Linear programming models for measuring economy-wide energy efficiency performance

P. Zhou a,⁎, B.W. Ang b

a Energy Studies Institute, National University of Singapore, 29 Heng Mui Keng Terrace, Singapore 119620, Singapore
b Department of Industrial and Systems Engineering, National University of Singapore, 10 Kent Ridge Crescent, Singapore 119260, Singapore

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Data envelopment analysis (DEA) has recently gained popularity in energy efficiency analysis. A common feature of the previously proposed DEA models for measuring energy efficiency performance is that they treat energy consumption as an input within a production framework without considering undesirable outputs. However, energy use results in the generation of undesirable outputs as by-products of producing desirable outputs. Within a joint production framework of both desirable and undesirable outputs, this paper presents several DEA-type linear programming models for measuring economy-wide energy efficiency performance. In addition to considering undesirable outputs, our models treat different energy sources as different inputs so that changes in energy mix could be accounted for in evaluating energy efficiency. The proposed models are applied to measure the energy efficiency performances of 21 OECD countries and the results obtained are presented.

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1. Introduction

With high energy prices and the concern about global warming and sustainable development, energy efficiency has become a vital part of the energy strategy in many countries (Ang, 2006). Researchers have developed appropriate indicators for monitoring economy-wide energy efficiency trends over time or comparing energy efficiency performances across countries/regions. A number of national energy agencies and international organizations have developed their energy efficiency measurement and monitoring systems. See, for example, IEA (2004a, 2007), EECA (2006), NRC (2006), OEERE (2007) and ODYSSEE (2007).

The foremost issue in the measurement of energy efficiency performance is to define the term “energy efficiency” (Patterson, 1996; Ang, 2006). There exist various definitions of energy efficiency, among which “the ratio of energy services to energy input” is a popular one. The definition given in the Directive 2006/32/EC of the European Council and the Parliament on energy end-use efficiency and energy services is a general one, namely energy efficiency is “a ratio between an output of performance, service, goods or energy, and an input of energy”. Different definitions of energy efficiency would lead to different indicators being used to monitor changes in energy efficiency, which can yield very different results and policy implications (Berndt, 1978). At the economy-wide level, since there is no single meaningful measure for energy services across all energy-consuming sectors and as such various approaches to measuring energy efficiency performance have been proposed in the literature.

A common practice to measure economy-wide energy efficiency performance is to first decompose the change in energy consumption or aggregate energy intensity into a number of contributing factors, and then aggregate the effects of energy intensity changes at energy end-use or sub-sector level to give a composite energy efficiency performance index (Ang, 2006). The decomposition of energy consumption or aggregate energy intensity can be implemented by the index decomposition analysis (IDA) technique (Ang and Zhang, 2000; Ang 2004; Liu and Ang, 2007). This IDA-based approach has been adopted by a number of countries including Canada, New Zealand and the United States to track economy-wide energy efficiency trends over time (EECA, 2006; NRC, 2006; OEERE, 2007).

It has been found that IDA-based energy efficiency studies mainly dealt with the measurement of energy efficiency changes over time in a specific entity, such as a country or a specific energy-consuming sector. Few of them dealt with the benchmarking of energy efficiency performance across different entities. In contrast, data envelopment analysis (DEA) has recently been

⁎ Corresponding author. Tel.: +65 6516 2000; fax: +65 6775 1831.
E-mail address: gt0300220@nus.edu.sg (P. Zhou).

1 Patterson (1996) classified various energy efficiency indicators into thermodynamic, physical–thermodynamic, economic–thermodynamic and economic
widely applied to evaluate the energy efficiency performances of different entities.

DEA, proposed by Charnes et al. (1978), is a well-established non-parametric frontier approach to evaluating the relative efficiency of a set of comparable entities featured with multiple inputs and outputs. The recent literature survey by Zhou et al. (2008a) found a rapid increase in the number of studies using DEA in the broad area of energy and environmental analysis. In energy efficiency studies, DEA has also gained in popularity. For instance, Boyd and Pang (2000) discussed the relationship between productivity and energy efficiency, and Ramanathan (2000) used DEA to compare the energy efficiencies of alternative transport modes. More recently, Onut and Soner (2006) applied DEA to assess the energy efficiencies of alternative government buildings. Wei et al. (2007) investigated the energy efficiency of energy-intensive manufacturing sectors. Wei et al. (2007) proposed an integrated DEA approach to assessing the energy efficiency of energy-intensive manufacturing sectors. Wei et al. (2007) investigated the energy efficiency of China’s iron and steel sectors by using DEA-based Malmquist index approach. Mukherjee (2008) proposed several DEA models for measuring the energy efficiency of manufacturing sectors. Lee (2008) combined regression analysis with DEA to study the energy efficiency of government buildings.

A common feature of the DEA models in the above-mentioned studies is that they model energy consumption as an input within a production framework where both energy and non-energy inputs are used to produce good or desirable outputs. However, energy use also results in the generation of some undesirable outputs, e.g., CO2 emissions, as by-products of producing desirable outputs. The measurement of energy efficiency without considering undesirable outputs does not seem to provide an equitable score for energy efficiency benchmarking and comparisons. It would therefore be appropriate to evaluate the economic-wide energy efficiencies within a joint production framework where both desirable and undesirable outputs are considered simultaneously.

This paper presents several DEA-type linear programming models within a joint production framework for measuring economy-wide energy efficiency performance. In addition to considering undesirable outputs, our models treat different energy sources as different inputs so that changes in energy mix could be accounted for in evaluating energy efficiency. The rest of this paper is organized as follows. Section 2 proposes the models for measuring energy efficiency performance. In Section 3, we present an empirical application study on measuring the energy efficiency performance of 21 OECD countries. Section 4 concludes this study.

2. Linear programming models for energy efficiency measurement

Consider a production process in which desirable and undesirable outputs are jointly produced by consuming both energy and non-energy inputs. Assume that \( \mathbf{x}, \mathbf{e}, \mathbf{y}, \) and \( \mathbf{u} \) are, respectively, the vectors of non-energy inputs, energy inputs, desirable outputs and undesirable outputs, where energy inputs consist of \( L \) different energy sources. \(^2\) Conceptually, the production technology for modeling the joint production process can be described as

\[
T = \{(\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) : (\mathbf{x}, \mathbf{e}) \text{ can produce } (\mathbf{y}, \mathbf{u})\} \tag{1}
\]

In production theory, \( T \) is assumed to be a closed and bounded set, which guarantees the output closeness and implies that finite amounts of inputs can only produce finite amounts of outputs (Färe and Primplont, 1995). In addition, inputs and desirable outputs in \( T \) are often assumed to be strongly disposable. Accordingly, if \( (\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) \in T \) and \( (\mathbf{x}, \mathbf{e}) \geq (\mathbf{y}, \mathbf{u}) \) (or \( \mathbf{y} \leq \mathbf{y} \)) then \( (\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) \in T \).

In order to reasonably model the joint production of both desirable and undesirable outputs, following Färe et al. (1989), we impose the following two conditions on \( T \):

(i) Outputs are weakly disposable, i.e., if \( (\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) \in T \) and \( 0 \leq \theta \leq 1 \), then \( (\mathbf{x}, \mathbf{e}, (\theta \mathbf{y}, (1 - \theta) \mathbf{u})) \in T \).
(ii) Desirable outputs and undesirable outputs are null-joint, i.e., if \( (\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) \in T \) and \( \mathbf{u} = \mathbf{0} \), then \( \mathbf{y} = \mathbf{0} \).

The first condition implies that the reduction of undesirable outputs is not free but the proportional reduction in both desirable and undesirable outputs is feasible. The second condition implies that the only way to eliminate all the undesirable outputs is to cease the production process.

Although the production technology \( T \) has been well defined for modeling the joint production of desirable and undesirable outputs, it cannot be directly used in empirical studies. In application, a popular practice is to formulate it within a non-parametric DEA framework. The resulting technology could therefore be termed as an environmental DEA technology (Färe and Grosskopf, 2004; Zhou et al., 2008b). In the case where there are \( K \) entities whose energy efficiency performances are to be measured, and for the \( k \)th entity the observed data on non-energy inputs, energy inputs, desirable and undesirable outputs are \( \mathbf{x}_k = (x_{1k}, \ldots, x_{nk}) \), \( \mathbf{e}_k = (e_{1k}, \ldots, e_{ek}) \), \( \mathbf{y}_k = (y_{1k}, \ldots, y_{jk}) \) and \( \mathbf{u}_k = (u_{1k}, \ldots, u_{jk}) \), the environmental DEA technology exhibiting constant returns to scale (CRS) can be expressed as

\[
T = \{(\mathbf{x}, \mathbf{e}, \mathbf{y}, \mathbf{u}) : \sum_{k=1}^{K} z_k x_{nk} \leq x_n, \quad n = 1, \ldots, N \\
\sum_{k=1}^{K} z_k e_{lk} \leq e_l, \quad l = 1, \ldots, L \\
\sum_{k=1}^{K} z_k y_{mk} \geq y_m, \quad m = 1, \ldots, M \\
\sum_{k=1}^{K} z_k u_{jk} = u_j, \quad j = 1, \ldots, J \\
z_k \geq 0, \quad k = 1, 2, \ldots, K \} \tag{2}
\]

It can be easily verified that the CRS environmental DEA technology, i.e., (2), satisfies all the conditions mentioned above. In empirical studies, the CRS environmental DEA technology integrated with various efficiency measures has been widely used in diverse areas, such as productivity estimation with pollutants considered and environmental performance measurement. Examples of such studies include Tyteca (1996), Boyd and

\(^2\) Most traditional energy efficiency indicators consider only energy inputs in energy efficiency assessment (Patterson, 1996). However, as discussed by Hu and Wang (2006), energy inputs alone cannot produce any outputs without incorporating other non-energy inputs. It would therefore be appropriate to consider both inputs together in assessing energy efficiency within a production framework. In the literature, this line of reasoning has been adopted by most DEA-related energy efficiency studies, e.g., Hu and Wang (2006), Onut and Soner (2006), Hu and Kao (2007), and Mukherjee (2008). Compared with the traditional energy efficiency indicators such as the energy intensity where only energy inputs are considered, DEA-based energy efficiency indexes could be treated as total-factor energy efficiency or productivity indexes.
EEPI1(x₀, e₀, y₀, u₀) = min θ
s.t. \[\sum_{k=1}^{K} z_k x_{nk} \leq x_{n0}, \quad n = 1, \ldots, N\]
\[\sum_{k=1}^{K} z_k e_{lk} \leq \theta e_{l0}, \quad l = 1, \ldots, L\]
\[\sum_{k=1}^{K} z_k y_{mk} \geq y_{m0}, \quad m = 1, \ldots, M\]
\[z_k \geq 0, \quad k = 1, 2, \ldots, K\] (3)

where the subscript “0” represents the entity to be evaluated. It can be seen that (3) attempts to proportionally contract the amounts of energy inputs as much as possible for a given level of non-energy inputs, desirable and undesirable outputs. It provides an aggregated and standardized index (dimensionless and lies in the interval (0, 1]) for measuring energy efficiency performance. If an entity has a larger EEPI1, it implies that this entity performs better in terms of energy consumption and therefore has higher energy efficiency compared with other entities. An entity with EEPI1 equal to unity means that it is located at the frontier of best practice and therefore could not reduce its energy consumption proportionally. Theoretically, EEPI1 is the reciprocal of the Shephard sub-vector distance function for energy inputs. Discussions on the Shephard input and output distance functions can be found in Färe et al. (1994) and Färe and Priont (1995).

Despite its many advantages, (3) adopts radial efficiency measure, which provides a pure technical efficiency index for measuring energy efficiency performance. As a result, EEPI1 may have weak discriminating power in energy efficiency comparisons. In addition, (3) does not consider the energy mix effects whereas such a consideration might provide additional insights in evaluating energy efficiency. Therefore, we propose the following non-radial DEA-type model:

EEPI2(x₀, e₀, y₀, u₀) = min θ
s.t. \[\sum_{k=1}^{K} z_k x_{nk} \leq x_{n0}, \quad n = 1, \ldots, N\]
\[\sum_{k=1}^{K} z_k e_{lk} = \theta e_{l0}, \quad l = 1, \ldots, L\]
\[\sum_{k=1}^{K} z_k y_{mk} \geq y_{m0}, \quad m = 1, \ldots, M\]
\[z_k \geq 0, \quad k = 1, 2, \ldots, K\] (4)

Model (4) could be treated as an extension to the Russell DEA model in the context of energy efficiency measurement. It is suggested for use as a replacement of (3) when non-proportional adjustments for energy inputs are allowable. Obviously, its optimum objective value, i.e. EEPI2, is larger than 0 but not larger than EEPI1. It therefore provides an aggregated and standardized index with higher discriminating power than EEPI1 for measuring economy-wide energy efficiency performance.

Since (4) allows for the non-proportional adjustments for energy inputs, it accounts for the energy mix effects in evaluating energy efficiency. As a result, (4) allows some energy inputs to increase so that other energy inputs achieve larger reductions in order to reach its ideal benchmarking point in the frontier of best practice. In the case where there is only one energy input, (4) will collapse to (3). Since EEPI2 is essentially the minimum average of the ratios of the expected energy inputs to the actual energy inputs, we may refer to EEPI2 as an average energy utilization performance index.

It should be pointed out that EEPI1 and EEPI2 are invariant to the measurement units of different energy inputs. Irrespective of the measurement units for different energy inputs, EEPI1 and EEPI2 remain unchanged and this should be treated as a strength of DEA-type models in measuring energy efficiency performance.

In the case where all the energy inputs have the same measurement unit, we may expect not only an energy efficiency performance index but also the amount of aggregate potential energy saving. To achieve the two objectives, as illustrated by Hu and Wang (2006), we may first estimate the aggregate potential energy saving for each entity and then use it to derive an energy efficiency performance index. The model for estimating the aggregate potential energy saving is as follows:

\[PES(x₀, e₀, y₀, u₀) = \max \sum_{l=1}^{L} s_l\]
\[\text{s.t.} \sum_{k=1}^{K} z_k x_{nk} \leq x_{n0}, \quad n = 1, \ldots, N\]
\[\sum_{k=1}^{K} z_k e_{lk} = s_l e_{l0}, \quad l = 1, \ldots, L\]
\[\sum_{k=1}^{K} z_k y_{mk} \geq y_{m0}, \quad m = 1, \ldots, M\]
\[\sum_{k=1}^{K} z_k u_{jk} = u_{j0}, \quad j = 1, \ldots, J\]
\[z_k \geq 0, \quad k = 1, 2, \ldots, K\] (5)

Model (5) does not assume that all the slack variables must be positive, which allows all the possible energy mix effects to be captured in evaluating energy efficiency. Provided that it is not allowable to increase the amounts of certain energy inputs, we can revise (5) by including the constraint that the slack variables for these energy inputs are non-negative. Once model (5) is resolved and following Hu and Wang (2006), we may define an energy efficiency performance index as the ratio of the amount of target energy consumption to that of actual energy consumption

\[EEPI3(x₀, e₀, y₀, u₀) = \frac{1 - PES(x₀, e₀, y₀, u₀)}{\sum_{l=1}^{L} e_{l0}}\] (6)

Compared with EEPI1, EEPI3 has a higher discriminating power in energy efficiency comparisons. A main advantage of using EEPI3 is that it provides the information on the amount of potential energy saving for each entity. Using the data on potential energy savings and the same formula given by (6), we can generate an overall energy efficiency index for measuring the collective energy efficiency of all the entities to be evaluated.

It is worth pointing out that EEPI1 and EEPI2 are not fully independent of each other when the energy inputs have the same unit of measurement. If we change the energy constraints in (5) to the form of the energy constraints in (4), as shown in (7), EEPI3 is essentially equal to the minimum weighted average of the ratios of the expected energy inputs to the actual energy inputs (with the weights equal to the shares of energy inputs in total energy consumption). As a result, we may refer to EEPI3 as a weighted
average energy utilization performance index.

\[ EEPI_3 \left( x_0, e_0, y_0, u_0 \right) = \min \sum_{l=1}^{L} \left( e_{0l} / \sum_{l=1}^{L} e_{0l} \right) \theta_{l} \]

s.t. \( \sum_{k=1}^{K} z_{nk} x_{nk} \leq x_{nk0}, \quad n = 1, \ldots, N \)

\( \sum_{k=1}^{K} z_{ik} e_{ik} \leq \theta_{i} e_{i0}, \quad i = 1, \ldots, I \)

\( \sum_{k=1}^{K} z_{mk} y_{mk} \geq y_{m0}, \quad m = 1, \ldots, M \)

\( \sum_{k=1}^{K} z_{uk} u_{uk} = u_{0k}, \quad j = 1, \ldots, J \)

\( z_{k} \geq 0, \quad k = 1, 2, \ldots, K \)

(7)

Up to now, we have offered three indexes for measuring energy efficiency performance, which can be obtained by solving different DEA-type linear programming models. When only the technical efficiency in energy consumption is of interest, \( EEPI_1 \) is recommended for use. When the energy mix effects are expected to be considered in evaluating energy efficiency, \( EEPI_2 \) and \( EEPI_3 \) would be better choices. The choice between \( EEPI_2 \) and \( EEPI_3 \) should depend on the characteristics of the data available and the purpose of the user of the models. If the energy inputs have the same unit of measurement and the results of potential energy savings are also expected, the use of \( EEPI_3 \) would be recommended. Otherwise, \( EEPI_2 \) would be a good option.

It should be pointed out that previous DEA-type models do not consider the slacks in non-energy inputs and desirable outputs as our primary objective is to measure pure energy efficiency performance. When analysts or decision/policy makers’ interest is to model economic-energy-environmental performance, the slacks in non-energy inputs and desirable outputs should also be incorporated in an appropriate manner as done by Zhou et al. (2006).

3. Empirical study

We study the economy-wide energy efficiency performances of 21 OECD countries using the proposed linear programming models and data from 1997 to 2001. Following the practice in macroeconomic efficiency analysis, we employ capital stock (in billions of 2000 US dollars using PPP) and labor force (in thousand) as non-energy inputs, GDP (in billions of 2000 US dollars using PPP) as the desirable output, and CO₂ emissions (in million tones) as the undesirable output.³ The data on labor force, GDP and CO₂ emissions were collected from OECD (2006), OECD (2007) and International Energy Agency (2004b), respectively. Capital stock was derived by multiplying GDP by “capital stock as a percentage of real GDP”, and the data for the latter were collected from Kamps (2004). We consider four categories of energy consumption by source as inputs, namely coal, oil, gas and other energy. The energy data, collected from Energy Information Administration (2005), are given in quadrillion British thermal unit (Btu). Table 1 shows the summary statistics for the above eight variables in 1997–2001.

Since the four energy inputs have the same unit of measurement, \( EEPI_1 \) is the recommended index for measuring and comparing the energy efficiency performances of these countries. Table 2 shows the results of \( EEPI_1 \) obtained from the relevant DEA-type model described in Section 2. The results of \( EEPI_3 \) are also included in the table for comparison purposes, while the results of \( EEPI_2 \) are not given as they are of high correlation with those of \( EEPI_1 \).

It can be seen from Table 2 that there exist differences between the results of \( EEPI_1 \) and \( EEPI_3 \). About three quarters of the countries are treated as energy efficient based on \( EEPI_1 \), but the number is less than half based on \( EEPI_3 \). Not surprisingly, \( EEPI_3 \) has a higher discriminating power than \( EEPI_1 \) as it accounts for not only technical efficiency but also fuel mix effects. All the energy-efficient countries as given by \( EEPI_1 \) are also energy efficient based on \( EEPI_3 \). This is due to the fact that \( EEPI_3 \) considers all the slacks while \( EEPI_1 \) considers only the radial adjustment in energy inputs. Increases in energy efficiency from 1997 to 2001 are observed in some countries, while decreases are observed in others. As a whole, the average energy efficiency performance changed little over time, whether it is given by \( EEPI_1 \) or \( EEPI_3 \).

Fig. 1 is a scatter plot of \( EEPI_1 \) versus aggregate energy intensity (or energy/GDP ratio) based on the data for 2001. The inverse of aggregate energy intensity is often taken as a proxy for economy-wide energy efficiency at the most aggregate level. Ignoring the countries with \( EEPI_3 \) equal to one, there exists a negative correlation between the two indicators. It indicates that aggregate energy intensity could partially reflect the contents underlying DEA-based energy efficiency performance index.

Although the negative correlation between the two indicators as shown in Fig. 1 is roughly valid, the detailed results show some striking differences. It is widely known that in terms of energy efficiency, Japan performs well while the US performs quite badly among the OECD countries when aggregate energy intensity is the

³ Note that CO₂ emissions can be estimated from the fuel consumption data and emission factors, as energy use is responsible for the major share of CO₂ emissions. This may cast some doubt on the reasonableness of including both energy and CO₂ emissions in a DEA model. Since CO₂ emissions are a major by-

(footnote continued) product of energy use, it seems logical to model both in a production framework to offer a more complete characterization of the production process. Therefore, in the empirical study, we include both energy use and CO₂ emissions, an approach that has been adopted in some earlier studies, such as Fare et al. (2004), Ramanathan (2005), Zhou and Ang (2008) and Zhou et al. (2006, 2007, 2008b). However, it should be pointed out that several other studies, e.g. Zaim and Taskin (2000) and Zofio and Prieto (2001), did not include energy consumption as an input in their DEA models in investigating the performance of CO₂ emissions.
Overall, these countries have potential to reduce their energy consumption followed by Japan in order to reach its GDP, it is found that Canada has the greatest potential to reduce amounts of non-energy inputs and CO$_2$ during the 5-year period 1997–2001. Without increasing the

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![Fig. 1. Plot of $EEPI_1$ versus aggregate energy intensity in 2001.](image1)

![Fig. 2. The total potential energy savings for “energy-inefficient” countries, 1997–2001.](image2)

![Fig. 3. Change in the overall energy efficiency performance index for the 21 OECD countries over time.](image3)

indicator (IEA, 2007). However, if DEA models are used, the converse is observed. Ignoring the bias in the data used, this contraction arises mainly from the different approaches and assumptions in deriving the energy efficiency indicators. For instance, the aggregate energy intensity treats energy and GDP as the only input and output, while the DEA models evaluate energy efficiency within a multiple inputs and outputs production framework. Since there exist substitution effects among capital stock, labor force and energy inputs, a lower aggregate energy intensity may arise from the transformation of energy inputs to non-energy inputs in producing GDP rather than from energy efficiency improvement (Berndt, 1978; Hu and Wang, 2006). Although the substitution effects cannot be reflected in the aggregate energy intensity, they could be captured by the multiple inputs DEA models, which could result in the contradiction between aggregate energy intensity and DEA-based energy efficiency indexes.

Fig. 2 shows the total potential energy savings (TPES) for the “energy-inefficient” countries based on $EEPI_1$ in descending order during the 5-year period 1997–2001. Without increasing the amounts of non-energy inputs and CO$_2$ emissions or decreasing GDP, it is found that Canada has the greatest potential to reduce its energy consumption followed by Japan in order to reach its ideal benchmarking point in the frontier of the best practice. Overall, these countries have potential to reduce their energy consumption by about 86 quadrillion Btu, or 8.5% of the total energy consumption in the 21 OECD countries in the 5-year period.

Based on the potential energy saving for each country, we can further derive the potential annual energy saving for the OECD countries as a whole. Using this estimate and Eq. (6), we could derive an overall energy efficiency performance index for the OECD countries. The results obtained for 1997–2001 are shown in Fig. 3. It can be seen that the 21 OECD countries as a whole has experienced little change in its overall energy efficiency performance. This observed trend is similar to that for the average $EEPI_3$ values in Table 2.

4. Conclusion

DEA has recently been widely applied to measure energy efficiency performance at different application levels. A common feature of previous DEA-related energy efficiency studies is that they model energy consumption as an input within a production framework without considering undesirable outputs. In real cases, energy use results in the generation of undesirable outputs as by-products of producing desirable outputs. However, none of previous studies attempt to evaluate energy efficiency within a join production framework of both desirable and undesirable products of producing desirable outputs. The main purpose of this paper is to fill this gap by providing several DEA-type linear programming models for measuring economy-wide energy efficiency performance.

Using the environmental DEA technology concept, we develop three alternative energy efficiency performance indexes. The first index, i.e. $EEPI_1$, attempts to proportionally reduce the energy inputs to the frontier of the best practice. Since it does not
consider the energy mix effects, the index could be treated as a purely technical efficiency index in energy consumption. To account for the energy mix effects in evaluating energy efficiency, we further developed EEPI$_2$ based on a non-radial DEA-type model and EEPI$_1$ based on a slacks-based DEA-type model. Each of these two indexes has its own features but they are not fully independent of each other. Using the proposed models, we finally present an empirical application study on measuring the energy efficiency performance of 21 OECD countries. Although our study mainly focuses on the measurement of economy-wide energy efficiency, given data availability, the proposed models could also be applied to measure the energy efficiency performance of lower-level entities such as electricity generation plants.

References


