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# ECONOMIC CONCEPTS OF ENERGY EFFICIENCY – A REVIEW

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## ABSTRACT

Energy security is the core of sustainable energy development. Energy efficiency is furthermore an important measure to ensure national energy supply security. According to the investigation of the number of production factors, energy efficiency indicators may be roughly divided into single-factor energy efficiency (SFEE) and total-factor energy efficiency (TFEE). SFEE means the ratio between the effective output and the energy input of an economy, while the energy consumption per unit of GDP (gross domestic product) is typically used as its index. TFEE, on the base taking into account the combination of multiple factors of various social inputs (i.e., capital, labor, energy, etc.), gets the efficiency frontier using statistical analysis method. In recent years, TFEE has been widely applied to the study of energy efficiency, while data envelopment analysis (DEA) is the more popular method to analyze TFEE currently. The purpose of this research is to comprehensively study the economic concepts of above-mentioned energy efficiencies, from development history, theoretical models, and literature review, their advantages and disadvantages are analyzed by comparisons, and the future directions of development are set forth as well.

**KEYWORDS**: Energy productivity; Traditional energy efficiency; Data envelopment analysis; Total-factor energy efficiency.

**Abbreviations**

SFEE Single-factor energy efficiency
TFEE Total-factor energy efficiency
GDP Gross domestic product
DEA Data envelopment analysis
GHG Greenhouse gas
EU European Union
SDA Structural decomposition analysis
IDA Index decomposition analysis
CRS Constant returns to scale
LMDI Logarithmic mean Divisia Index
DMU Decision making unit
CCR Charnes, Cooper and Rhodes
BCC Banker, Charnes and Cooper
VRS Variable returns to scale
LP Linear programming
OTE Overall technical efficiency
PTE Pure technical efficiency
SE Scale efficiency
PFEE Partial-factor energy efficiency
TFEPI Total-factor energy productivity change index
EATFEE Economy-adjusted total-factor energy efficiency
EST Energy-saving target

EVA Economic value added
CTE Comprehensive technical efficiency

## INTRODUCTION

With the rapid economic development, energy supply is the key to a country's economic development, but also the most important input factor to promote the business growth. In fact, studies show that there is a positive relationship between energy consumption and economic growth (Abosedra et al., 2009; Narayan et al., 2010). Energy provides tangible and intangible technological progresses as well as productivity growth (Berndt 1990; Narayan and Wong 2009). At the same time, the development and utilization of energy often have a negative impact on environment, such as the burning of fossil fuels is the main source of greenhouse gas (GHG) emissions seriously impacting on earth environment (Herring 1999; Miketa and Mulder 2005; Sari and Soytas 2009).

Reducing $CO_2$ emissions is not only a common global responsibility and obligation, but also an impact on a nation's product carbon footprint and industry's international competitiveness. So as to meet international carbon reduction commitments, the reduction of carbon dioxide is a key energy policy for world's major countries. Since the first oil crisis in 1973, many developed countries have launched related policies to improve energy efficiency and reduce energy consumption (Geller et al. 2006).

While developed countries formulate energy policies to improve energy efficiency under the premise that there is no damage to economic performance, some may be impractical or undesirable (Tolon-Becerra et al. 2010), so investigations and tests in the future are still needed. However, it is certain that energy efficiency improvement is a common goal for all energy policies. The EU (European Union) points out that improving energy efficiency can reduce GHG emissions, improve energy supply stability, reduce production costs, and enhance economic competitiveness. Boyd and Pang (2000) pointed out that energy efficiency improvement was crucial for the enhancement of total-factor productivity. Blomberg et al. (2012) and Clinch et al. (2001) defined energy efficiency as a reflection of energy source used whether effectively or not.

In recent years, Taiwan has been driven by highly developed economy and significant increase of energy consumption, but Taiwan's indigenous energy source has always been very scarce. With very high dependence on foreign imports, the energy dependence (particularly the indigenous/imported energy ratio trend in 1994-2014) is higher than 97%. Such as in 2014, Taiwan imported energy amounted to 144.6 million kiloliters of oil equivalent, with energy imports value vs total imports value up to 23.44%. So in order to address the uncertainty of international energy supply and reduce the impact caused by energy shortage, fully grasping the changes in consumption and efficient use of energy becomes an important issue for the country.

## ECONOMIC CONCEPTS OF ENERGY EFFICIENCY

According to different attributes of energy demands, the affecting factors on analyzing the energy efficiency can be divided into two categories: namely, intermediate demand and final demand. Wherein, the intermediate demand can be divided into three levels: industrial aspect (industrial restructuring), process aspect (improvement in process technology), and device aspect (promoting the end-use appliance efficiency), while the final demand can also be divided into three levels: sector aspect (adjusting the structure of sector), consumption activity aspect (various changes in consumption patterns), and the device aspect (appliance efficiency upgrade). If further explore the implicit impact variables on the three levels of energy efficiency, it can be found that the exchange rates, elements of the market price, resource endowments, product supply and demand structures in international market, technical progress speed, research, and development all have direct or indirect relationship with each other. Thus, the issue of energy intensity reduction (i.e., energy efficiency improvement) and overall economic factor has a relationship of "cause" to "effect", and vice versa, rather than one-way relationship. Cui et al. (2014) pointed out that there are two major issues for energy efficiency research, namely, the identification of impact elements (such as factor decomposition analysis) and the energy efficiency assessment (such as DEA). This chapter focuses on the relevant theories and estimation methods for energy intensity, and then discusses literatures as a basis for empirical analysis.

For the measurement of traditional energy intensity changes, a single energy input factor—productivity—is estimated, i.e., an index method proposed by Patterson (1996). If investigate the effect source of variation, some separation techniques can be further used to separate the effects, such as SDA (structural decomposition analysis) or IDA (index decomposition analysis). In recent years, Hu and Wang (2006), who proposed a new energy efficiency estimation method, claimed that only studying a single factor of energy efficiency—productivity—cannot effectively understand the changes in energy efficiency, and therefore, based on the concept of DEA, proposed an estimation method named Total-factor Energy Efficiency (TFEE). Yang (2012) had sorted the categories and the literature application statuses of energy efficiency index to organize a table (Table 1). This section sequentially describes the mentioned concepts (Fig. 1) as follows.

***Table 1. Energy efficiency indicator category comparison table***

| Indicator type | Calculation method | Problem and applicability |
|---|---|---|
| Energy productivity (reciprocal of energy intensity) | Ratio between useful output and energy input | - Easy for data acquisition and calculation<br>- Productivity does not equate to efficiency<br>- Calculation commonly using GDP and energy use, and unable to remove other impacts on GDP<br>- Unable to reflect individual elements of efficiency<br>- Unable to reflect the differences between resource allocation efficiency and technical efficiency |
| Energy productivity after factor decomposition | - Laspeyres Index<br>- Divisia Index | - Driven by energy productivity changes analysis, the relation between energy consumption and economy being purified<br>- Limited by decomposition method, and difficulty to get empirical support |
| Comprehensive energy efficiency index | - Technical efficiency<br>- Allocative efficiency<br>- Economic efficiency (Commonly used estimation methods include: stochastic frontier analysis, distance function method, DEA) | - Can be used to compare efficiency differences between manufacturers, can also estimate efficiency changes trend over time<br>- Can be applied to the comparisons in the levels of manufacturer, industry, region, and nation<br>- Unable to evaluate the efficiency of individual elements, (Hu and Wang (2006) further proposed TFEE method for the relative analyses) |
| Individual element efficiency index | Ratio between conditional element demand and actual | Inconsistent phenomenon possibly occurred between |

| | | |
|---|---|---|
| | element input | energy efficiency and cost efficiency |

Source: Yang(2012); Ou(2014)。

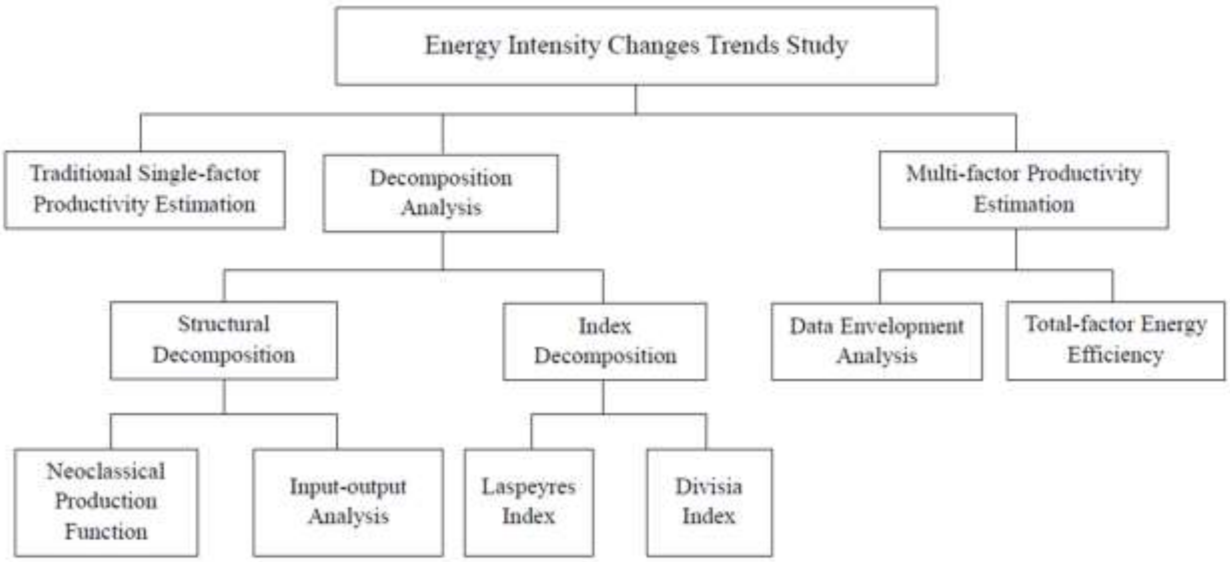


***Fig. 1 Energy intensity changes trends study chart***

Source: Ou (2014)

## TRADITIONAL ENERGY EFFICIENCY INDICATORS AND DECOMPOSITION ANALYSIS

Ways to measure the indicator of energy use can generally be divided into two kinds, wherein two indicators are basically reciprocal to each other. That is, (1) energy intensity: energy use per unit of activity output, and (2) energy productivity: activity output per unit of energy use. Patterson (1996) defined energy efficiency as:

Energy efficiency = (process useful output) ÷ (process energy input) (1)

This formula implies that value added created by per unit of energy input is energy efficiency. Considering the difference between output amount and energy input amount in terms of measure way and unit, we summarize at least four indicators used to estimate the energy intensity, as shown in Table 2, referring to formula (1) at the same time.

***Table 2. Summarized by Patterson (1996), four kinds of indicators used to estimate energy intensity***

| | |
|---|---|
| Thermodynamic indicator | - Numerator and denominator are based on thermodynamic units as measurement standards. |
| Physical-thermodynamic indicator | - Numerator energy portion is based on thermodynamic units as measurement standards<br>- Denominator activity portion is based on physical units as measurement standards |
| Economic-thermodynamic indicator | - Numerator energy portion is based on thermodynamic units as measurement standards<br>- Denominator activity portion is based on economic and monetary units as measurement standards |
| Economic indicator | - Both numerator and denominator are based on economic and monetary units as measurement |

| |
|---|
| standards |

The so-called "energy intensity" is usually obtained by dividing energy use amount with GDP, therefore implying the energy consumption amount that must to be input therein to increase one unit of GDP. If analyze in terms of energy intensity changes, there are two major decomposition analysis methods, namely, SDA (Structural Decomposition Analysis) and IDA (Index Decomposition Analysis). SDA method, analyzes inputs and outputs as the main theoretical foundation, also known as equilibrium analysis method, mostly used for researches in the fields of energy consumption and energy-related carbon dioxide emissions factors, for example, Su and Ang (2012) and Liao et al. (2013). IDA can be divided into two categories: Laspeyres Index and Divisia Index. Laspeyres Index uses a base year as base value to obtain its weight, measuring the change percentage of time-varying variable. Divisia Index, on the other hand, in a given form of linear integral, presents the growth rate of logarithm as its weight. It can be decomposed into pure intensity effect and pure industrial structure effect. Grasping the intrinsic elements of trend change allows us to better understand the current energy consumption change trend in entire industry and the variation trends of energy intensities between various sectors.

**Structural Decomposition Analysis, SDA**

SDA can be divided into two kinds: neo-classical production function method and input-output method. Regarding energy as one element of various production inputs, meanwhile emphasizing the demands of all input factors (e.g., labor, capital, energy, raw materials, etc.) determined at the same time, it is possible to analyze the demand elasticity, income elasticity and cross-elasticity for various input factors. The concept of input-output method first appeared in the economic theory of French economist Quesnay in 1758. Leontief in 1936 further developed a more complete model. Input-output method basically has to meet three hypotheses: (1) the fixed coefficient assumption; (2) the fixed proportion assumption; and (3) the single product assumption (Miller and Blair, 2009), as shown in Table 3:

***Table 3. Three assumptions developed by (Miller and Blair, 2009) for SDA***

| | |
|---|---|
| (1) Fixed coefficient assumption | Technical relation between input and output is constant; the production characteristic of each industry is CRS (constant returns to scale); that is, when all the elements simultaneously increase n times, its production also increases n times. |
| (2) Fixed proportion assumption | Each industry uses same fixed element proportion to produce, while this proportion is not influenced by yield level; this assumption implies irreplaceable natures existing between the elements of production. |
| (3) Single product assumption | Each industry only produces one kind of product. If manufacturer produces two or more products, the manufacturer should be classified into an industrial category of the main product produced by the manufacturer. |

Although SDA has been widely applied in energy economy and other related areas with more detailed analysis, there are some restrictions on application as the following:

(1)Too many required coefficients to be estimated, when processing time series analysis, it may be limited by the number of years observed, resulting in the problem of freedom degree shortage.

(2)Taiwan's energy element market is not totally competitive, wherein energy prices are not solely determined by market supply and demand or by relative prices of other elements of production.

(3)Due to the assumption of fixed technical coefficients, it is impossible to evaluate the energy-saving effect resulted from technological advances.

(4)Due to the assumption of a fixed return to scale, it is impossible to predict the economic scale resulted from energy use.

(5)Due to the emphasis of fixed proportion of direct input, it is impossible to make alternations between energy and other elements or between energy sources.

In early years, Jorgenson and Fraumeni (1980) used neo-classical production function model to analyze energy economics. Chen and Wu (1994) applied input-output method of structural decomposition model to analyze the sources of Taiwan industrial sector electricity demand changes in 1976-1986. The results showed that economic rapid growth was the most major factor impacting on Taiwan's electricity consumption in the industrial sector in 1976-1978, followed by the negative impacts of substitutive effect and technical progress. In addition, export demand and alternatives between energies were also the important factors contributed to the increase of industrial sector's electricity consumption. Although technical progress had a strong negative effect on electricity consumption, the effect had been markedly declined in the second half period of verification, and final demand changes in 1984-1986 also caused the decrease of electricity consumption.

Wang and Huang (1996) regarded that energy is a resource that must be used in various industries, so energy is a derived demand, while the purpose of the input-output model is to describe the industrial interdependence in entire economic system, thus the input-output model is particularly adaptable to depict the processes of energies used by various industries.

**Index Decomposition Analysis, IDA**

IDA, also known as factor decomposition analysis, focusing on the energy as a single factor of production, explores various effects on energy intensity changes, irrespective of the relationship between energy and other input elements. IDA has the characteristics of clear definition and high applicability of practical analysis. IDA, using mathematical identical relation as starting point, through simple mathematical calculation and transformation, explores the constituent of energy intensity. The purposes of factor decomposition of energy intensity are to decompose the constituent elements of energy intensity, and then calculate the contributions of various constituent elements to the energy intensity changes. Domestic and foreign literatures usually adopt factor decomposition method to decompose energy intensity changes into pure intensity effect and industrial structure changes effect.

(1)The effect of pure intensity

When the industrial yield and structure are unchanged, the total energy intensity change is the result of energy use efficiency changes in some sector.

(2)The effect of pure industrial structural changes

Assuming the various industries have fixed energy efficiencies, due to different energy intensity levels between industries, the total energy intensity changes effect is the result of the dynamic changes of the yield of each industry.

IDA can be applied to data of time series of a specific period, but the decomposition results are very sensitive to the choice of base year during the study period. In terms of the selection of base period, it can be divided into Laspeyres Index of fixed weights and Divisia Index of variable weights. They are described respectively as follows:

(1)Laspeyres Index of fixed weights

Taking prior period as base period, other variables fixed under base period are unchanged. When a particular variable changes, the changes effect of the variable is examined accordingly. The advantage of calculation is simple and the effect is obvious. The disadvantage is that the weights of each effect cannot be adjusted over time, because the base period value must be fixed to the prior period. Afterwards, Paasche further improved the concept of Laspeyres Index, taking current period as fixed base period weights. Fisher in 1972 further proposed the geometric mean of Laspeyres Index and Paasche Index as an indicator.

The representative example of Laspeyres Index of fixed weights is Jenne and Cattell (1983), who analyzed the energy use trends of the UK's industries in 1968-1980. Sun (1998) extended Laspeyres Index to study China's energy consumption, efficiency and saving effects in 1980-1994. The results found that, because of economic reform, China's energy efficiency was boosted. Reddy and Ray (2010) then used Laspeyres Index to study final energy consumption and energy intensity of Indian manufacturing industries. The study results found that the decline in energy intensity (i.e., the boost of energy productivity) is purely structural effect change, rather than the improvement of actual energy efficiency.

(2)Divisia Index of variable weights

Divisia Index was proposed by F. Divisia in 1925. Its biggest advantage is that the residual effect is less than the cross effect of Laspeyres Index or Paasche Index. That is, Divisia Index can better fully explain the changes connotation of energy intensity, and another advantage is that, under Divisia Index, the weights of each effect will vary with time changes.

Divisia Index was first used by Boyd et al. (1987), followed by the extension and improvement by many experts. It can be applied to survey the driving forces of energy consumption and carbon dioxide emissions. Ang (2004) provided the summary of a variety of methods and their respective advantages and disadvantages. Wherein, LMDI (Logarithmic Mean Divisia Index), because of its theoretical basis, adaption capability, ease of use, and explanatory power of results, became a popular method preferred by most disassemble analysis researchers. However, when data involves zero value, the complexity increases, because the formulas of LMDI contain logarithm items. Thus, Ang and Liu (2007) proposed eight strategies to deal with the zero value problem of LMDI decomposition. Sheibaum-Pardo et al. (2012) applied LMDI to assess the industrial activities, structures, substantial intensities, and relative contributions of the fuel switching changes in different sub-sectors in Mexico. Wang et al. (2014), with the combination of C-D production function and LMDI, analyzed the main drivers leading energy consumption in China in 1991-2011. The study found that, during the study period, the effect of energy intensity played a leading role in reducing energy consumption, and the effect of investment and labor was a key reason for the growth of energy consumption.

## DATA ENVELOPMENT ANALYSIS, DEA

### DEA's milestones

Debreu (1951), Farrell (1957), and Koopmans (1951) first proposed the concepts of efficiency and productivity. Farrell (1957), based on Pareto Optimality and Isoquant, proposed the concept of production frontier, and thereby established the theoretical basis for measuring the overall efficiency. They further divided the productivity of DMU (Decision Making Unit) into two parts: technical efficiency and price efficiency, which had non-parametric advantages as well as no limitation by functional forms. However, when Farrel (1957) proposed a technical measuring method based on single-input-and-single-output applied to the production efficiency analysis of multiple production factors, it met a considerable degree of difficulty.

Thereafter Charnes, Cooper and Rhodes (1978) extended Ferrell's model into the field of multiple inputs and outputs. Under the assumption of CRS, they calculated the optimum piecewise linear efficiency frontier using the mathematical linear programming, wherein the relative efficiencies of all DMUs may be further compared. It was the first time when the term of DEA was proposed. This first-presented DEA model was called DEA model of CCR (Charnes, Cooper and Rhodes) mode. Since the launch, CCR-DEA model had been widely used in the researches related to efficiencies of various industries, including banking, manufacturing, and health care. It had also been used to assess the performance of university, city, region, and country.

Because CCR mode is based on CRS principle, it cannot measure the inefficiencies caused by inappropriate setting of the scale of production. Therefore, Banker, Charnes and Cooper (1984) amended CCR mode to propose BCC (Banker, Charnes and Cooper) mode allowing VRS (variable returns to scale). Wherein, the all DMUs and commented objects with equivalent conditions are analyzed. At the same time, using four axioms that may be set by production and the distance function proposed by Shephard *et al.* (1970), the technical efficiency is decomposed into PTE (pure technical efficiency) and SE (scale efficiency) to investigate the effect of different returns to scale efficiency values.

DEA's CCR and BCC modes are the two most influential modes recognized by scholars, which not only can be used to assess an organization's performance, but also can be applied in many fields (Seiford and Zhu 1998; Wu and Ho 2009; Chang and Hsieh 2009). In terms of energy efficiency research and study, they indeed provide an effective tool for energy efficiency analysis. For in-depth understanding of DEA model can further refer to the following articles: Charnes *et al.* (1995), Ray (2004), and Huang *et al.* (2009)...

### DEA application procedures

Based on Golany and Roll (1989), standard application procedure of DEA is presented (Fig. 2). The general use patterns can be roughly divided into following four steps.

(1) Defining the DMUs

The purpose of DEA is to compare the relative efficiencies of DMUs. Therefore, in order to avoid interferences on DMUs from external variables leading to distortion of the compared results, DMUs must have the same target bases, namely, on comparison bases satisfied with the assumptions of same natures (homogeneous) and same market conditions.

(2) Deciding the number of appraised DMUs

In accordance with rule of thumb of Golany and Roll (1989), the number of DMUs must meet twice the items sum of input and output or above. Wherein, the outlier has to be removed to avoid the results from interference. In general, although the more number of DMUs is, the more accurate assessment on the relationship between input and output by the constructed efficiency frontier will be, but it is also possible to cause a result of the decline of the same nature(s).

(3) Selecting inputs and outputs

In general, the selection criteria of inputs and outputs can refer to the relevant literatures, the judging/screening methods based on management experiences, the non-DEA quantitative method, and the sensitivity analysis. Cui *et al.* (2014) had systematically organized the literatures of inputs and outputs. However, it must take into account the data natures and the correlation coefficient between the inputs and outputs, to judge if monotone principle is met.

(4) Results evaluation and analysis
The analyses and evaluations of DMUs' relative efficiency values obtained by the DEA model include: the efficiency analysis, the slack variable analysis, the sensitivity analysis, *etc.*

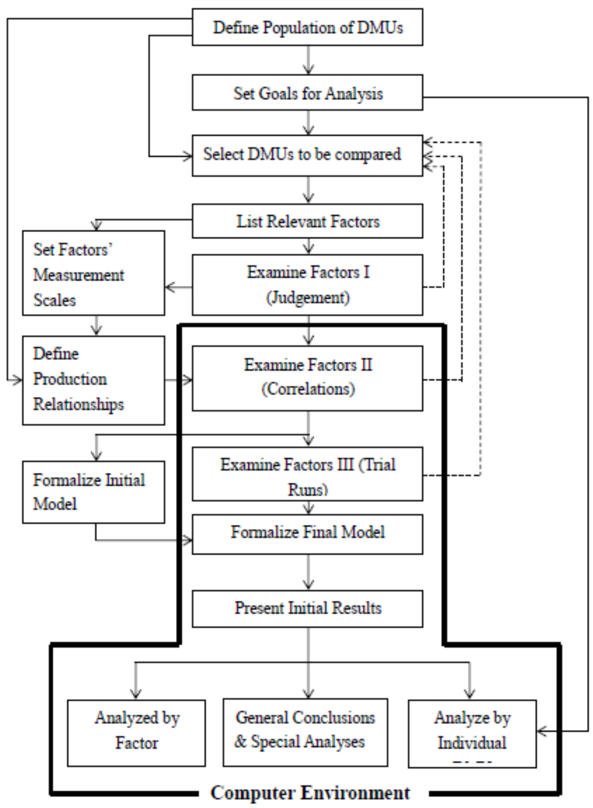


*Fig. 2* ***DEA application flow chart.***

Source: Golany and Roll (1989)

**Basic concepts of DEA model**

DEA uses the mathematical linear programming (LP) to obtain an optimal solution based on non-parametric method from the observed multiple-input-and-multiple output vectors, wherein a line segment (piecewise) non-parametric production frontier is estimated. Ji and Lee (2010) improved Coelli *et al.* (2005) and Cooper *et al.* (2006) to further explain the basic concepts of DEA. Literatures using multi-stage DEA model are: Coelli *et al.* (2005), Copper *et al.* (2006)...

**Efficiency analyses**

Efficiency analyses are divided into three categories: overall technical efficiency, pure technical efficiency, and scale efficiency, the definitions of which are described as below:

(1) Overall Technical Efficiency (OTE): refers to a minimum amount of input factor under a given level of output.
According to CRS-DEA model in CCR mode, the efficiency performance value of the appraised object is calculated to thereby assess whether the DMU has efficiency in the use of the input variables. When technical value is closer to 1, indicating that the use of input variables is more efficient, vice versa, the more inefficient.

(2) Pure Technical Efficiency (PTE): refers to a minimum amount of input factor, at a given output level of same scale.
According to VRS-DEA model in BCC mode, the efficiency performance of the assessed unit is calculated to thereby evaluate the pure technical inefficiency share in the overall inefficiency of DMU. The purpose is to

analyze whether there is room for the improvement of input and output ratio on the production efficiency frontier. When the efficiency value is less than 1, indicating there is no pure technical efficiency.

(3) Scale Efficiency (SE): refers to the optimum production activities of production scale on the productivity frontier.

SE can be obtained by dividing OTE with PTE, aiming to analyze whether the overall input amount is too much or the output items are too little. When DMU is in increasing returns to scale, it should expand the scale of production, and increase the use of production inputs. If DMU is in decreasing returns to scale, it should reduce the scale of production, and at the same time reduce the use of production inputs.

Relationship among the three efficiencies can be expressed as:

$$OTE = PTE * SE \qquad (2)$$

**Total-factor Energy Efficiency (TFEE)**

Based on DEA model concept, Jin-Li Hu and Shih-Chuan Wang proposed in 2006. Through linear programming, TFEE identifies the optimal energy inputs of inefficient DMU, and calculates the corresponding efficiency as output. Wherein, the adjustment values can be divided into "radial adjustment value" and "slack adjustment value." Wherein, "radial adjustment", representing the projected point of inefficiency point on the frontier, along radial line, adjusts its input level distance. On the other hand, "slack adjustment", in the non-parametric frontier piecewise linear form, is the second stage transferring the projection point to the actually lowest input point on the frontier, which represents the distance between two points moving along the frontier, as shown in Fig. 3.

(1) Total adjustment amount = "radial adjustment value"

Such as point B is the actual input value, while point B' is the projected point on the frontier (as target value of DMU B); through reducing radial value, BB' is adjusted in order to improve its efficiency.

(2) Total adjustment amount = "radial adjustment value" + "slack adjustment value"

In order to determine the point of actual minimum input, it needs a second phase adjustment through a piecewise linear movement along frontier. Such as point A' is the target projected point of DMU A on the frontier. Through reducing the radial line to adjust the AA' value, the target input amount can be reached. At point A', the input level can be further lowered down to C point, while the output maintains the same level. CA' should be the slack adjustment value by moving point A' along the production frontier. Thus, in order to select a total input adjustment amount (CA) for achieving an optimal DMU productivity, the radial adjustment value (AA') and the slack adjustment value (CA') are added together, likely implying that when improving efficiency, it is necessary to enhance the technical level and adjust the production process simultaneously.

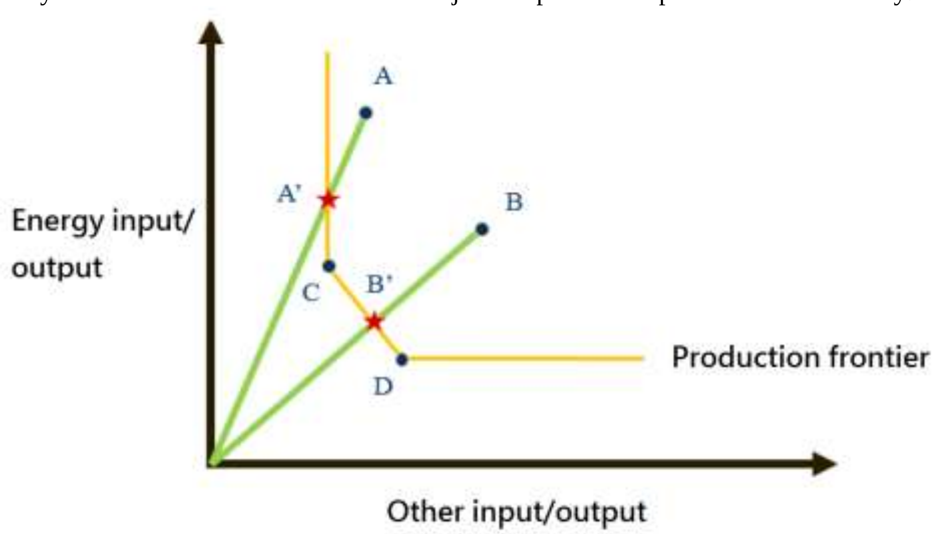


***Fig. 3*** ***Illustration of radial and slack adjustments of input-oriented CRS-DEA.***

Source: Ou (2014)

When production function combines energy as inputs, the target level of energy input is called "target energy inputs", which presents the optimum energy efficiency with an actually lowest level of energy input. The total energy input adjustment amount will be considered as inefficient energy consumption. The increase of total adjustment amount of energy input represents the more efficiency of consumption energy. If the total energy input adjustment amount is 0, it represents the region with target energy amount put into production, regarded as a maximal output under optimal energy consumption. In general, TFEE is built on the viewpoint of total-factor productivity, which is defined as the ratio of the optimum energy input and the actual energy input. The formula is expressed as follows:

$$\text{TFEE}\ (i, t) = \frac{\text{Target Energy Input}\ (i,t)}{\text{Actual Energy Input}\ (i,t)}\ \ (t^{\text{th}}\ \text{year and}\ i^{\text{th}}\ \text{industry}) \qquad (3)$$

TFEE index indicates the efficiency level of regional energy efficiency, in which "target energy input" is the minimized energy input level, so "actual energy input" will be greater than or equal to "target energy input." Thus, TFEE index value will be between 0 and 1. When a DMU's actual energy input level is equal to target energy input level, TFEE equals 1, and vice versa, if TFEE index value is closer to 0, representing the more inefficient.

## LITERATURES REVIEW OF TFEE BASED ON DEA

Hu and Wang (2006), based on DEA model in CRS mode, innovated the TFEE index method. In their study, a multi-input-and-single-output model was adopted to analyze the energy efficiencies of China's 29 administrative regions during the period of 1995-2002. By taking labor, capital, energy consumption, and farming acreage (rather than biomass energy potential) as four inputs, the real GDP was the only output. Their empirical results showed substantial differences to the estimated results of traditional partial-factor energy efficiency (PFEE) that only considered the energy productivity of local effect. Namely, the estimated results of TFEE index model showed more realistic data. According to China's regional TFEE index rankings, the eastern region (China's most economically developed region) was superior to the western region (China's least economically developed regions), followed by the central region (China's economically developing region), which was different from the expected results: "Eastern > Central > Western," because the total adjustment amount of energy consumption in China's central region was more than half of the country's total. Finally, there was a U-shaped relationship between TFEE and per capita income in each Chinese region, implying a trend that energy efficiency would be ultimately improved in the meantime of economic growth.

Mukerjee (2008) estimated the energy efficiency of the manufacturing sector in the United States during the period of 1970-2001 from a theoretical point of view. Based on DEA, Mukerjee proposed four models: the first and second models considered reducing the use of energy in a given level of output without increasing other inputs; the third model, based on the concept of minimal cost, estimated the energy efficiency; the fourth model, only considering the slack of capacity utilization, tested whether there had been over- or underutilized energy. The results showed that, although there was as quickly as possible over time to adjust the investment proportion in facing energy impact, the manufacturing sector still encountered bottleneck of decision latency. In the four studied industries, the paper manufacturing and its products was the most energy efficient industry in the manufacturing sector. Basic metal industry had the worst performance in the manufacturing sector. By comparing cross-border efficiencies, the results showed that studied samples appeared to be more effective during the last few years, implying there had been technically progressive.

Based on energy audit data of Taiwan's non-manufacturing industries, Chang and Hsieh (2009) systematically applied factor decomposition analysis and DEA assessment model to estimate energy-saving performances and potentials for Taiwanese non-manufacturing sector during the period of 2004-2008. The results showed that the lowest energy intensity subsectors in the non-manufacturing sector from 1982 to 2007 were "wholesale and retail trade" and "finance, insurance, and real estate." Results by DEA model showed that the efficiency of "medical health and social work services" maintained high level in calendar years, while "wholesale and retail trade" was the lowest, followed by "real estate industry," and "public administration and defense."

Based on concepts of TFEE and Luenberger production index, Chang and Hu (2010) proposed a dynamic indicator named total-factor energy productivity changes index (TFEPI). Extending the study of (Hu and Wang, 2006), Chang and Hu (2010) evaluated China's energy productivity changes in the period of 2000-2004. Wherein, TFEPI could be in turn decomposed into two items: (1) the energy efficiency changes (the subject matter is close to or away from its annual frontier); and, (2) the energy use technology shift (the production frontier is shifted under the total-factor framework). The results of study found: (1) the traditional energy productivity index overestimated the energy productivity changes; (2) China's total-factor energy productivity had been decreasing 1.4% every year since 2000, including an average TFEE change improvement of about 0.6% per year, while the total-factor energy use technical change was gradually down 2% in each year. Thus, the resulted energy productivity decline was mainly due to the negative growth of technology, rather than the result of relative efficiency changes. Finally, by examining the affecting factors of TFEPI, the results showed that: (1) the TFEPI of the eastern region was higher than those of the central and western regions; and (2) improving the development status of energy consumption and increasing the share of electricity use would elevate the performance of regional TFEPI, but if the GDP increase was contributed by the second grade industry, the regional TFEPI performance would be deteriorated.

Under TFEE framework based on DEA and with directional distance functions, Wang *et al.* (2011) built up two energy efficiency models. Meanwhile, with concepts of SFEE, TFEE and target energy intensity, Wang *et al.* (2010) analyzed the energy efficiencies of all Chinese provinces during the period of 2004-2008. The empirical results showed that: (1) the overall level of China's energy efficiency was lower, because the energy input and economic output did not achieve a good ratio, showing the situations of high input, low output, and low efficiency, so there was still considerable room for improvement; (2) the energy efficiency developments of Chinese provinces or three regions were significantly imbalanced, wherein the eastern coastal region had higher energy efficiency, while the central and western regions had lower energy efficiencies; and, (3) general speaking, the whole energy intensity was high, so there was considerable room for improvement.

Liang (2011) applied Divisia Index and DEA methods to explore the energy efficiency of services sector in Taiwan from 2003 to 2008. Wherein, Divisia Index method could decompose the economic energy intensity indicators into value added changes and structural changes to observe the energy efficiencies of overall sector and individual industry during the study period. DEA and statistical analysis then further discussed the energy use characteristics and the energy saving potentials. The study found that the energy efficiency of services sector had been improved, mainly due to the improvement of physical energy intensity as well as the enhancement of value added. Meanwhile, the energy prices were the main cause of the reduction of physical energy intensity. Although the energy prices hikes were somewhat helpful for the decline of energy intensity in the services sector, regulations were more effectively to improve the energy efficiencies of the relative industries by means of the setup and establishment of relevant measures, for example, the minimum energy efficiency standards for appliances and the energy efficiency classification system.

Fang *et al.* (2013) used a VRS-DEA input-oriented method to evaluate three energy efficiency indices for the services sector of Taiwan during the period of 2001 to 2008. The three energy efficiency indices were PTE, TFEE, and EATFEE (Economy-adjusted Total-factor Energy Efficiency). Through the combination of industrial characteristics and the four-stage DEA proposed by Fried *et al.* (1999), Fang *et al.* (2013) investigated the impacting effects of industrial characteristics on EST (energy-saving target). Wherein, three inputs (labor, capital, and energy consumption) and an output (real GDP) of DEA model were used. The study found that the most energy efficient industry in services sector was the finance, insurance and real estate. Its average TFEE and EATFEE were 0.994 and 0.807 respectively. Both were the highest scores in services sector. Finally, EST (as a dependent variable), panel data, and random effects Tobit regression model were used to test "capital-labor" ratio hypothesis of the energy efficiency. The results showed that the services industries with more GDP output also had more energy overuse situations. In the "capital-labor" ratio aspect, there was a significantly positive effect. Because a lot of high-tech services industries in Taiwan used energy-consuming equipment, an energy use inefficient phenomenon was resulted. On the other hand, the time trend variable had significantly negative effect on ETS. With the capital investment by Taiwan's services sector, the situation of excessive use of energy was improved under the development of energy-saving technologies.

Cui *et al.* (2014), first, with EVA (economic value added), selected inputs and outputs that significantly affected the energy efficiency of energy industry. According to the results, three inputs were selected: the number of labor, the energy consumption, and the energy services amount, while the two outputs were $CO_2$ emissions per capita and industrial total profits. Secondly, with DEA-Malmquist Index, Cui *et al.* (2014) calculated three energy indices: CTE (comprehensive technical efficiency), PTE and SE for nine countries in 2008-2012 to observe their changes in energy efficiency. The study found that the average CTEs of nine countries had significant gap during the study period, but afterwards, the gap had a trend of becoming smaller and smaller. Moreover, each country's energy efficiency index change had different reason, so the development of energy project should be based on each country's situation. Finally, through panel regression model analysis, Cui *et al.* (2014) identified the impact factors on energy efficiency. The results pointed out that, in terms of energy efficiency index, the most important factor of positive effect was "high-tech energy enterprise tax exemption (tax-free)," through an impact on energy efficiency index by PTE change index; the minor factor of positive effect was "energy technology (R&D input)," through an impact on energy efficiency index by technical progress change index; the main factors of negative effect were "non-renewable energy consumption rate (consumption)" and "exhaust energy emissions intensity." The results showed that technical index and management index were the two main reasons affecting energy efficiency. Wherein, the technical index affected on the energy efficiency index mainly through technical advances, while the management index affected on the energy efficiency index mainly through PTE changes. In the study period of 2008-2012, the average energy efficiency performance of Chinese government ranked first among the nine countries, showing that China had taken many effective measures of technology and management upgrades for the improvement of overall energy efficiency.

Honma and Hu (2014), with DEA concept, computed the industry-level TFEEs and energy-saving potentials for 14 developed countries in EU KLEMS database in 1995-2005. Finally, a sensitivity analysis was conducted to test the results' robustness, while the results were compared with traditional partial-factor energy productivity. Wherein, the model used labor, capital stock, energy, and non-energy intermediate input as four inputs, and the industrial value added as only output. The results pointed out that Japan's three industries—construction, food and metal—obtained efficient TFEE scores throughout the study period; but chemical, machinery, non-metallic mining, paper and other industries obtained inefficient TFEE scores in some years. Japan's weighted TFEE fell from 0.986 in 1995 slightly to 0.927 in 2005, showing that Japan could further optimize its projects of energy conservation and carbon reduction. During the study period, Germany, Britain and the United States frequently became the efficient industrial benchmarks for Japan, while the United States was the benchmark for every industry in Japan. Through learning the energy-saving technologies from benchmark countries, Japan could further improve its industrial energy efficiency. In addition, Japan's energy-efficient industries could also become the benchmarks for other country's inefficient industries, such as Italy's food industry and Czech Republic's chemical industry. Japan, through the provision of energy-saving technologies, could improve the energy efficiencies of other country's energy-inefficient industries.

With traditional energy efficiency index, DEA models and TFEE model, Ou (2014) explored the development trends and improvement potentials of energy efficiencies for Taiwan's top three energy-intensive industries accounting for more than 10%, namely, chemical materials, basic metals, computers and audio-visual electronic communications for the study period of 1990–2012. The empirical results showed that the energy efficiency changes trends estimated by the three indices were roughly the same but with the exception of traditional energy efficiency index. In the traditional energy efficiency index analysis, since 2006 was selected as the base period value (i.e., 2006 = 100), its estimated value was higher than those of DEA model and TFEE model, likely misleading a result that the overall energy efficiency performance was good. The frontier efficiencies of DEA model and TFEE model were self-constructed through mathematical programming. Under the implementation of multi-input and single output, the actual application was more comprehensive, including that DEA model took into account the changes in circumstance of three inputs simultaneously. Therefore, the estimated results might be affected by the two inputs of capital and investment, resulting in that the overall efficiency was better than the efficiencies separated by TFEE (in some years even more so). However, TFEE could improve the shortcomings of DEA, e.g., isolating the technical efficiency of a single factor. The results showed that, in terms of the evaluation of energy efficiency performance, in addition to traditional energy intensity index, Hu and Wang (2006), after improving DEA, further proposed TFEE that was a good choice and reference capable of being used as a supplement for traditional energy efficiency index.

## CONCLUSIONS AND DISCUSSIONS

At present, there are numerous domestic and foreign researches on energy efficiency. Depending on the measuring methods of output and input, energy efficiency has different forms of variants. To avoid confusion, in generally, based on the number of the production elements examined by the energy efficiency indicators, the energy efficiencies can be roughly classified into SFEE and TFEE (or multi-factor energy efficiency).

SFEE means the ratio between the effective output and the energy input of an economy, while the energy consumption per unit of GDP is typically used as its index. TFEE, on the base taking into account the combination of multiple factors of various social inputs (i.e., capital, labor, energy, etc.), gets the efficiency frontier using statistical analysis method. In recent years, TFEE has been widely applied to the study of energy efficiency, while DEA is the more popular method to analyze TFEE currently.

All in all, among the traditional energy efficiency indicators and decomposition analyses, the neo-classical production function method and input-output analysis of SDA have the superiority in the overall analysis, but also inevitably have certain shortcomings and restrictions on applications. The biggest problem is that, when processing analysis by either neo-classical production function method or input-output analysis, a relatively large amount of data is required. Meanwhile, a number of basic assumptions of input-output method are questionable. Moreover, Taiwan's energy market is not a fully competitive market, so it is also necessary to consider the applicability of the data (Wang *et al.*, 1994).

Although IDA's LMDI has been successfully applied to the study of energy consumption and the decomposition analysis of carbon dioxide, the investigation of other factors is also included, for example, the fixed capital investment or labor. Only using energy as single input is unable to produce its outputs, so when measuring productivity, it must also consider other inputs, for example, labor and capital stock. Basically, when using DEA model to analyze the optimal input target of a country's energy-intensive industries, the technical level lag or inefficiency in the manufacturing process will consume unnecessary energy. Through DEA to calculate the slack and radial adjustment values, Hu and Wang (2006) proposed TFEE, wherein DEA is applied to a multi-input-and-single-output framework that is constructed by target energy inputs ratios and an output of value added (GDP). Multiple inputs of energy, labor, and capital stock are incorporated into the methodology, amending the traditional methods that only consider the energy as an input (Patterson, 1996).

In past studies, the majority of inputs and outputs of energy efficiency were determined through qualitative analysis and literature review, but the rationality is questionable due to lack of persuasiveness. Cui *et al.* (2014) recommended that the input and output variables of energy efficiency to be calculated should be selected through quantitative analysis of EVA, while the important factors affecting energy efficiency can be analyzed through the panel regression model. In the future, researchers may also consider the use of performance evaluation stochastic frontier method and other parameters method for the test.

SFEE is often defined as the ratio of useful output and energy input of an economy. In life, the most commonly used indicator of SFEE is GDP energy consumption index. TFEE method was oriented from the total-factor productivity on microeconomics. Various input elements of social production, to a certain extent, can substitute for each other, and the final output is the combination of various production elements, rather than some production element, like energy or labor and so on.

Single-factor method only measures the energy efficiency of a proportional relationship between energy input and output, without taking into account the other input factors affecting the production, so it is impossible to measure the potential technical energy efficiency, neither can measure the impacts of other combination of input factors on energy efficiency, because GDP output is the results by the combination of mutual alternative elements of energy, capital, labor, and others. With above obvious defects, SFEE index is difficult to reflect the real "efficiency" factor. Based on the total factor productivity theory of microeconomics, TFEE not only considers the impacts of energy and other social input portfolio elements, but also can measure the potential energy efficiency in production technology. Compared with conventional SFEE, TFEE has obvious advantage of make up its shortcoming to some extent.

Existing research methods, either the traditional single-factor method or the total-factor method based on DEA, has its own advantages and disadvantages. Overall, the single-factor method, simple to use and easy to understand, but ignores the contribution of capital and labor to GDP and the substitutive effects among energy use, labor, and capital. Compared with the single-factor method, the total-factor method has a great advantage in this regard; namely, it not only can accurately measure the substitution effect between production elements, but also can reflect the energy use comprehensive level in a region under a given production element structure. However, total-factor approach also has its drawbacks. First, the total-factor efficiency index is relative. This relativity is reflected in two aspects: one is the relative efficiency of the frontier; second is the relative size of the data sample. Moreover, there are drawbacks for DEA itself either. Essentially, DEA is an extreme value method. When efficiency frontier is estimated, its quality is vulnerable to the impact of the sample data. In general, when studying a country's energy efficiency levels, there are relatively a lot of data errors, so the results based on the data obtained by DEA need more rigorous testing.

Therefore, when studying energy efficiency, it is necessary to consider the advantages and disadvantages of different methods. Appropriate method should be mainly based on TFEE, whereby certain design methodology is introduced to reduce the negative impacts due to the data quality problems caused by the results of DEA model. In the all possible situations, we should try to use several different methods to compare and verify the objectivity of the final results.

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