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# Inefficiency countervailed DEA (IC-DEA) method for assessing corporate environmental performance☆

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Data envelopment analysis (DEA) is a method frequently used to evaluate relative firm performance. However, high values in a few indicators can lead to a company being regarded as 'efficient', despite valuing poorly in other essential indicators. The Inefficiency Countervailed DEA (IC-DEA) method is thus developed. The method first defines an inefficient frontier using the proposed Reverse DEA (RDEA) model. An IC-DEA value is then determined by summing both the DEA and RDEA values. The IC-DEA method was applied to assess the environmental performance of major opto-electronic companies in Taiwan, demonstrating its applicability.

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## Introduction

In recent decades, global warming and other environmental issues have attracted significant public and private sector attention. Simultaneously, corporate environmental performance (CEP) has been increasingly prioritized, with most companies recognizing it as a key component of business sustainability. The continuous growth in waste and greenhouse gases emissions seriously threaten the environment, and thus firms must improve their environmental performance to protect both the environment and society (Moneva and Ortas, 2010).

Data envelopment analysis (DEA) (Charnes *et al*, 1978) is a Pareto optimality-based method that can measure the relative efficiency among multiple indicators of evaluated companies. A primary advantage of DEA is that the basic functional relationships among indicators and the associated weight set do not require any prior assumptions to determining their relative efficiency (Seiford and Thrall, 1990). On the basis of this and other advantages, various studies have reported the application of DEA for assessing worldwide environmental performance. For example, Sarkis (2000) compared DEA with other multi-criteria decision making tools in assessing solid waste management systems. Furthermore, Zofio and Prieto (2001) used DEA to measure the relative environmental efficiencies of OECD industries. In addition, Lansink and Bezlepkin (2003) used DEA to determine $CO_2$, energy, and overall technical efficiencies for different firms in the Netherlands. Ramanathan (2005) applied DEA to estimate energy consumption of rail and/or road transport in India under a pre-specified DEA efficiency. Moreover, Nakashima *et al* (2006) proposed a DEA-based method to assess the relative environmental performance of several Japanese companies. Lu and Lo (2007) used the cross-efficiency measure, a method proposed by Sexton *et al* (1986) to improve the discrimination power of DEA, to assess the economic-environmental performance of 31 regions in China. In addition, Alsharif *et al* (2008) applied DEA to assess the relative efficiencies of water supply systems in the USA. Gomes and Estellita Lins (2008) applied DEA models to determine national carbon emission quota and zero sum gains DEA models to evaluate carbon quota trade or emission reallocation. Feroz *et al* (2009) ranked global warming and environmental production

☆Corporate environmental performance (CEP) assessment has become an important task worldwide. The DEA method is thus frequently applied to evaluate relative firm performance based on multiple inputs and outputs. However, high values in a few indicators can lead to a company being regarded as 'efficient,' despite valuing poorly in other essential indicators. To resolve such problems, the Reverse-DEA (RDEA) model is proposed to determine the inefficient frontier and identify companies that are not truly efficient. Then, an IC-DEA value is computed by summing both the DEA and RDEA values for comparing CEP among companies. The proposed IC-DEA method improves the original DEA method by simultaneously considering both the efficiency and inefficiency frontiers to provide an unbiased method for assessing relative CEP.

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efficiency of the Kyoto Protocol nations using a DEA-based model. However, these studies exhibit a common critical problem in applying the DEA method: that is an evaluated unit that value highly in just one or few indicators can obtain a high DEA efficiency score, despite scoring very poorly in other evaluated indicators (Angulo Meza and Estellita Lins, 2002). This study thus attempted to develop a new method for resolving this problem.

DEA does not assign a common weight for each indicator, but rather assigns different weights so as to maximize the final efficiency score for each individual evaluated company. Although this weight flexibility is one of the main advantages of DEA, some evaluated units achieve their scores by assigning extreme weights to indicators, and essential indicators may be ignored and assigned zero weight during the analysis. Therefore, besides the aforementioned problem of obtaining a high score with high value in only one indicator, a company can achieve a high score despite having very poor value for certain key indicators. Figure 1 presents an example of this phenomenon, on the basis of data from Nakashima *et al* (2006). Companies A, B and F are efficient and lie on the DEA frontier. Although companies A and F receive the highest DEA score of 1, in each case they score very poorly in one major output indicators: company A has the worst value for undesirable output indicator 1 and company F values poorly for undesirable output indicator 2. Some researchers have thus proposed various weight restriction methods to resolve this problem, such as direct weight restrictions (Dyson and Thanassoulis, 1988), contingent weight restrictions (Pedraja-Chaparro *et al*, 1997), assurance region (Thompson *et al*, 1986) and polyhedral cone-ratio (Charnes *et al*, 1990). These methods are mainly designed to establish upper and lower bounds within which the weights can vary, preserving some weight flexibility.

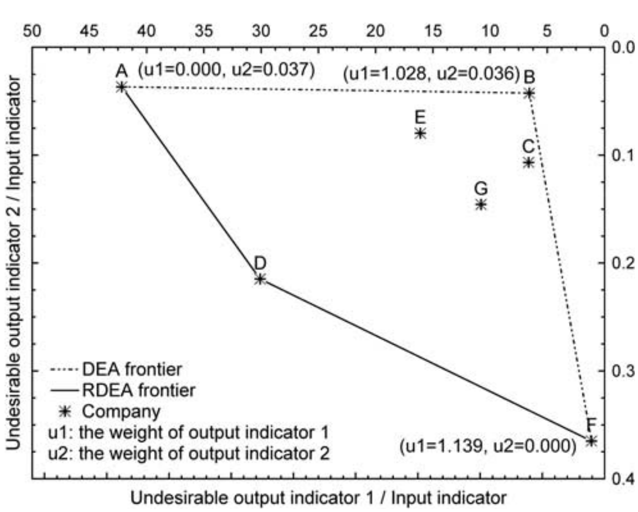


**Figure 1** An example illustrating the DEA scores, a DEA efficiency frontier and an RDEA inefficiency frontier.

However, the values of the bounds depend on both the context and information provided by experts, and thus are subjective. Besides, some evaluated units can still achieve high scores within the weight bounds, despite having extremely poor values for essential factors.

The inefficiency state should be considered by performance assessments. That is, a company at the inefficient frontier should not be considered 'efficient', even if it is at the efficient frontier determined by the original DEA method. In applying the DEA method, all outputs are often assumed as 'good'. However, some outputs may be 'bad'. As described by Färe *et al* (1989), waste and pollutants manufactured along with final products in production processes are usually assumed weakly disposable and producers cannot reduce such pollution without cost. These pollutants are undesirable outputs and should be reduced. Färe *et al* (1989) developed a nonlinear DEA model. Tyteca (1997) revised various DEA models to deal with undesirable outputs. However, these models integrate efficiency with inefficiency performance to establish a new efficiency model without calculating efficiency and inefficiency performance separately.

Yamada *et al* (1994) developed the Inverted DEA (IDEA) model to measure relative inefficiency by exchanging inputs and outputs. Since the scores obtained by the IDEA and original DEA are determined by different objective functions and constraints in different coordinate scales (Entani *et al*, 2002), scores cannot be directly summed to acquire a final score. Although Angulo Meza *et al* (2005) used a normalized approach to construct an efficiency indicator, the efficiency and inefficiency scores cannot be described directly using the same coordinate scale. This study thus establishes the Inefficiency Countervailed DEA (IC-DEA) method, and proposes the Reverse DEA (RDEA) model, such that both efficiency and inefficiency scores can be described using the same coordinate scale and can be summed for a final score. The only drawback of the proposed method, compared with the IDEA method, is that no undesirable output can be zero because the denominator of an inverse function cannot be zero. However, for a CEP assessment, having an output that is zero is impossible. In cases when a zero occurs, an extremely small value may be used to replace the zero.

The proposed method is expected to provide more reasonable relative efficiency evaluation than the original DEA method. The reminder of this paper is organized as follows. The next section presents the DEA, proposed RDEA and IC-DEA models using a typical example. The next section describes a case study for assessing the relative environmental performance of major opto-electronic companies in Taiwan, followed by input and undesirable output indicators selection. The subsequent section then demonstrates and discusses the application of the proposed IC-DEA model to the case study. Finally, the last section concludes this study.

## Methodology

### *The DEA method*

Before assessing CEP using the DEA method, input and output indicators suitable for evaluating CEP should be selected. Input indicators generally comprise resources invested by a company. Meanwhile, output indicators for assessing CEP generally are pollutants or waste, generated by a company. After selecting both input and output indicators, the DEA method can be applied to assess CEP. The weight set for each company is determined based on the distance of its performance from the efficient frontier determined by the DEA method. The DEA efficient frontier is defined as the collection of the best performances achieved by various companies. The boundary in the indicator space, along the upper edge of the region enclosing all performance indicator values is known as the efficient frontier. The DEA method is applied to generate initial weight sets for this study. Indicator weights are estimated using a linear programming model to maximize the relative efficiency of each company. This study used the linear constant return-to-scale output-oriented model (Charnes *et al*, 1978) to calculate the relative efficiency of each company. The linear model is as follows.

$$g_k^{-1} = Minimum \quad \sum_{i=1}^{m} v_{ik} X_{ik} \tag{1a}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_{rk} Y_{rk} = 1 \tag{1b}$$

$$\sum_{i=1}^{m} v_{ik} X_{ij} - \sum_{r=1}^{s} u_{rk} Y_{rj} \geqslant 0, \quad j = 1, \ldots, n \tag{1c}$$

$$u_{rk}, v_{ik} \geqslant 0, \quad r = 1, \ldots, s, \ i = 1, \ldots, m \tag{1d}$$

where $g_k$ denotes the DEA score for company $k$; $s$ and $m$ represent the number of output and input indicators, respectively; $u_{rk}$ refers to the weight of output indicator $r$ for company $k$; $v_{ik}$ is the weight of input indicator $i$ for company $k$; $X_{ij}$ denotes the value of input indicator $i$ for company $j$; and $Y_{rj}$ represents the value of output indicator $r$ for company $j$. In this study, since the original output indicators are undesirable and their magnitudes reflect the inefficiency status, this study uses the inverses of undesirable outputs as output values.

Equation (1a) is the objective function for optimizing a set of weights to maximize the total DEA score ($g_k$) for company $k$. Each company has its own weights to maximize its score. Equation (1b) is a normalization constraint expressed in a linear form converted from a fractional equation by setting the weighted-sum of outputs to 1. Using the weight set determined for company $k$, Equation (1c) limits the weighted-sum ratio of inputs and outputs for each company to a value of 1 or more, to ensure that the DEA score of each company must have a value of 1 or less. Equation (1d) sets the lower bounds of all the weights, $u_{rk}$ and $v_{ik}$, to be determined.

Figure 1 uses an example to illustrate DEA scores in the indicator space and an efficient frontier. The data are obtained from Nakashima *et al* (2006). Three companies, A, B and F, lie on the DEA frontier. Although companies A and F both obtain the highest score of 1, one of their undesirable output indicators, undesirable output indicator 1 for A and undesirable output indicator 2 for F, has a poor value and is assigned a zero weighting. These two companies thus should not be considered efficient. The proposed RDEA method is expected to resolve this problem.

### *The RDEA method*

The zero weights assigned to poorly valued indicators resulted in inappropriately high efficiency scores for some companies, while the DEA scores of some other companies were depressed due to these companies having inappropriately high DEA efficiency. To resolve these problems, this study proposed the RDEA model to calculate the relative inefficiency of each company, based on the inverse of output values in the DEA model. The RDEA model is formulated as follows.

$$-g_k'^{-1} = Minimum \quad \sum_{i=1}^{m} v_{ik} X_{ik} \tag{2a}$$

$$\text{s.t.} \quad \sum_{r=1}^{s} u_{rk} Y_{rk}^{-1} = 1 \tag{2b}$$

$$\sum_{i=1}^{m} v_{ik} X_{ij} - \sum_{r=1}^{s} u_{rk} Y_{rj}^{-1} \geqslant 0, \quad j = 1, \ldots., n \tag{2c}$$

$$u_{rk}, v_{ik} \geqslant 0, \quad r = 1, \ldots, s, i = 1, \ldots, m \tag{2d}$$

where $g_k'$ denotes the RDEA score for company $k$; $s$ and $m$ represent the number of the output and input indicators, respectively; $u_{rk}$ is the weight of output indicator $r$ for company $k$; $v_{ik}$ refers to the weight of input indicator $i$ for company $k$; $X_{ij}$ is the value of input indicator $i$ for company $j$; and $Y_{rj}$ is the value of output indicator $r$ for company $j$ in the DEA model. Since the inverses of undesirable outputs are used as outputs for the DEA model, $Y_{rj}^{-1}$ is thus the double inverse of undesirable output and is the original value of undesirable output indicator $r$ for company $j$. Equation (2a) is the objective function for optimizing a set of weights to minimize the reciprocal of the RDEA score ($g_k'$) for company $k$. Each company has its own indicator weights to achieve its optimal value. Equation (2b) is a normalization constraint in a linear form converted from a fractional equation by setting the weighted-sum of inverse outputs to equal 1. Using the weight set determined for company $k$, Equation (2c) limits the weighted-sum ratio of inputs and reverse outputs for each company to be 1 or more. That is, the absolute value of the RDEA score of each company has to be 1 or less. Equation (2d) sets the lower bounds of the weights, $u_{rk}$s and $v_{ik}$s, to be determined.

Figure 1 shows that companies A, D and F lie on the RDEA inefficient frontier, while companies A and F lie on the DEA efficient frontier. Because one of their undesirable output indicator values of companies A and F is the largest among all companies, they got the worst inefficiency score of $-1$. Therefore, companies A and F should not be regarded as efficient and their inefficient performance should also be considered in assessing CEP. This study thus proposes the IC-DEA method to develop a new IC-DEA score for assessing CEP.

### *The IC-DEA method*

Performance assessment should not only consider the efficient portion, but should also evaluate inefficient situations. This study thus modified the conventional DEA method to establish the RDEA model. The proposed IC-DEA method then recalculates the efficiency score based on the scores obtained using both models, as formulated below.

$$E_k = g_k - g'_k, \quad k = 1, \ldots, n \tag{3}$$

where $E_k$ denotes the IC-DEA score; $g_k$ represents the score determined using the DEA model; and $g'_k$ is the score determined with the RDEA model.

Figure 2 compares the DEA, RDEA and IC-DEA scores of all evaluated companies. The IC-DEA scores of both companies A and F are 0 because these two companies simultaneously have the highest DEA score of 1 and the lowest RDEA score of $-1$. Both companies are inefficient owing to their poor performance in one undesirable output indicator. Meanwhile, companies B, C and E have positive

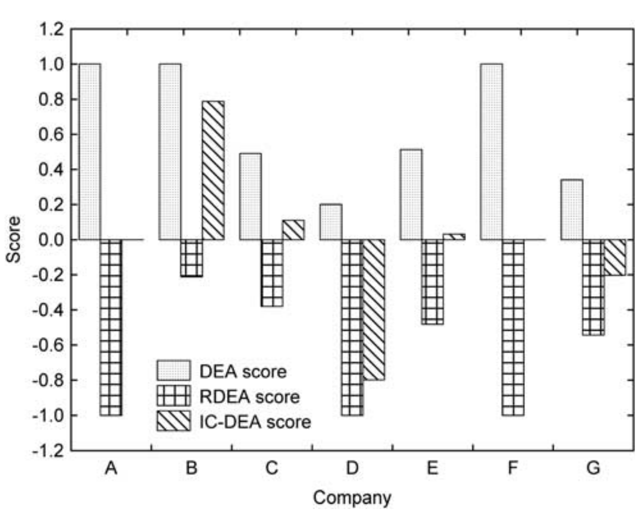


**Figure 2** The DEA, RDEA and IC-DEA scores of all evaluated companies of the example.

IC-DEA scores, and thus outperform other companies in terms of their environmental performance. Two companies, D and G, have negative IC-DEA scores, that is they are less efficient than other companies in terms of their environmental performance.

## Case study

### *An application study*

During recent decades, the opto-electronic industry has developed rapidly in Taiwan, as capital- and technology-based industries have gradually replaced labour-intensive industries. Opto-electronics manufacture has become the mainstay local industry, accounting for over 35% of the entire industrial structure in Taiwan, with output value growing from US$78.4 billion in 2002 to US$ 156.6 billion in 2008 (ROCEY, 2009). The opto-electronics industries have been the backbone of Taiwan's economic development. Taiwan is crucial to various world opto-electronic supply chains and markets. Taiwanese opto-electronics industry products include semiconductors, opto-electronic components, electrical facilities, and so on. This production activity has significant environmental impacts, which intensify as output increases.

The major greenhouse gases emitted by the opto-electronic industries in Taiwan are $PFC_s$ and $SF_6$. Although the amount of these greenhouse gases is small compared to other greenhouse gases, the $CO_2$-equivalent ($eCO_2$) emissions of the opto-electronics industry in Taiwan contribute a significant portion of the national emissions, about 4.63% (Lu, 2003), because the Global Warning Potentials (IPCC, 2001) of $PFC_s$ and $SF_6$ are both relatively high, at 65 000–92 000 and 23 900, respectively, and long atmospheric lifetime. Besides, the electricity consumptions of much of the manufacturing equipment in the opto-electronic industry are large, about 30% of total industrial electricity consumption in Taiwan (Wu and Hong, 2008), which significantly increase the greenhouse gases emissions of the industry. Furthermore, waste generation of the opto-electronics industry also increases with increasing production. The opto-electronic industry generates significant waste, totalling approximately 200 000 tons in 2008 (ROCEPA, 2009). Thus it is essential to assess the environmental performances of local opto-electronic companies to examine their environmental management efficiency and reduce their environmental impacts.

### *Inputs*

Various inputs may be used to assess CEP, for example sales, production quantity, cost, number of employees, land usage and capital stock. Selected input indicators should be highly correlated to the manufacturing process that poses environmental impacts. Employee number and land usage, although essential to a company, are not strongly related to the environmental impacts of a company. Costs comprise the monetary value of expenditures on supplies, services, labour, products, equipment and other items purchased for use. The company capital stock represents the original capital paid or invested in the organization by its founders. Cost and capital stock are both estimated based on various different activities, and thus they are inferior to company sales for expressing production or market share. Although production quantity is a good input indicator for individual companies, different companies produce different products that may be counted by different units and thus are not comparable. Therefore, this study finally selected company sales, also used by Nakashima *et al* (2006), as the input indicator. Several companies also use sales as an indicator of product eco-efficiency (eg, Hewlett-Packard Development Company, 2008; Sony Corporation, 2008; Chi-Mei Corporation, 2009). Moreover, environmental performance with sales can provide a good reference to assist customers in differentiating products.

### *Undesirable outputs*

Pollution and waste are major undesirable byproducts of manufacturing activities that can cause significant environmental deterioration. A large number of greenhouse gases and waste are emitted and generated during product manufacturing processes. Hence, emission control of pollution and waste reduction must be assessed. Major greenhouse gases emitted by the opto-electronic industry include $CO_2$, $PFC_s$, $SF_6$, $CH_4$, $N_2O$, $CFC_s$. The total $eCO_2$ emissions, calculated based on the gas Global-warming Potentials (GWPs), of industry represent 10% of total Taiwanese emissions (Li, 2006). The $eCO_2$ emission volume is thus selected in this study as a major output indicator.

Waste generated from the opto-electronic industry includes hazardous industrial waste and general industrial waste. Specifically, opto-electronic industry waste includes cleaning liquid, etching liquid, lithographic liquid, alkali, materials to adsorb toxic gases, sludge, packaging materials, respirators, gloves, shoe covers, etc. The opto-electronic industry is the largest producer of hazardous waste in Taiwan, accounting for about 43% of total national hazardous waste production (ROCEPA, 2009). The ratio of hazardous waste to general waste is about 0.58 (ROCEPA, 2009). The opto-electronic industry uses a lot of toxic chemical materials in its manufacture process, generating significant highly dangerous carcinogenic waste. Without proper disposal and treatment, this waste would considerably harm the health of employees, surrounding residents and the environment. Therefore, the quantity of waste generated is also selected as one of the output indicators.

The $eCO_2$ emission volume and quantity of waste generated are thus the two main undesirable output indicators selected for applying DEA in this study. Nakashima *et al* (2006) also used the same set of output indicators for assessing CEP to establish a Plan-Do-Check-Act management cycle in the system. The information is used to continuously improve company environmental management.

This study selects 10 major electronic companies in Taiwan, and assesses their CEP using the proposed IC-DEA method. Table 1 lists the data used in this study for the 10 opto-electronic companies. The data were collected from either their Corporation Sustainability Reports or via a questionnaire sent by the authors.

**Table 1** Data for the 10 opto-electronic companies in Taiwan

| *Company code* | *Sales (million NTD)* | *Quantity of waste generated (ton)* | *$eCO_2$ emission volume (tone $eCO_2$)* |
|---|---|---|---|
| O1 | 299 898 | 37 694 | 1 115 268 |
| O2 | 479 726 | 75 200 | 2 840 000 |
| O3 | 155 972 | 19 297 | 636 588 |
| O4 | 24 303 | 1313 | 324 288 |
| O5 | 136 771 | 20 229 | 1 600 000 |
| O6 | 319 167 | 44 103 | 3 696 075 |
| O7 | 35 566 | 20 140 | 265 000 |
| O8 | 24 024 | 15 340 | 20 922 |
| O9 | 20 900 | 1175 | 34 294 |
| O10 | 27 858 | 5013 | 53 878 |

**Table 2** The DEA score and indicator weights of each evaluated company

| *Company code* | *DEA score* | *Indicator weight* | |
|---|---|---|---|
| | | *Quantity of waste generated/Sales (ton/million NTD)* | *$eCO_2$ emission volume/Sales (tone $eCO_2$/million NTD)* |
| O1 | 0.447 | 0.120 | 0.162 |
| O2 | 0.355 | 0.151 | 0.205 |
| O3 | 0.452 | 0.119 | 0.161 |
| O4 | 1.000 | 0.054 | 0.000 |
| O5 | 0.369 | 0.145 | 0.197 |
| O6 | 0.395 | 0.136 | 0.184 |
| O7 | 0.161 | 0.172 | 5.185 |
| O8 | 1.000 | 0.000 | 0.871 |
| O9 | 1.000 | 0.054 | 0.073 |
| O10 | 0.708 | 0.039 | 1.177 |

## Results and discussion

### *Data envelopment analysis (DEA)*

Since waste and $eCO_2$ emission are undesirable outputs, this study uses the inverse of waste quantity and $eCO_2$ emission volume as the output indicators, with a higher value indicating less waste generation or $eCO_2$ emission. These two output indicators are used to assess environmental performance with the DEA method. Table 2 lists the DEA scores and weight sets of all companies, and Figure 3 shows the DEA scores in the indicator space and the DEA efficient frontier. Three companies, O4, O9 and

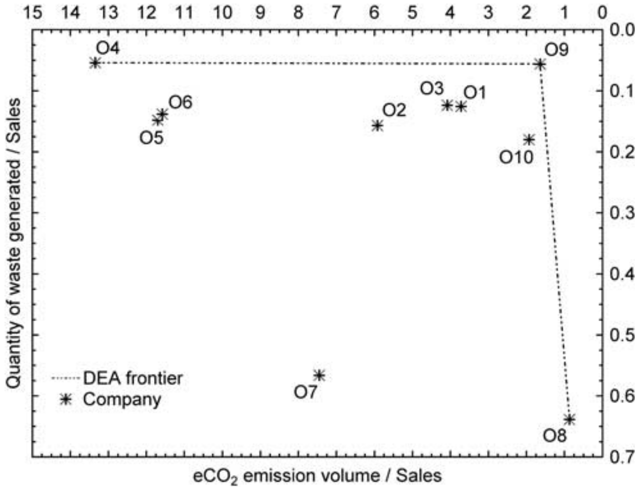


**Figure 3** DEA scores of 10 Taiwanese opto-electronic companies.

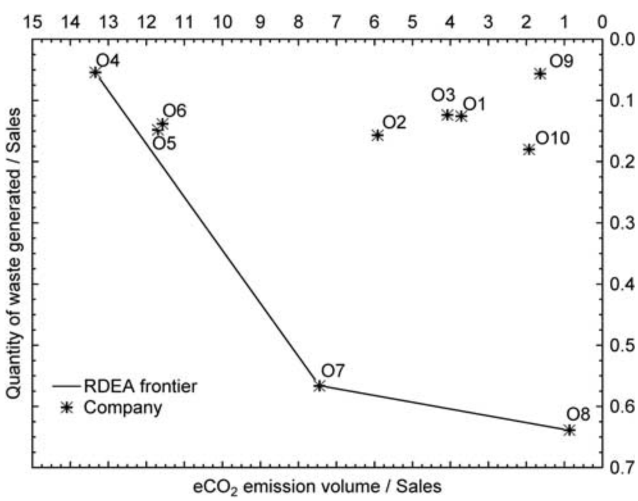


**Figure 4** RDEA scores of the 10 companies.

O8, lie on the DEA efficient frontier. Although companies O4 and O8 both achieve the highest score of 1, one of the weights is set to 0, that is one of the indicators has a poor value. For company O8, the indicator with a poor value is the quantity of waste generated per sale amount, while for company O4, it is $eCO_2$ emission volume per sale amount. Companies O4 and O8 should not be regarded as efficient, despite obtaining the highest DEA efficiency score of 1, because they both perform worst for one of the indicators. The RDEA method described below is thus proposed to identify these inefficient companies.

### *Reverse DEA (RDEA)*

Figure 4 shows the RDEA scores in the indicator space and the inefficient frontier. Three companies, O4, O7 and O8, lie on the RDEA inefficiency frontier, while companies O4 and O8 also lie on the DEA efficiency frontier, as shown in Figure 3. Because one of their undesirable output indicator values is the largest among all companies, these companies thus received the worst inefficiency score of −1 and should not be regarded as CEP efficient companies.

The DEA method can identify good performing indicators. Meanwhile, the proposed RDEA method can effectively identify poor performing indicators that need improvement. Inefficiency should also be evaluated in assessing environmental performance efficiency. On the basis of the RDEA and original DEA scores, a new IC-DEA score is determined for assessing the environmental performance efficiency of each evaluated company, as described below.

### *Inefficiency Countervailed DEA (IC-DEA)*

Figure 5 shows both DEA and RDEA scores. The IC-DEA scores of points on the neutral line shown in the figure all equal zero. The DEA score of any point on this neutral line equals the absolute value of its RDEA score. Companies lying in the upper right corner are efficient, while those lying in the lower left corner are inefficient. The best possible IC-DEA score is 1. Figure 6 compares the DEA, RDEA and IC-DEA scores of all companies. The IC-DEA scores of companies O4 and O8 are both 0 because these companies simultaneously have the highest DEA scores, 1, and lowest RDEA scores, −1. Four companies, O1, O3, O9 and O10, have positive IC-DEA scores, meaning they are more efficient than other companies, generating less waste or $eCO_2$ emissions per unit sales. Four companies, O2, O5, O6 and O7, have negative IC-DEA scores, which mean they are less efficient than other companies because they produce more waste or $eCO_2$ emissions per unit sales.

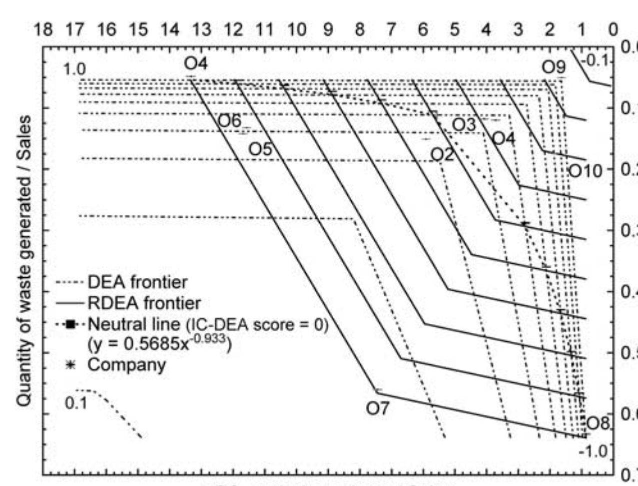


**Figure 5** DEA, RDEA and IC-DEA scores and IC-DEA neutral and contour lines.

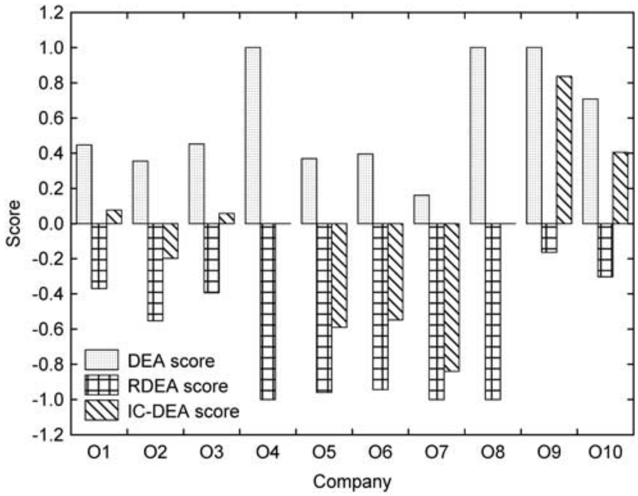


**Figure 6** The DEA, RDEA and IC-DEA scores of each company.

The IC-DEA scores range from $-1$ to 1, unlike the DEA scores, which range from 0 to 1. However, like the DEA scores, companies with higher IC-DEA score are still regarded as more efficient. Applying the DEA method, a company with one or several superior output indicators can be regarded as efficient, even when it performs worst in some major output indicators. Any company with significantly poor value for any major indicator should not be considered efficient and its efficiency score should be offset by its poor performance. The proposed IC-DEA can effectively identify companies that are not truly efficient, while also recognizing those companies with truly efficient environmental performance.

## Conclusions

CEP assessment recently has become an important task in Taiwan and numerous other countries. The DEA method can evaluate multiple inputs and outputs to determine relative efficiencies among companies. However, a company lying on the DEA efficient frontier with the highest efficient score of 1 may perform well for only one undesirable output indicator, with other poorly performing undesirable output indicators being assigned a zero or low weighting. To resolve such problems, the RDEA model is proposed to determine the inefficient frontier and identify inefficient companies. The proposed IC-DEA method is then applied to generate new IC-DEA performance scores based on both DEA and RDEA scores, with company DEA efficiency score being offset by its RDEA inefficiency score.

The proposed IC-DEA method was demonstrated by applying it to assess the relative environmental performances of 10 major opto-electronic companies in Taiwan. Two of these companies, O4 and O8, perform worst for one of the evaluated undesirable output indicators, but still achieve the highest DEA efficiency score of 1 because a zero or minimum weight is assigned to the worst performing indicators. This problem was resolved after their IC-DEA scores were determined using the proposed method. Unlike the range of 0–1 for DEA scores, IC-DEA scores range from $-1$ to 1. The neutral line, formed by points whose IC-DEA scores are zero, can provide a good reference to indicate whether a company is relative efficient or inefficient. Companies placed below the neutral line should carefully examine their management policies and actions to improve their environmental performance. The proposed IC-DEA method improves on the original DEA method by simultaneously considering both the efficiency and inefficiency frontiers to provide an unbiased method for assessing relative CEP.

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## References


Alsharif K, Feroz EH, Klemer A and Raab R (2008). Governance of water supply systems in the Palestinian territories: A data envelopment analysis approach to the management of water resources. *J Environ Mngt* **87**: 80–94.

Angulo Meza L and Estellita Lins MP (2002). Review of methods for increasing discrimination in data envelopment analysis. *Ann Opns Res* **116**: 225–242.

Angulo Meza L, Biondi Neto L, Soares de Mello JCCB and Gomes EG (2005). ISYDS—Integrated system for decision support (SIAD Sistema Integrado de Apoio a Decisão): A software package for data envelopment analysis model. *Pesqui Oper* **25**: 493–503.

Charnes A, Cooper WW and Rhodes E (1978). Measuring the efficiency of decision making units. *Eur J Opl Res* **2**: 429–444.

Charnes A, Cooper WW, Huang ZM and Sun DB (1990). Polyhedral cone-ratio DEA models with an illustrative application to large commercial banks. *J Econometrics* **46**: 73–91.

Chi-Mei Corporation (2009). *Corporate social responsibility report 2008*. Chi-Mei Corporation: Tainan, R.O.C.

Dyson RG and Thanassoulis E (1988). Reducting weight flexibility in data envelopment analysis. *J Opl Res Soc* **39**: 563–576.

Entani T, Maeda Y and Tanaka H (2002). Dual models of interval DEA and its extension to interval data. *Eur J Opl Res* **136**: 32–45.

Färe R, Grosskopf S, Lovell CAK and Pasurka C (1989). Multilateral productivity comparisons when some outputs are undesirable: A nonparametric approach. *Rev Econ Stat* **71**(1): 90–98.

Feroz EH, Raab RL, Ulleberg GT and Alsharif K (2009). Global warming and environmental production efficiency ranking of the Kyoto Protocol nations. *J Environ Mngt* **90**: 1178–1183.

Gomes EG and Estellita Lins MP (2008). Modelling undesirable outputs with zero sum gains data envelopment analysis models. *J Opl Res Soc* **59**: 616–623.

HP (2008). *Global citizenship customer report 2008*. Hewlett-Packard Development Company: Texas, USA.

Intergovernmental Panel on Climate Change (IPCC) (2001). *IPCC third assessment Report: Climate change 2001*. Working

Group I: The Scientific Basis, Cambridge University Press, Cambridge, United Kingdom and New York: NY, USA.
Lansink AO and Bezlepkin I (2003). The effect of heating technologies on $CO_2$ and energy efficiency of Dutch greenhouse firms. *J Environ Mngt* **68**: 73–82.
Li CI (2006). *Introduction of Energy Consumption Indicators for Industries in Taiwan*. Industrial Development Bureau Ministry of Economic Affairs: Taipei, R.O.C.
Lu IC (2003). *Analysis of correlation between energy consumption and pollutant emission for industries in Taiwan*. Master Thesis, Department of Environmental Engineering, National Cheng Kung University: Tainan, R.O.C.
Lu WM and Lo SF (2007). A benchmark-learning roadmap for regional sustainable development in China. *J Opl Res Soc* **58**: 841–849.
Moneva JM and Ortas E (2010). Corporate environmental and financial performance: A multivariate approach. *Ind Mngt Data Syst* **110**(2): 193–210.
Nakashima K, Nose T and Kuriyama S (2006). A new approach to environmental- performance evaluation. *Int J Prod Res* **44**(18–19): 4137–4143.
Pedraja-Chaparro R, Salinas-Jimenes J and Smith P (1997). On the role of weight restrictions in data envelopment analysis. *J Prod Anal* **8**: 215–230.
Ramanathan R (2005). Estimating energy consumption of transport modes in India using DEA and application to energy and environmental policy. *J Opl Res Soc* **56**: 832–837.
ROCEPA (2009). *2009 Yearbook of Environmental Statistics*. Environmental Protection Administration, Executive Yuan: Taipei, R.O.C.
ROCEY (2009). *The Republic of China Yearbook 2008*. Government Information Office, Executive Yuan: Taipei, R.O.C.
Sarkis J (2000). A comparative analysis of DEA as a discrete alternative multiple criteria decision tool. *Eur J Opl Res* **123**: 543–557.
Seiford LM and Thrall RM (1990). Recent developments in DEA: The mathematical programming approach to frontier analysis. *J Econometrics* **46**: 7–38.
Sexton TR, Silkman RH and Hogan AJ (1986). Data envelopment analysis: Critique and extensions. *New Dir Program Eval* **32**: 73–105.
Sony (2008). *Corporate Social Responsibility Report 2008*. Sony Corporation: Japan.
Thompson RG, Singleton FD Jr, Thrall RM and Smith BA (1986). Comparative site evaluations for locating a high-energy physics lab in Texas. *Interfaces* **16**(6): 35–49.
Tyteca D (1997). Linear programming models for the measurement of environmental performance of firms: Concepts and empirical results. *J Prod Anal* **8**: 183–197.
Wu RH and Hong DL (2008). Energy management policy for industries. In: Hong DS (ed). *Energy Monthly*. Vol. 10. Bureau of Energy, Ministry of Economic Affairs: Taipei, R.O.C, pp 5–7.
Yamada Y, Matui T and Sugiyama M (1994). New analysis of efficiency based on DEA. *J Opns Res Soc Jpn* **37**: 158–167, (In Japanese).
Zofio JL and Prieto AM (2001). Environmental efficiency and regulatory standards: The case of $CO_2$ emissions from OECD industries. *Resour Energy Econ* **23**: 63–83.

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