical support of regulation [20]. Policymakers often pursue to maximize the energy efficiency of industries, and policy choices should be decided seriously because of the heterogeneity of energy sources when researches do cross-industries benchmarking in economic performance [21]. It can be summarized that the strength of environmental indicators involved in energy efficiency performance is that it can highlight the potential trends through controlling measure, which means framing a function of an early-warning system for industries.

Speaking of environmental indicators adopted by industries, air pollution is a significant indicator. Say [22] studied the SO_2 emission of thermal power industries and the regions in which the air pollution was concentrated. He further quantified the SO_2 through the IPCC methodology, which adopting the data of the fuel consumption and its used weight in energy production. The formulas are as follows [22].

$$SO_2 = EF \times FC, \tag{5}$$

$$EF = 2 \times (s/100) \times (1/Q) \times 106 \times ((100 - r)/100) \times ((100 - n)/100), \tag{6}$$

where EF is the emission factor (kg/TJ), FC means the fuel consumption (TJ), Q represents the net calorific value (TJ/kt), s expresses the sulfur content in fuel (%), r stands for the sulfur retention in ash (%), and n stands for the productivity of emission control technology (%) [22].

Kaneko et al. employed the SO_2 intensity in an nonparametric distance function approach, and analyzed the regional allocation strategies to reduce the SO_2 emissions in coal-fired sectors utmostly [23]. They found out that it had a significant negative relation with energy efficiency. There is an increasing number of studies on methodologies for evaluating energy efficiency in consideration of air pollution, including Chung et al. [24], Boyd and McClelland [25], Hailu and Veeman [26], Lee et al. [27], Färe et al. [28], Picazo-Tadeo et al. [29], Hamamoto [30], Watanabe and Tanaka [31], Färe et al. [32], Riccardi et al.[33].

Structural indicators: Both industrial energy intensity and energy consumption are affected by structural indicators. It can be described as that structural indicators quantify the mix of production activities in one sector, and it can also be called energy consumption of plant-levels. Phylipsen et al. [34] illustrated an example, which is the higher energy demand for heating in cold climates. This case needed to separate the influence of different plant-level indicators for measuring heating efficiency. It demonstrated the importance of involving different aspects of structural sectors into one energy efficiency indicator. Therefore, with the development of methodology, the indicators will become more complex. The influence of structural indicators can be named as “accounting for the sector” [34], and all of them need to be taken into account.

The actual energy consumption and the reference energy consumption are two types of energy consumption of plant-levels. The difference between them is the pursuing objective. The actual energy consumption presents the real energy demand of specific plant-levels, and the reference energy consumption is framed by a planned weight average of production outputs. Phylipsen et al. concluded that the following reference energy consumption normally depended on the objective of analysis [35].

(1) Best practice observed value. It represents that the plant is already fully operating with the lowest energy consumption.
(2) Best practical stands for the manufacturing plant with the lowest energy consumption that employing advanced technology at reasonable costs.
(3) Best available technology. It stands for the manufacturing plant with the lowest energy consumption that employing technology.

GDP: Wei et al. analyzed that the secondary industry share in GDP is negatively correlated with the energy efficiency of industries [36]. However, if the share of production outputs in GDP is from the government investment, then they are highly positive associated with the efficiency ratio. The usefulness of GDP had been pointed out by Hu and Wang [37]. The study presented that the traditional analysis of energy efficiency indicators only treated energy as a single input [1]. With the higher requirement of energy efficiency, GDP and capital investment are two prominent factors of evaluating outputs.

Energy price: Economists promote to adopt the market price of energy sources to evaluate the influence of fluctuation of energy prices on energy efficiency. Bernard and Côté [38] estimated the evolution of the energy price by different energy sources, and then measured by the energy efficiency index for the overall producing departments.

Labor: The efficiency of labor takes an important position in the evaluation of the industrial energy efficiency within the development of global economic growth. Firms that having higher labor efficiency will affect energy intensities and have better energy efficiency performance. Boyd and Pang [39] analyzed the relationship between productivity and energy efficiency of glass industry. In the data set of influential factors, they adopted labor as one of the economic variables in their study. Subrahmanya [40] particularly analyzed the link between labor efficiency and energy intensity. The study proved that the proxy of labor to value of output is 0.73 at the 1% significant level, which means that the labor efficiency had a significant positive impact on value of productions. There is an increasing number of studies on methodologies for evaluating energy efficiency in consideration of labor, including Herring [41], Thoresen [42], Brookes [43], Bjørner and Jensen [44], Knittel [45], Johannsen [46], Worrell et al. [47], Boyd et al. [48], Li et al. [49].

4. Models of energy efficiency evaluation

Evaluation of energy efficiency contains the reliability of energy supply and the effective control of energy consumption in different power systems. Methodologies need to consider a series of factors in order to obtain the maximization of outputs. Moreover, environmental friendly tasks are the new requirement for industries. Efficiency management consists of modeling, planning and monitoring activities that are the strategies to incentive industries to restrain the footprints of energy usage. Therefore, computational models attract an increasing number of attentions in these two decades. It has been achieved a common knowledge that models are the scientific standard tools to apply different indicator factors comprehensively. Appropriate methodology is necessary, which is for the evaluation of energy efficiency under different situations. This section presents an overview of the various types of energy efficiency modeling for high energy-consuming industries.

4.1. Stochastic frontier analysis

Scholars and scientists primarily tried developing energy efficiency linking both energy costs and outputs, and stochastic frontier analysis (SFA) models are the fundamental models. A brief review of SFA models has been presented in this part.

In 1970s, pioneering works of the SFA model have been established by Farrell [50] to bridge the gap between theoretical study and empirical work. This method figured out that there was a parametric relationship between inputs and production outputs. The SFA model was first employed in the estimation of production function by Aigner et al. [51]. Authors further extended this approach to evaluate the frontier production function based on the beginning study. Authors proved that the random volatility of variables can affect outputs. Therefore, they involved the specification of the statistical error, which is made up of two components, one-sided distribution and normal distribution. The SFA model is possible to capture the influential pattern of efficiency, which is relative to the stochastic frontier. This improved method overcomes the disadvantages which excluding the possibility of measurement errors. The formula is as follows.

Previous equation:

$$y_i = f(x_i;\beta) + \varepsilon_i \quad i = 1,\ldots N, \tag{7}$$

where y_i stands for the maximum outputs, x_i is the vector of inputs, β is a parameter of vector, and $\varepsilon_i \leqslant 0$, it is an assumption for the disturbance term.

Extended work:

$$\ln y = \beta_0 + \beta_0 \ln x + \beta_2(\ln p \times \ln z) + \varepsilon_i \tag{8}$$

where y is outputs, x means one independent variable, p is the gross book value of equipment per output, z stands for the ratio of the gross book value of equipment per output, and ε_i represents error.

The SFA model can also be adopted as a tool to estimate distance functions when there are multiple inputs and single output. It has been primarily applied to evaluate the industrial energy efficiency by Schmidt and Lovell [52] and Jondrow et al. [53]. The study illustrated how a technical evaluation process of industrial energy efficiency can be modeled. Authors employed the approach by using data on more than 100 power generating plants. They treated capital investment, fuel and labor as inputs that seeking to minimize the manufacturing cost of power generation to a stochastic frontier constraint [52]. Timmer measured the technical efficiency by the frontier production function. He adopted capital, labor and investment for estimating the outputs. He further compared the results with the traditional covariance methodology to prove the accuracy of estimation results. Moreover, the typical principle of the SFA model is shown in Fig. 1 to interpret the methodology [54]. Boyd and McClelland employed the SFA model not only to calculate the overall energy efficiency of plants but also to measure how environmental constraints affect the energy efficiency of plants [55]. The purpose of their study was to find out that whether simultaneous improvements in production outputs and environment performance are workable. The influential input factors contained capital stock, cost of fuel and labor, cost of materials and cost of electricity. The outputs are air pollution and productivity efficiency. They figured out that more environmental constraints will generate larger productivity losses. They could not be improved instantaneously without policy. Kopp and Smith [56] further compared the estimation of the SFA model with the results of normal least square stochastic frontier method. The inputs are consisted of 43 public coal-fired plants from 1861 to 1972. The empirical results presented that the SFA methodology was better than the normal frontier function.

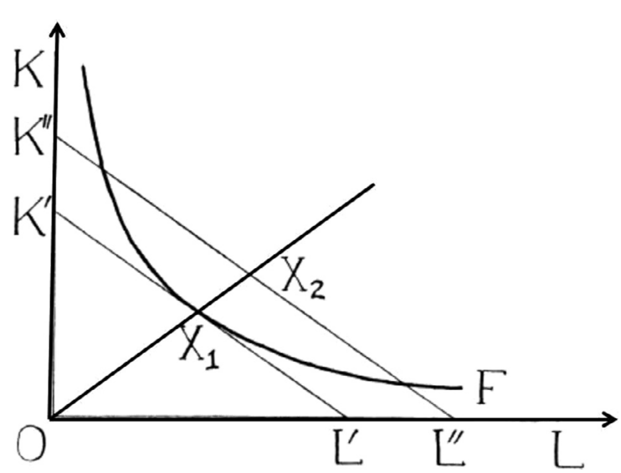

Fig. 1. The technical efficiency measurement by the SFA model [54].

With the development of higher requirement needed, the total factor productivity analysis was extended based on the SFA model. It is employed to estimate the maximum production possibility frontier, and to calculate which firm falls below the frontier. Schmidt and Lovell [52] and Greene [57] extended the methodology for the changes in various factors, and to observe how many firms above the cost frontier. Greene extended the methodology for decomposing rates of change in factor demands and for estimation of differential technological effect over several periods. The total factor-SFA model has been applied to electricity distribution include Burns and Weyman-Jones [58] and Kumbhakar and Hjalmarsson [59]. Burns and Weyman-Jones focused the characteristics of the cost function on estimating the economic of scale, and measuring whether electricity sectors were efficiently [58]. The latter study paid attention to the various inputs function, especially the importance of labor. Hiebert [60] provided an analysis of operating cost efficiency of fossil-fueled power plants, and examined the influential factors include units' capacity, fuel costs, number of units and outputs. The author reported that more plants capacity utilization led to the higher operating efficiency. There are increasing studies of SFA models on the measurements of energy efficiency of thermal power plants, includes See and Coelli [61], Lin and Yang [62], He [63], Lin et al. [64], Abbott [65], Granderson [66], Goto and Tsutsui [67], Graus et al. [68], Jung and Lee [69].

According to the increasing demand of energy efficiency evaluation and more influencing factor exists, extended models have been applied for the multiple outputs and multiple inputs of industries [70]. Knittel applied the SFA model on the energy efficiency measurement in the coal gas power plants. It concerned on energy use for producing outputs in multiple energy inputs, such as fuel cost, labor and heat rate. The study investigated how the factors affect the plant-level efficiency and the changes of efficiency. The study further analyzed the incentive regulation program, where regulators motivated the units to achieve the specific manufacturing efficiency [45]. More recently, Boyd's studies [71] proposed the use of the SFA model to estimate plant-level energy- use efficiency by involving the product mix. The study also investigated the ability to measure the "gap" between actual and best practice of energy efficiency. Zhou et al. applied the Shephard energy distance function, which is one of the SFA model to estimate economy-wide energy efficiency performance [72].

Environmental factors attract more attention since 2007. Watanabe and Tanaka [31] applied a distance function to evaluate the energy efficiency of industries at the provincial level in China.

Their results demonstrated that the sulfur dioxide positive correlated with the efficiency. They suggested that the environmental pollutants should be involved in the performance evaluation in countries like China.

The representative milestone of the SFA model should be the energy star program. This program was held by the US Environmental Protection Agency (EPA) in 1992. The purpose of the energy star program was to identify energy efficiency of industries. To promote them to reduce energy consumption, improve technology and reduce pollution in order to achieve the higher energy efficiency standards. The SFA model was treated as a tool for measuring energy efficiency of plants. The final ranking of products or the labeling of products were required for providing plant-level information. Boyd pointed out that the SFA model measured the energy performance indicator of overall industry level [71].

Until now, it can be summarized that, the SFA approach is a solid fundamental work in modeling application. The SFA approach not only allows the random fluctuation of variables but also contains measurement errors. Moreover, it is possible to analyze the inter-correlation of the determinants of energy efficiency performance. On the other hand, the major weakness of the SFA approach has been recognized, as follows:

(1) This methodology will lead to the superposition of measurement errors. Li et al. [73] have pointed out these problems and further developed a new hybrid methodology for evaluating energy efficiency precisely. The new method eliminated the above problems, and it can straightly evaluate the energy efficiency of power plants without artificial intervention [73].
(2) It is difficult to ascertain the specification of the error structure.

Because of the drawbacks mentioned above, more researches began to pay attention to the data envelopment analysis (DEA) models.

4.2. Data envelopment analysis

4.2.1. Background

Normally, there are two fundamental methodologies applied to the measure of frontiers. They are well-known as the parametric analysis and non-parametric method. The representative of parametric analysis is the SFA model, which was presented as above. The nonparametric method is the DEA model. The application of DEA model on the energy efficiency of industries will be reviewed in this part.

The DEA model was initiated by Charnes, Cooper, and Rhodes [74]. It is an extended comprehensive approach from a single input-output evaluation to a multiple inputs-outputs analysis. The efficiency of a decision making unit (DMU) is relative to all other DMUs with comparison [74], and it is judged by a simple requirement that all units lie on or below the energy efficiency frontier line. There are two types of DEA model, the CCR ratio model (Charnes, Cooper and Rhodes) [74] and the BCC model (Banker, Charnes and Cooper) [75]. The purpose of the CCR model is to evaluate the overall efficiency of a unit that contains both technical efficiency and scale efficiency. This model is designed with the assumption, which is that outputs increase proportionally with an increase in inputs. The BCC model evaluates the pure technical efficiency of a unit. Its precondition is that assumption of variable returns to scale, which means that the outputs of BCC model will not increase proportionally with an increase in inputs.

CCR model

The function of the DMUs is to convert all the best inputs into outputs, and the other DMUs are ranked related to the most efficient DMU. In the CCR model, the DMU is evaluated as follows [74].

$$\max h_0 = \frac{\sum_r u_r y_{rj_o}}{\sum_i v_i x_{ij_0}} \tag{9}$$

$$\text{Related to } \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leqslant 1 \text{ for each unit } j, u_r, v_i \geqslant 0, J = 1,2,\ldots,n, r = 1,\ldots,s; i = 1,\ldots,m \tag{10}$$

where h_0 is the efficiency index of DMU_0, i is the subject of inputs, j means the distribution, r is the subject of outputs, x_{ij} is the ith inputs of jth distribution. y_{rj} is the rth outputs of the jth distribution, u_r is the weight of rth output and v_i is the weight of ith input. The maximum energy efficiency index is 1, and there is no larger than 1 for any DMU. The DMUs located on the frontier means their efficiency level is 1, and the other DMUs will be at a less than full efficient level if they located inside the frontier line. Then the mathematical equation for the CCR ratio model is as follows.

$$\max \sum_r u_r y_{ro} \Big/ \sum_i v_i x_{io}, \tag{11}$$

under the following constraints:

$$\sum_r u_r y_{rj} / \sum_i v_i x_{ij} \leqslant 1 \quad \text{for } j = 0,1,\ldots,n, \tag{12}$$

$$u_r, v_i \geqslant 0 \tag{13}$$

BCC model

The BCC model is closed to the CCR model, its equation is as follows [75].

$$\min(\theta,\lambda) = \theta \tag{14}$$

$$\sum_{j=1}^{n} X_j \lambda_j \leqslant \theta X_0 \tag{15}$$

$$\sum_{j=1}^{n} Y_j \lambda_j \geqslant \theta Y_0 \tag{16}$$

$$\text{Subject to } \sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geqslant 0, \quad j = 1,\ldots,n \tag{17}$$

4.2.2. The application on high energy-consuming industries

The DEA model has become a widespread tool for benchmarking. This section merely provides an overview of the application of the DEA model on the energy efficiency index of high energy-consuming industries. Since the initial work studied by Charmes, Copper and Rhodes, the acceptance of DEA model has developed rapidly because of its strength and easy applicability in past two decades. There are numerous studies adopted the DEA model as the analysis methodology. It has been explored to evaluate the public sectors (eg. hospitals, office building and industries), private sectors (banks, telecommunications and airline companies). Boyd and Joseph [76] employed total-factor productivity to evaluate the productivity efficiency at the plant-levels in glass industries. The variables included cumulative outputs, capital, labor, consumption of electricity, cost of fuels and cost of other materials. The study estimated the difference of energy intensities at the plant-levels, and analyzed the relationship between energy intensity and productivity. They concluded that industries could reduce inputs and emission by 2–8% without decreasing productivity.

According to the study of Zhou et al. [77], 38% of studies focused on the energy efficiency performance of electricity power generation industries because the greenhouse effect is mainly caused by the fossil fuels fired. Around 80% of electricity is generated from

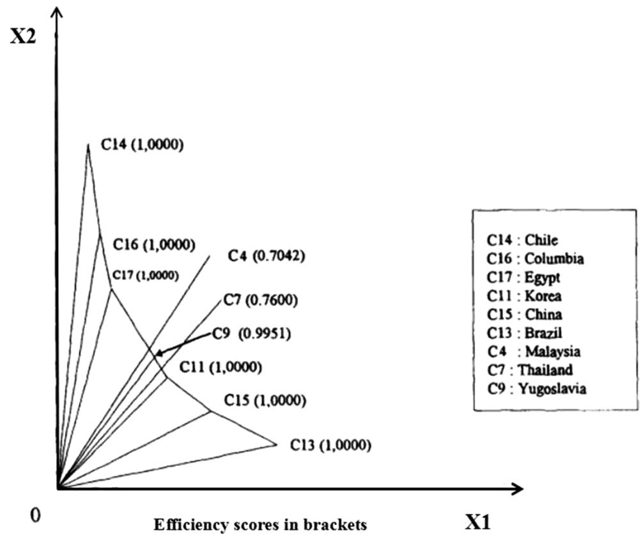

Fig. 2. The efficiency scores of electricity sector comparison in international level by the DEA model [86].

fossil fuels in thermal power plants, and the other 20% of electricity is produced from the clean energy sectors. The energy efficiency performance of thermal power industries is normally measured by the energy inputs-outputs analysis.

Most of the energy inputs-outputs methods are based on the evaluation and benchmarking of power plants with respect to the efficiency index. They focus more for the generation rather than on distribution of industries. These models are in consideration of fuel resource cost, capital investment and environmental factors. The primary study of energy inputs-outputs method was proposed by Färe et al. [78]. Authors applied the original DEA model for evaluating the energy efficiency of thermal power industries in Illinois. Labor, coal consumption and capital are the inputs adopted. Technical efficiency and scale efficiency are both identified in this study. Wang et al. adopted the Malmquist–Luenberger productivity index, which is the extended DEA model to calculate the cost efficiencies of thermal power industries in China's 30 provinces. Besides the variables mentioned above, carbon emissions are considered [79]. Färe et al. [80] further calculated six efficiency measures in a sample of private electricity industries and public owned electrical utilities. Golany et al. [81] applied the DEA model to measure the efficiency of power plants in Israel. Similar studies have been done by Hjalmarsson and Veiderpass [82] for estimating the Swedish industries. More than 45 oil firms have also been examined by the DEA model for the efficiency from 1980 to 1986 [83]. The production costs of oil and natural gas are analyzed as inputs. The productions of oil in barrels and natural gas in thousand cubic feet are treated as outputs. These papers normally follow the value of DMU ranking, such papers include Dyson and Thanassoulis [84] and Thompson et al. [85,86].

Yunos and Hawdon [87] applied efficiency comparisons at the international level. This is also the first time for the DEA model to use time-series data. Their study adopted installed capacity, labor total system losses and generation capacity factor as the input variables, and they treated gross electricity production as the output. The economic scale of international electricity utilities is demonstrated in Fig. 2 [86]. Pollitt [88] tried to analyze the efficiency in energy production units. The author examined the productive efficiency of 78 publicly-nuclear power plants and privately-owned nuclear power plants in the UK. Bagdadioglu et al. [89] further applied the similar scenario in Turkish electricity power industries. Authors found out that private firms relatively more efficient than public plants. Athanassopoulos et al. [90] not only estimated the operational efficiency but also paid attention to the development of decision-making. The study tried to explore the improved policy for efficiency performance of industries. Sueyoshi [91] extended a marginal cost measurement based upon the DEA approach to investigate the tariff issues among the 9 electric power companies in Japan. The study treated labor price, capital and material costs as inputs, and adopted commercial services as outputs. Park and Lesourd [92] did a similar study for the 64 coal-fired power plants in South Korea. Net electrical energy was an output, then fuel consumption, labor and installed capacity were treated as inputs. It should be mentioned that, authors adopted the econometric coefficient analysis to examine the correlation relationship. Raczka did heat plants study in Poland [93]. A slack-adjusted DEA model has been explored and applied by Sueyoshi and Goto [94]. They used this model to measure the efficiency performance of 25 Japanese electricity power plants. The study examined both technical efficiency and scale efficiency.

Because of the higher consumption of energy, some studies argued that the expenditure and the environmental constraint should be involved in the evaluation. Nowadays, the majority of the electric power industries are coal-fired plants. The main input is coal, which produces SO_2 emissions. Therefore, the SO_2 emissions should be considered as an undesirable output which should be evaluated to achieve the environmental regulation. Yaisawarng and Klein [95] measured the efficiency of coal-fired plants with consideration of emission pollutants. They treated fuel, labor and capital as variable inputs for the only one outputs, electricity. Moreover, they contained the environmental variables. The sulfur is an undesirable input and SO_2 emission is an output. The environmental DEA methodology has been widely applied in environmental performance measurement, such studies are include: e.g., Färe et al. [28], Zofío and Prieto [96], Tyteca [97], Zaim [98], Zhou et al. [77,99]. They not only considered the energy supply and labor but also involved the CO_2/SO_2 emissions.

Since 2001, there are growing number of studies adopted the DEA model in China. Lam and Shiu [100] adopted the DEA model to evaluate the technical efficiency of coal-fired plants in China. The panel data is the cross-sectional data from 1995 to 1996. Their result demonstrated that the fuel efficiency, and the installed capacity are important factors to the technological efficiency. Power plants had higher technological efficiency in the provinces of the eastern coast in China. Chien et al. [101] adopted the Malmquist productivity index based upon the traditional DEA model. The study measured the changes of productivity of power plants in Taiwan from 1994 to 1999. It further discussed the managerial policies. Liu et al. examined the operational efficiency of thermal power industries in Taiwan from 2004 to 2006 [102]. Wei et al. analyzed energy efficiency in iron industries and steel industries in China by using Malmquist productivity index [103]. Authors concluded that the energy efficiency of Chinese iron industries and steel industries are improved by 60% from 1994 to 2003. The upward shift in efficiency frontier was affected by the improved technology. Song et al. [104] applied the CCR method of DEA model to evaluate the generalized energy efficiency index and special energy efficiency index for 34 thermal power plants in China. For the generalized energy efficiency index, the coal consumption, the oil consumption, the water consumption and the electricity consumption are involved in inputs. The special energy efficiency index was only calculated based upon the coal consumption and the electricity consumption.

Yang and Pollitt [105] evaluated the efficiency performance of Chinese thermal power plants by adopting both uncontrollable variables and undesirable outputs. Besides the normal inputs variables, authors considered SO_2 emissions as the undesirable output. They further involved the NOx emissions and CO_2 emissions to measure the environmental performance of Chinese thermal power industries [106]. Zhang and Choi [107] employed the total factor-DEA model to calculate the efficiency of 93 Chinese power plants from 2005 to 2010. They also considered the pollution, and found out that the CO_2 emissions demonstrated a U-shaped trend. There are many studies that have focused on the air pollution issues in the Chinese industries. eg. Liu and Wen [108], Kaneko et al. [109] and Ma et al. [110].

The application of DEA models has been widely adopted around the world. The obvious advantage is that there is no assumption needed before the productivity functions. Furthermore, the DEA methods are easy to select multi-inputs and multi-outputs for the stochastic productivity systems, and inputs and outputs can have very different units. Moreover, it makes the scale of technology and the scale of productivity measurable that allowing for increasing or decreasing efficiency based on size of scale and output levels. The same characteristics that make the DEA a comprehensive tool can also create drawbacks. Because the DEA is a non-parametric methodology, the statistical hypothesis tests are difficult. It does not allow the exist of measurement errors or the influence of observable variables. This model is good at evaluating relative efficiency of DMUs. It can only provide the comparison information of DMUs, but nothing about the influential degrees of the variables.

4.3. Exergy analysis

Exergy analysis is a traditional methodology that performs in the field of industries to use energy more efficiently and optimize operational procedure. The thermodynamic exergy performance evaluation is based on the second law of thermodynamics that has been mainly applied for the evaluation, optimization, and improvement of industries. Some studies advised that exergy method is a powerful tool because exergy efficiency is always a measure of the approach towards the ideal. It not only measures the specific magnitudes of manufacturing progress but also designs more efficient energy systems by reducing the inefficiencies. In recent decades, more scientists recommended that the energy efficiency performance of industries is better measured by evaluating an exergy analysis because exergy analysis can provide more inside information.

Some studies prefer to apply both energy analysis and exergy analysis for a comprehensive methodology. Regulagadda et al. [111] earlier advised that the application of both energy and exergy analysis are more accurate for the overall efficiency of power generation. Rosen [112] applied the thermodynamic exergetic analysis for a 32 MW thermal power plant. The study combined the exergy analysis with the economic theory for identifying major sources of losses and improving the system performance. It was necessary for a detailed techno-economic assessment. The working fluid process diagram for the power plant is shown in Fig. 3, and the exergy of the state points are involved in the analysis [112]. Erdem et al. [113] compared the performance of 9 power plants from both energetic analysis and exergetic viewpoint. Authors summarized that considering energy and exergy approaches together can evaluate the inefficiencies in the process objectively. Ganapathy et al. [114] analyzed the energy losses and the exergy losses of the individual components of thermal power plants. Zubair and Habib [115] applied the exergetic analysis on the Rankine cycle power plants. Yang et al. [116] quantitatively measured the energy-savings potential of the overall efficiency from different plant-levels. Other similar studies are Sengupta et al. [117] and Regulagadda et al. [118].

The main limitation of exergy analysis is its weak application in energy industries. The reasons are as below.

(1) The exergy analysis merely considers the conversion efficiency, and it presents gains and loss of energy. The influence of economic and environmental factors are not involved.
(2) The computational results of exergy analysis is suitable for the expert, and it is not very convenient to interpret to the publics.

4.4. Comparing energy efficiency through industrial indicators

As an overview mentioned above, there are numerous studies for the evaluation of industrial energy efficiency based upon various methodological models. Some other papers prefer to adopt the industrial structure indicators for elaborating how these indicators can be applied in comparing energy efficiency levels. This section will summarize some representative papers.

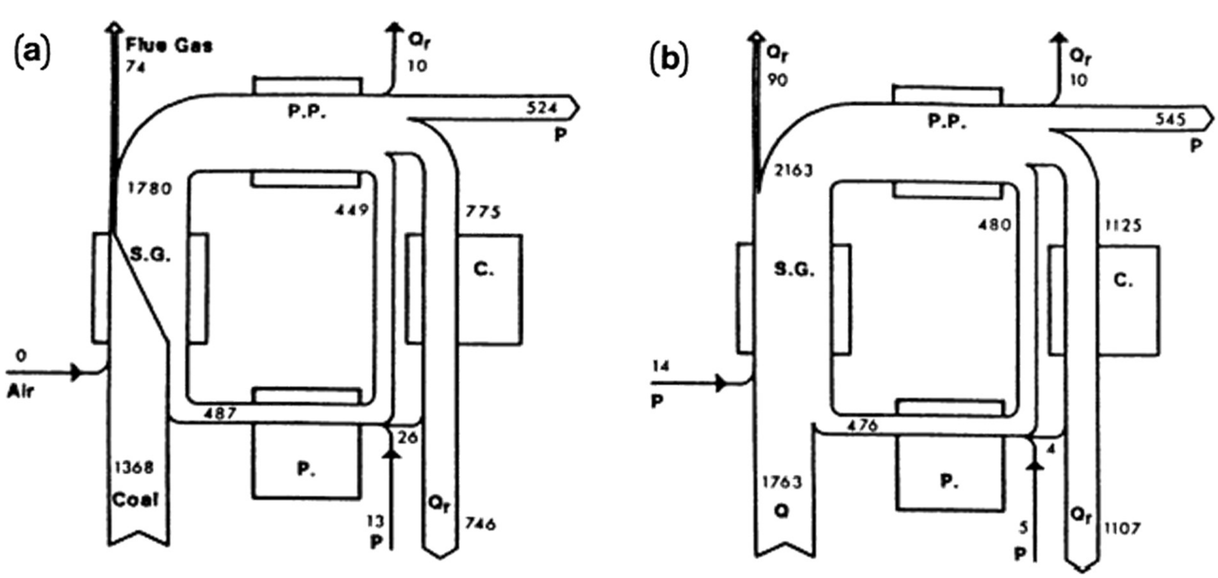

Fig. 3. Process flow diagram of exergy analysis for single units of the coal-fired Nanticoke generating station (a) and the Pickering nuclear generating station (b), illustrating net energy flow rates (MW) for streams [112].

In 1990s, Phylipsen et al. [34] has tried to identify structural physical indicators for the iron and steel industries. The study made cross-country comparisons of energy efficiency levels. Worrel et al. [119] not only compared the energy consumption of the iron industries and steel industries across countries but also found out the correlation relationship between economic indicators and energy consumption indicators. Farla and Blok [120] adopted physical indicators of productions for energy intensity of three Swedish steel industries. They further treated energy cost as a techno-economic indicator.

In recent years, the most well-known indicator comparison method is the top runner program in Japan [121]. In this program, the energy efficiency targets were set for different manufacturing industries, such as passenger vehicles (gas, diesel), motor trucks, and air conditioners (heating and cooling, cooling only). All industries were obligated to achieve the target level. Fig. 4 illustrates detailed methods about how to determine whether the target is achieved or not. It was decided by whether the sum of the difference in energy efficiency times the weighted number of units within the product division is positive or negative [121]. The basic function is as follows.

$$F = X_1 \times Y_1 + X_2 \times Y_2 + X_3 \times Y_3 + X_4 \times Y_4 \tag{18}$$

where F is the sum energy efficiency index, X_n represents products, Y_n stands for the difference between the product and the target value of energy saving. If the value of F is positive, it means that the target value has been achieved, vise versa.

Wu et al. [122] further developed the Taylor series expansion methodology for evaluating energy efficiency index at the process level of industries. The international energy agency (IEA) demonstrated a pyramid structure of the energy efficiency indicator system (shown in Fig. 5) [123]. The indicators at the top level normally are energy intensities, and the indicators at the bottom level are energy consumption per units (ECPU) of products [123]. Wu's study mainly focused on the ECPU. Song et al. [124] further developed a hierarchical indicator comparison (HIC) system based on the normal energy efficiency indicators. The HIC system focused on the Chinese energy conservation assessment program, especially the high energy-consuming industries. The basic principle of the HIC was to compare the actual energy efficiency indicators with the reference values. If the results were lower than the criteria, the plants will be non-qualified. The implement flow is presented as Fig. 6 [124]. Hasanbeigi et al. [125] employed the factor analysis to make an accurate comparison of the energy intensity between Chinese steel industries and American's. The study adopted energy use per unit mass to analyze the influence of specific factors on trends of energy efficiency index.

Although benchmarking method of energy efficiency is workable for the comparison in high-consuming industries, it has drawbacks as follows.

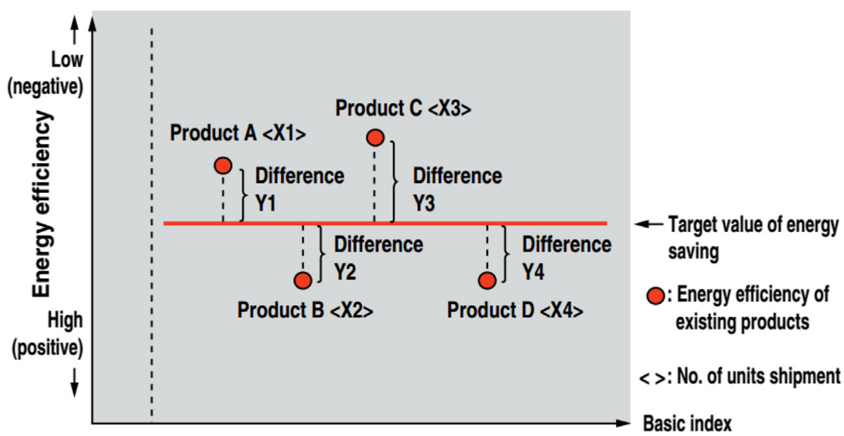

Fig. 4. Illustration of the indicator comparison method in top running program of Japan [121].

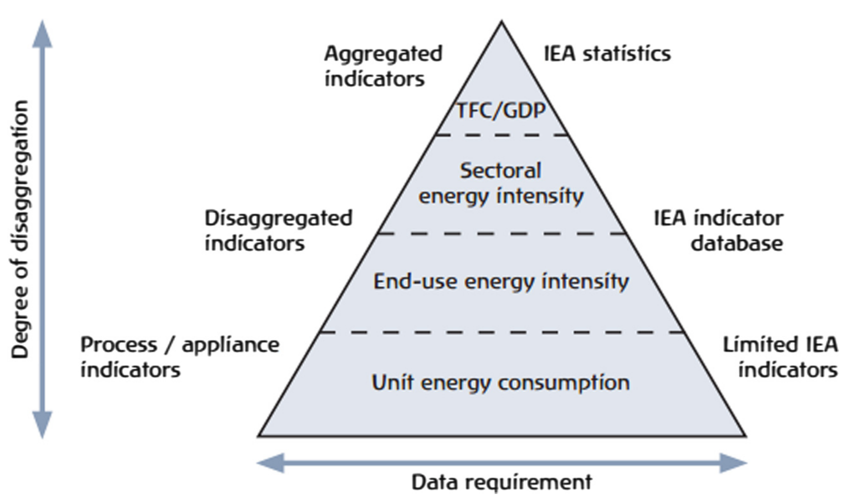

Fig. 5. The IEA energy indicators pyramid for the degree of comparison [123].

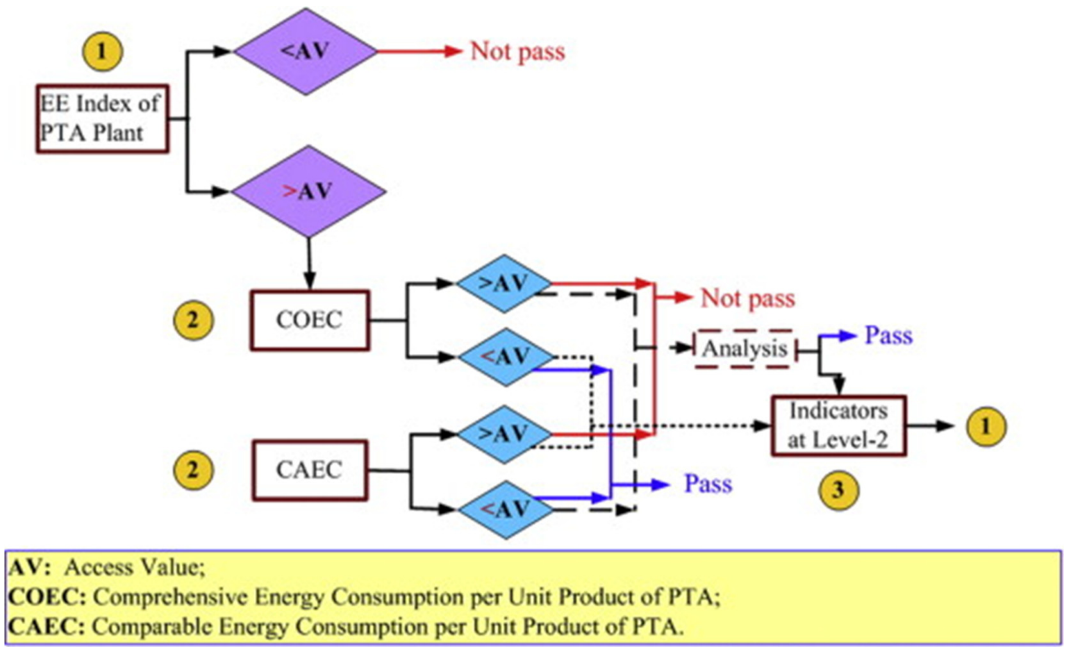

Fig. 6. The Implementation process of the HIC method for PTA industry [124].

(1) It is uncertain that adequate data can be acquired, especially these data are identified as the standard and a key limitation.
(2) Speaking at the operational aspects, it is not convenient to be adopted in comprehensive procedures having many influencing factors.
(3) Because of these unresolved challenges, the benchmarking method are mainly adopted by managers to select the best practices.

5. Policy of energy efficiency

5.1. Policy application

Governments and industries are increasingly paying more attentions on seeking energy conservation indicators and forward-looking indicators in order to publish related policies of high energy-consuming industries. The policy of energy efficiency requires detailed data at plant-levels to enable clarify policy objectives. This section mainly reviews the related polices of generating energy efficiency index.

Different countries published various industries policies and arts. The USA implemented the Energy Policy Act [126] and the EU announced the energy labels. The Japan Energy Conservation Law [127] and the Dutch Covenant [128] both expressed energy intensity as the units of energy per unit of GDP. Canada published the "Canadian GHG Challenge Registry" plan to motivate Canadian industries to reduce CO_2 emissions in order to achieve the target [129]. The UK presented the UK Emission Trading System [130] and the UK Climate Change Agreement [131]. Both set targets of energy efficiency in industrial sectors. The draft 13th Five-Year Plan of China has been released in March and scheduled to be passed. First, the overall target is to set a standardized measurement for energy use, which is a total energy consumption cap of 5 billion tons. Second, the non-fossil energy sources are becoming the prominent part of the Chinese energy. Third, the five-sixths of the reducing carbon target will be achieved by developing technology and improving energy efficiency of high-consuming industries. The remaining one-sixth will be depended upon the rapid growth in renewable energy and nuclear energy.

5.2. Suggestion: Need to combine energy policy, carbon schemes and the energy performance contracting (EPC)

According to the above-mentioned policies, almost energy policies always set the required target of national energy consumption. This paper believes that a more feasible way to reduce energy consumption is not only to promote polices but also support a combined regulation of polices, including carbon trade schemes and the EPC.

The necessary trend is a shift from fossil fuel, especially coals and gas, towards non-fossil fuel, such as nuclear and renewable energy. Therefore, the objective of carbon tax is not only to limit the usage of energy, but raising money to pay for the transformation towards CO_2 reduction.

The EPC includes project development, design, financing, and operation, measurement and verification. All of these sectors are carried out comprehensively. It is a contractual arrangement between the beneficiary and the providers for an improvement of energy efficiency performance. For example, power industries can employ the EPC companies to design and update the energy efficiency measurement. Customers can purchase electricity from companies, in combination with a package of EPC measures. The providers of EPC treat specified units of energy savings as their benefits over a defined period and providers further finances the capital investment from these savings. On a national scale, the revenue from the carbon taxes and energy-saving could be further adopted to promote the establishment of carbon trade schemes.

6. Conclusion

High energy-consuming industries possess a large, highly concentrated potential space for improving energy efficiency. This paper provides an overview and a literature review for methodological models of energy efficiency evaluation and their measurement in high energy-consuming industries, especially in the power plants. Various models and methodologies have been reviewed globally. The study also categorizes the classification of energy efficiency index and the related polices. The following significant influential factors in the energy utilization such as capital investment, environmental indicators, structural indicators (including energy consumption of plant-levels), GDP, energy price and labor have been considered with the variables in the function of linear frontier models. Moreover, the study discloses that technological indicators, environmental factors, demand and resource can be treated as constraints in models. The energy efficiency of industries is affected by the technology that is used and by the production level.

It has been summarized that the characteristic of linear regression models is merely present in the all-inclusive energy efficiency through single-entity models. The different types of DEA model are best suited to the multi-inputs and multi-outputs analysis. Moreover, it has been observed that the analysis of behavioral of mutual relationships between overall energy efficiency and influential factors are suitable for econometric models. Furthermore, it has been found out that the energy-economic models enable the decision-makers to plan and predict the future energy allocation.

There is also normal benchmarking for energy efficiency, which is carried out by comparing the obtained performance value from linear functions. Although these methods can be treated as the easy comparison between industries, they are not capable of making further analysis if the effect of production efficiency is involved.

It is expected that this study can help researchers and policy makers, who in the field of energy management for high energy-consuming industries, understand the overall situation of energy efficiency performance. Further study in energy efficiency performance is needed to combine other areas, such as carbon tax, carbon emission trade schemes and the EPC. The energy efficiency issues will not only be a technological issue of industries but also the comprehensive energy internet of the society.

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