COMPOSITE INDICATORS IN ENERGY AND ENVIRONMENTAL MODELING

ZHOU PENG

(*M.Sc., Dalian University of Technology*)

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SUMMARY

Energy and environmental (E&E) modeling is useful to decision makers dealing with complex E&E issues in making rational decisions. Among the wide spectrum of E&E modeling techniques, the construction of various E&E related composite indicators has recently received much attention. These indicators can offer decision makers condensed information for performance evaluation and comparisons, and make decision making in E&E systems more quantitative, empirically grounded and systematic. Realizing the importance of E&E related composite indicators, this thesis focuses on some key methodological issues related to applying data envelopment analysis (DEA) and multiple criteria decision analysis (MCDA) to construct various E&E related composite indicators.

This thesis is divided into four parts. In the first part, we present a relatively comprehensive literature review of DEA and MCDA in E&E studies, which justifies the significance of the research work presented in this thesis.

In the second part, we focus on the development of more practical DEA type models for measuring environmental performance. We first characterize different environmental DEA technologies, which are the basis of developing an environmental performance index, and present their radial implementations in environmental performance measurement. Since radial DEA type models often have weak discriminating power in environmental performance comparisons, we further present a non-radial DEA approach to measuring environmental performance. By considering the slacks in inputs and desirable outputs, we also propose two slacks-based efficiency measures for modeling environmental performance, which is particularly useful when the objective is to develop a composite indicator for modeling economic-environmental or sustainability performance.

In the third part, we propose the Shannon-Spearman measure for comparing alternative MCDA aggregation methods in constructing composite indicators based on the concept of "information loss". The Shannon-Spearman measure has been applied to compare several popular MCDA methods in constructing composite indicators. It is suggested that the weighted product method may be a better choice when the information loss criterion is concerned. Using the "minimum information loss" concept, we further present an information-theoretic approach to constructing composite indicators. It is found that the weighted product method highlighted by previous studies is a special case of our approach in dealing with quantitative data. This offers practitioners further evidence in applying the weighted product method to construct composite indicators.

In the final part, we present a linear programming approach to constructing composite indicators in virtue of the idea of DEA and MCDA. The proposed approach considers data weighting and aggregation simultaneously and avoids the subjectivity in determining the weights for sub-indicators. It can also easily incorporate additional information on the relative importance of sub-indicators when they become available. It therefore provides a more reasonable and flexible way for constructing composite indicators.

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LIST OF NOTATIONS

AHP	Analytic Hierarchy Process
AQI	Air Quality Index
CAQI	Composite Air Quality Index
CCI	Climate Change Indicator
CI	Composite Indicator
CO_2	Carbon Dioxide
CRS	Constant Returns to Scale
DA	Decision Analysis
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DSS	Decision Support Systems
DT	Decision Tree
E&E	Energy and Environmental
EEI	Energy Efficiency Indicator
EPI	Environmental Performance Index
ESI	Environmental Sustainability Index
GDP	Gross Domestic Product
HDI	Human Development Index
IAEA	International Atomic Energy Agency
ID	Influence Diagram
IDA	Index Decomposition Analysis
LN	Linear Normalization
LPI	Living Planet Index

List of Notations

MADM	Multiple Attribute Decision Making
MAUT	Multiple Attribute Utility Theory
MCDA	Multiple Criteria Decision Analysis
MPI	Malmquist Productivity Index
MEPI	Malmquist Environmental Performance Index
MODM	Multiple Objective Decision Making
NIRS	Non-increasing Returns to Scale
OECD	Organization for Economic Co-operation and Development
REI	Renewable Energy Indicator
RTS	Returns to Scale
SAW	Simple Additive Weighting
SEI	Sustainable Energy Index
SODA	Single Objective Decision Analysis
SSM	Shannon-Spearman Measure
VN	Vector Normalization
VRS	Variant Returns to Scale
WDI	Weighted Displaced Ideal
WEF	World Economic Forum
WP	Weighted Product
WWF	World Wildlife Foundation

CHAPTER 1 INTRODUCTION

This thesis contributes to some methodological issues in applying data envelopment analysis (DEA) and multiple criteria decision analysis (MCDA) to construct various energy and environmental (E&E) related composite indicators (CIs), e.g., environmental performance index and sustainability energy index, which could be helpful to analysts and decision makers in dealing with complex E&E issues. In this introductory chapter, some background information is first provided, which is followed by a brief introduction to CIs. We then give the scope and objective of our study. Finally, a summary of the contents of this thesis and its structure are presented.

1.1 Background information

There has been a growing concern about global environmental issues and sustainable development, which has attracted the concerted efforts of researchers from different disciplines including natural science, engineering and social science (McMichael et al., 2003). As a result, decision making in energy and environmental systems, particularly at macro level, becomes more and more significant because it usually has direct impact on both regional/national and international economic-energy-environmental systems.

Today it is known that E&E modeling is very useful to decision makers dealing with complex E&E issues for making rational decisions. However, before the 1973/1974 world oil crisis few energy researchers realized it. It was the world oil crisis that awoke the enthusiasm of energy researchers in applying analytical/modeling techniques to cope with E&E issues (Loken, 2007). The enthusiasm was further enhanced by the world-wide awareness and concern about environmental issues in the 1980s. A number of modeling techniques have as a result been developed and employed to address complex E&E issues. For example, Ang and Zhang (2000) listed 124 studies that applied index decomposition analysis techniques to study energy demand and gas emissions. Jebaraj and Iniyan (2006) reviewed different types of models for energy planning and forecasting. The applications of decision analysis (DA) in E&E studies have been reviewed by Huang et al. (1995) and updated by Zhou et al. (2006a). Greening and Bernow (2004) discussed the potential of MCDA in formulating coordinated E&E policies.

Among the wide spectrum of E&E modeling techniques, the construction of various E&E related CIs is also an important and indispensable one. Over three decades ago, some researchers, e.g., Dee et al. (1973), began to develop CIs for modeling E&E issues such as quantifying environmental impacts and evaluating environmental systems. In general, CIs offer decision/policy makers condensed information for performance evaluation, and make E&E decision making more quantitative, empirically grounded and systematic (Esty et al., 2005). In the next section, we shall give a brief introduction to the concepts of CIs and their uses in practice.

1.2 Motivations of composite indicators

According to the definition given in the *OECD Glossary of Statistical Terms* (http://stats.oecd.org/glossary), "*a composite indicator* (CI) *is formed when individual indicators are compiled into a single index, on the basis of an underlying model of the multi-dimensional concept that is being measured*". Technically, it is a mathematical aggregation of a set of individual indicators that measure multi-dimensional concepts but usually have no common units of measurement (Nardo et al., 2005). Just like a coin has two sides, the approach of CIs has its pros and cons. Table 1.1 shows some major ones as discussed in Nardo et al. (2005) and Saisana et al. (2005).

Table 1.1 Pros and cons of composite indicators

Pros	Cons
+ Can summarize complex or multi-dimensional issues in view of supporting decision/policy makers	- May send misleading, non-robust policy messages if a CI is poorly constructed or misinterpreted
+ Can provide a big picture which is easier to interpret than trying to find a trend in many separate indicators	- May invite politicians or stakeholders to draw simplistic policy conclusions
+ Can offer a rounded assessment of countries' or regions performance	- May involve stages where judgmental decisions have to be made
+ Can reduce the size of a set of indicators or include more information within the existing size limit	- May disguise serious failings in some dimensions and increase the difficulty of identifying proper remedial action
+ Can facilitate communication with general public, e.g., citizens and media	- May lead to inappropriate policies if dimensions of performance that are difficult to measure are ignored

Despite the ceaseless debate on their uses, CIs have been increasingly applied for performance monitoring, benchmarking, policy analysis and public communication in wide ranging fields including economy, energy, environment and society by many national and international organizations. For instance, CIs might be used to compare different companies in the same industry, and so provide inputs to investors about their efficiencies and environmental performance. They can also be used to compare different countries in terms of their energy efficiency and carbon emissions performance, and so provide information to policy makers in international negotiations. Their popularity has been pointed out by Saisana et al. (2005) as "*the temptation of stakeholders and practitioners to summarize complex and sometimes elusive process (e.g., sustainability or a single-market policy) into a single figure to benchmark country performance for policy consumption seems likewise irresistible*".

Four well-known examples of CIs relevant to E&E or sustainability field are described below, namely the (a) Air Quality Index (China, US, etc), (b) Living Planet Index (World Wildlife Foundation), (c) Environmental Performance/Sustainability Index (Yale, Columbia, World Economic Forum & the Joint Research Center of European Commission), and (d) Human Development Index (United Nations).

The Air Quality Index (AQI) is a well-known CI adopted by many countries such as China and US for reporting the air quality of different cities or regions over certain period of time. Its purpose is to help people understand how clean or polluted the local air is, and what associated health effects might be a concern for people (Bell et al., 2005). Since different countries may have different pollution characteristics and therefore different emphases in environmental protection, the pollutants used to calculate AQI in different countries may be slightly different. For instance, in US the Environmental Protection Agency calculates the AQI (termed as Pollutant Standards Index, or PSI) for the following five air pollutants: particulate matter, sulfur dioxide, nitrogen dioxide, carbon monoxide and ground-level ozone. However, in China the latter two pollutants are excluded in calculating the AQI (termed as Air Pollution Index, or API).

The Living Planet Index (LPI) was first released in 1998 and has been updated periodically by the World Wildlife Foundation (WWF) for measuring the overall state of the Earth's natural ecosystems, which includes national and global data on human pressures on natural ecosystems arising from the consumption of natural resources and the effects of pollution (WWF, 2004). It is derived from three sub-indicators that track trends in approximately 3,000 populations of more than 1,000 vertebrate species living in terrestrial, freshwater and maritime ecosystems around the world. The LPI together with Ecological Footprint published by the WWF provide vital information for gauging the world's progress towards sustainable development.

The Environmental Performance/Sustainability Indexes (EPI/ESI) were initiated by the World Economic Forum (WEF) in 2002 for measuring environmental protection results at the national scale. Two versions of EPI have been published so far and the latest, the 2006 EPI (Esty et al., 2006), is based on 16 sub-indicators falling into six well-established policy categories including environmental health, air quality, water resources, productive natural resources, biodiversity and habitat, and sustainable energy. The 2002 EPI includes 23 OECD countries but the 2006 EPI covers 133 countries and provides a solid foundation for assessing the progress of these countries towards sustainability. Compared to the EPI, the ESI combines more sub-indicators in a broader range and therefore provides a bigger picture for measuring long-term environmental prospects (Esty et al., 2005). The 2005 ESI covers 146 countries and involves 76 underlying sub-indicators.

The Human Development Index (HDI) was introduced by the United Nations Development Program in 1990, which was later published annually in the Human Development Report (Sagar and Najam, 1998). The HDI was constructed based on three sub-indicators that reflected three major dimensions of human development: *longevity*, *knowledge* and *standard of living*. It offers an alternative to national income as a summary measure of human well-being. The latest version of HDI can be found in the Human Development Report 2005 (UNDP, 2005), which covers 175 UN member countries and has been reported by a number of world's major news media such as *BBC*, *Economist*, *Financial Times*, *Guardian*, *Los Angeles Times* and *New York Times*.

Besides the above four CIs, there are several others which are listed in the information server: http://farmweb.jrc.cec.eu.int/ci/ maintained by the Joint Research Center of European Commission. Given the popularity of CIs in practice, there is no doubt that the construction of CIs plays a significant role in the field of E&E modeling. Nevertheless, some methodological issues in constructing E&E related CIs need to be further clarified and studied.

1.3 Research scope and objective

There have been a large number of techniques that can be used to construct E&E related CIs, e.g., life cycle assessment, environmental accounting approach, production efficiency theory and statistical models (Olsthoorn et al., 2001; Nardo et al., 2005). From the viewpoint of operations research, as discussed in Zhou and Ang (2008a), the existing aggregation techniques for constructing E&E related CIs can be broadly divided into two categories. One might be treated as "the direct approach", in which a CI can be directly obtained from the original data by using DEA type models from the point of view of productive efficiency. Compared with the direct approach, the indirect approach will often involve the normalization of the original data and the weighting and aggregation of the normalized data, in which MCDA plays an important role. It is worth pointing out that DEA and MCDA were initially developed to address different issues in operations research. MCDA usually involves value judgments and has been widely used to rank alternatives from most to least desirable when there are multiple conflicting objectives, whereas DEA was often taken as an effective tool for evaluating the technical efficiency of an entity relative to other similar entities. In this thesis, both of them are studied within the same application context, i.e., the construction of E&E related CIs.

1.3.1 DEA for constructing EPI

DEA, a well established nonparametric approach to efficiency measurement, has been widely applied to study various E&E issues in the past several decades. In recent years, it has also gained great popularity in environmental performance measurement owing to its ability in combining multi-dimensional data into a CI called environmental performance index (EPI).

In general, the use of DEA in constructing EPI starts from the incorporation of undesirable outputs, e.g., pollutants, into the traditional DEA framework. A large number of methods have been proposed to incorporate undesirable outputs. These methods can be roughly divided into two groups. One is based on data translation and the use of traditional DEA models, e.g., Seiford and Zhu (2002). The other uses original data but is based on the concept of environmental DEA technology as discussed in Färe and Grosskopf (2004). Although the data translation approach has some good theoretical properties, the concept of environmental DEA technology seems to be more popular in the field of EPI construction. For instance, Zaim and Taskin (2000a) applied the hyperbolic graph measure to construct an EPI for comparing carbon dioxide emissions in OECD countries. Färe et al. (2004) provided a formal approach to construct an EPI by using the theory of Malmquist quantity index number. Using the same idea as that in Färe et al. (2004), Zaim (2004) thereby developed an EPI for measuring the environmental performance of state manufacturing.

It is found that in most previous studies the environmental DEA technology used was always assumed to satisfy constant returns to scale. However, in actual situations, other cases such as variant returns to scale are likely to be observed (Tyteca, 1996). It is worthwhile to characterize different environmental DEA technologies and to investigate the incorporation of them with some commonly used efficiency measures. Therefore, in this thesis we characterize the environmental DEA technologies that exhibit non-increasing returns to scale and variant returns to scale and present their radial implementations for constructing various EPIs.

Although previous studies proposed many DEA type models with good theoretical properties for constructing EPIs, most of them follow the concept of radial efficiency measures. As a result, the EPIs developed in these studies usually have weak discriminating powers, and comparisons among different entities in environmental performance become difficult. In order to tackle this problem, we present the non-radial and slacks-based DEA type models for constructing EPIs with higher discriminating power. Some empirical application studies have also been presented with the main purpose of demonstrating the applicability of the models developed. It is hoped that the DEA type models newly developed could not only provide some more practical tools for measuring environmental performance but also contribute to the field of DEA.

1.3.2 MCDA for constructing CIs

MCDA is a well-established methodology that can guide/help decision makers to evaluate existing or potential alternatives under the situation with multiple conflict criteria (Yoon and Hwang, 1995). It has been widely accepted as a useful tool for modeling complex E&E issues such as E&E policy analysis, in which E&E related CIs are often constructed for the use of decision/policy makers.

The general procedure for applying MCDA to CI construction involves the normalization of different sub-indicators and the weighting and aggregation of the normalized data. At the stage of data aggregation, there exist many MCDA methods which can be used to perform this task. For instance, Esty et al. (2005) applied the simple additive weighting (SAW) method to construct the environmental sustainability indices for 76 countries. Compared with the SAW method, the weighted product (WP) method has been recommended more highly by Ebert and Welsch (2004) in order to construct a meaningful environmental index. Despite the popularity of the SAW and WP methods, Diaz-Balteiro and Romero (2004) found that the weighted displaced ideal (WDI) method may be suitable for constructing an index for assessing sustainability performance. Munda (2005) highlighted the applicability of non-compensatory MCDA methods in constructing CIs. More recently, Singh et al. (2007) applied the analytical hierarchy process (AHP) to develop a composite sustainability performance index.

Not surprisingly, the existence of many MCDA aggregation methods makes the choice of an appropriate one quite difficult. A large number of criteria have therefore been developed by researchers for aiding analysts to select an appropriate MCDA method for use, which are mainly based on the generic application domain of MCDA, i.e., ranking alternatives. In the context of CI construction, Esty et al. (2005) suggested the choice of an aggregation method should depend on the purpose of CIs as well as the nature of this subject. Despite its usefulness, this criterion is quite subjective. We therefore develop an objective measure called the Shannon-Spearman measure for comparing alternative MCDA methods in constructing CIs, which should be objective in principle and reasonable in logic.

The Shannon-Spearman measure proposed is based on the "minimum information loss" concept and can only be used to compare the MCDA aggregation methods available. Thus, we apply the same concept to develop an information-theoretic aggregation approach to constructing CIs, which is not too complex but has some good theoretical advantages. It would become a better alternative for constructing CIs than some traditional MCDA methods if the information loss criterion is concerned by users.

In the Shannon-Spearman measure as well as the information-theoretic approach to constructing CIs, it is assumed that the weights for sub-indicators are known. Nevertheless, the determination of the weights for sub-indicators is not an easy task. We therefore present a linear programming approach to constructing CIs in virtue of the idea of DEA. One main feature of the proposed approach is that it simultaneously considers data weighting and aggregation in CI construction and therefore avoids the subjectivity in determining the weights for sub-indicators.

1.4 Organization of the thesis

This thesis focuses on the study of DEA and MCDA in constructing E&E related CIs, with an emphasis on the development of more practical methods for use. It consists of nine chapters. Figure 1.1 shows the main contents of each chapter and the relationships among different chapters.

Chapter 2 presents a literature review of various decision analysis (DA) methods in E&E studies in a more comprehensive manner since our study falls into the broad area of DA in E&E modeling. Although DEA may be considered as a particular MCDA method, it starts with the purpose of evaluating relative efficiencies rather than choosing a specific course of action highlighted in traditional DA methods (Doyle and Green, 1993; Stewart, 1996). Therefore, the applications of DEA and traditional DA methods in E&E studies are separately reviewed in this chapter.

In Chapter 3, we characterize different environmental DEA technologies and present their radial implementations in measuring environmental performance. Based on the environmental DEA technology exhibiting constant returns to scale, Chapter 4 and Chapter 5 respectively present the non-radial and slacks-based DEA type models for modeling environmental performance. In Chapters 3 to 5, some application studies on measuring carbon dioxide emissions or environmental performance of different countries/regions are also presented, which not only demonstrate the use of the proposed models but also provides some useful information to policy makers.

While Chapters 3 to 5 deal with the direct approach to constructing EPI, Chapters 6 to 7 are mainly concerned with the indirect approach to constructing various CIs inclusive of E&E related CIs. In Chapter 6, we present the Shannon-Spearman measure for comparing alternative MCDA aggregation methods in constructing CIs. The validity of the Shannon-Spearman measure is assessed by the variance-based sensitivity analysis technique. We also apply the Shannon-Spearman measure to compare a number of MCDA methods in constructing CIs by using one real dataset and several simulation studies.

Using the same concept embodied in the Shannon-Spearman measure as described in Chapter 6, Chapter 7 proposes an information-theoretic aggregation approach to constructing CIs, which can deal with both quantitative and qualitative data. The WP method reported in previous studies can be shown to be a special case of this approach, which provides further evidence for practitioners to apply the WP method in constructing CIs.

In Chapter 8, we develop a linear programming approach to constructing CIs in virtue of the idea of DEA and MCDA. The proposed approach uses two sets of weights that are most and least favourable for each entity to be evaluated and therefore could provide a more reasonable and encompassing CI. As shown in Fig. 1.1, this work makes a bridge between the direct approach and the indirect approach to constructing CIs. We also present an application study on constructing the sustainable energy index for eighteen APEC economies.

Chapter 9 gives the conclusion of this thesis as well as some potential future research topics.

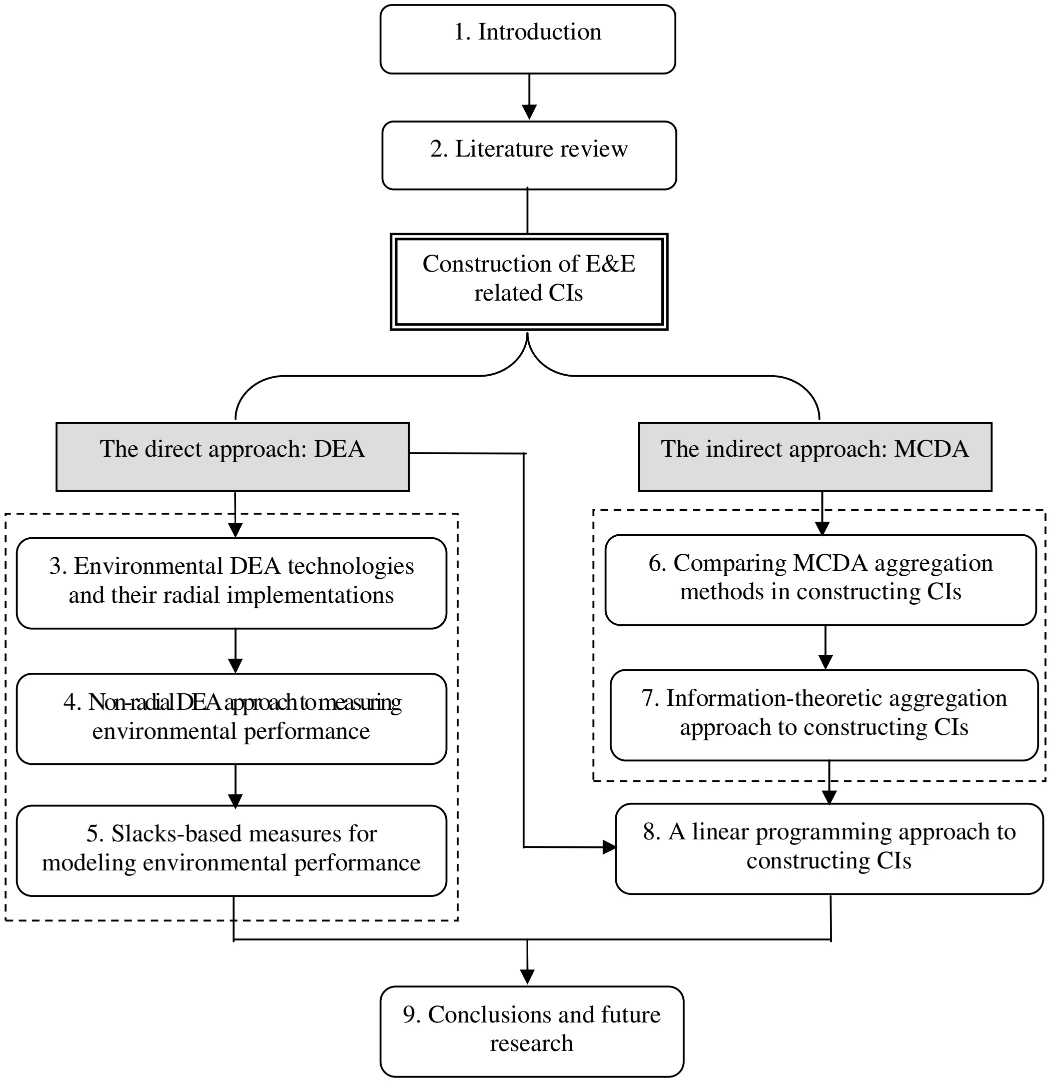

Fig. 1.1 Structure of the thesis

CHAPTER 2 LITERATURE REVIEW[1]

E&E issues are generally complex and conflict with multiple objectives. They usually involve many sources of uncertainty, long time frame, capital intensive investment and a large number of stakeholders with different views and preferences, which make decision making in E&E systems, particularly at macro-level, rather difficult. It is therefore necessary to use E&E modeling techniques, which could integrate objective measurement and subjective judgment into a unified framework, to help analysts and decision makers address complex E&E issues. In this chapter, we give a review of two commonly used modeling techniques: (a) data envelopment analysis (DEA), (b) decision analysis (DA) applications in E&E studies. The two E&E modeling techniques are focused on because they are closely linked to the theme of the thesis, i.e., the use of DEA and MCDA in constructing E&E related CIs.

Although DEA may be regarded as a particular MCDA method, it starts with the purpose of evaluating relative efficiencies rather than choosing a specific course of action highlighted in traditional decision analysis (Doyle and Green, 1993; Stewart, 1994, 1996). It is therefore not surprising that none of the previous literature reviews on MCDA in E&E studies, such as Huang et al. (1995), Hobbs and Meier (2000), Greening and Bernow (2004) and Zhou et al. (2006a), has included DEA-related studies. In E&E studies, DEA is mainly used for efficiency evaluation, performance measurement and benchmarking, while MCDA methods put an emphasis on choosing the "best" alternative for the involved E&E problem covering a wide range of topics,

[1] The work presented in this chapter has been published as Zhou et al. (2006a, 2008a).

such as power plant siting, energy and environmental policy formulation, and environmental impact assessment. Hence, we shall separately review their applications in E&E studies. A survey of DEA in E&E studies is first presented in Section 2.1. Section 2.2 presents a comprehensive literature review on various DA methods including MCDA in dealing with E&E issues. Section 2.3 summarizes the concluding comments.

2.1 DEA in E&E studies

DEA, developed by Charnes et al. (1978), is a nonparametric approach to efficiency evaluation and performance comparisons. Along with the wave of deregulation in energy sectors since the late 1980s, DEA has been widely accepted as a major frontier technique for benchmarking energy sectors, particularly in the electricity industry (Jamasb and Pollitt, 2001). In recent years, DEA has also gained popularity in areas such as energy efficiency study and environmental performance measurement. It is the purpose of this section to present the results of our survey on DEA in E&E studies. In the sections that follow, we shall first introduce the basic DEA methodology. Next, we introduce the most common extensions to basic DEA models based on our survey and the DEA structure. We then classify a total of 100 studies published from 1983 to 2006 by the methodological aspect, application scheme, and several other relevant attributes. We present the main features observed and findings. Finally, we discuss some issues on the selection of DEA models and the determination of inputs and outputs.

2.1.1 Basic DEA methodology

Built upon the earlier work of Farrell (1957), DEA is a well established methodology to evaluate the relative efficiencies of a set of comparable entities by some specific mathematical programming models. These entities, often called decision making units (DMUs), perform the same function by transforming multiple inputs into multiple outputs. A main advantage of DEA is that it does not require any prior assumptions on the underlying functional relationships between inputs and outputs (Seiford and Thrall, 1990). It is therefore a nonparametric approach. In addition, DEA is a data-driven frontier analysis technique that floats a piecewise linear surface to rest on top of the empirical observations (Cooper et al., 2004).

Since the work by Charnes et al. (1978), DEA has rapidly grown into an exciting and fruitful field, in which operations research and management science researchers, economists, and experts from various application areas have played their respective roles (Førsund and Sarafoglou, 2005). For DEA beginners, Ramanathan (2003) and Coelli et al. (2005) provided excellent introductory materials. The more comprehensive DEA expositions can be found in the recent publication by Cooper et al. (2006). In the sections that follow, we shall briefly introduce the basic DEA methodology.

Assume that there are K DMUs, e.g., electricity distribution utilities, to be evaluated that convert N inputs to M outputs. Further assume that DMU$_k$ consumes $x_{nk} \geq 0$ of input n to produce $y_{mk} \geq 0$ of output m and each DMU has at least one positive input and one positive output (Färe et al., 1994a; Cooper et al., 2004). Based on the efficiency concept in engineering, the efficiency of a DMU, says DMU$_o$

($o = 1,2,\cdots,K$), can be estimated by the ratio of its virtual output (weighted combination of outputs) to its virtual input (weighted combination of inputs). To avoid the arbitrariness in assigning the weights for inputs and outputs, Charnes et al. (1978) developed an optimization model known as the CCR model in ratio form to determine the optimal weights for DMU$_o$ by maximizing its ratio of virtual output to virtual input while keeping the ratios for all the DMUs not more than one. If the maximal value of the objective function is less than one, it indicates that DMU$_o$ will impossibly get a weight combination to let its efficiency score equal to one and is therefore relatively inefficient. Using the Charnes-Cooper transformation, this problem can be further transformed into an equivalent “output maximization” linear programming problem as follows:

$$
\begin{aligned}
&\max \textstyle\sum_{m=1}^{M} u_m y_{mo} \\
&\text{s.t. } \sum_{m=1}^{M} u_m y_{mk} - \textstyle\sum_{n=1}^{N} v_n x_{nk} \leq 0,\ k = 1,2,\cdots,K \\
&\qquad \sum_{n=1}^{N} v_n x_{no} = 1 \\
&\qquad u_m, v_n \geq 0,\ m = 1,2\cdots,M;\, n = 1,2,\cdots,N
\end{aligned}
\tag{2.1}
$$

Model (2.1) is known as the CCR model in multiplier form. The efficiency scores of DMU$_1$ to DMU$_K$ can be derived by solving K such models. If the optimum objective function value of (2.1) is equal to 1, it implies that the DMU concerned is relatively efficient since we can find a weight combination to make its efficiency score to be equal to one. Despite the linear form of (2.1), efficiency score is usually calculated based on its dual problem:

$$
\begin{aligned}
&\min \theta \\
&\text{s.t.} \sum_{k=1}^{K} x_{nk}\lambda_k \leq \theta x_{no},\ n = 1,2,\cdots N \\
&\quad \sum_{k=1}^{K} y_{mk}\lambda_k \geq y_{mo},\ m = 1,2,\cdots,M \\
&\quad \lambda_k \geq 0,\ k = 1,\cdots,K
\end{aligned} \tag{2.2}
$$

Model (2.2) is known as the input-oriented CCR in envelopment form (or the Farrell model), which attempts to proportionally contract DMU$_o$'s inputs as much as possible while not decreasing its current level of outputs. In economic literature, model (2.2) may date back to the activity analysis models introduced by von Neumann (1945) and Koopmans (1951). It has also a close relationship with the input distance function introduced by Shephard (1970). In a similar way, we can also derive the output-oriented CCR in envelopment form if efficiency is initially specified as the ratio of virtual input to virtual output.

Note that the constraint set in model (2.2) nicely corresponds to the piecewise linear production technology that exhibits constant returns to scale (CRS) and has strong disposable inputs and outputs (Färe et al., 1994a):

$$
\begin{aligned}
T = \{(\mathbf{x},\mathbf{y}) : &\sum_{k=1}^{K} z_k x_{nk} \leq x_n,\ n = 1,2,\cdots,N \\
&\sum_{k=1}^{K} z_k y_{mk} \geq y_m,\ m = 1,2,\cdots,M \\
&z_k \geq 0,\ k = 1,2,\cdots,K\}
\end{aligned} \tag{2.3}
$$

where $\mathbf{x} = (x_1, x_2, \cdots, x_N)$ and $\mathbf{y} = (y_1, y_2, \cdots, y_M)$ are respectively the vectors of inputs and outputs. Here we call T the reference technology that consists of all the feasible combinations of inputs and outputs.

According to (2.2) and (2.3), we may break a DEA model down into two parts: the efficiency measure such as the objective function in (2.2) and the reference technology. A DEA model is fully characterized by its reference technology and efficiency measure. Furthermore, the reference technology can be characterized by the type of returns to scale (RTS), and the disposability and operating characteristics of inputs and outputs. The efficiency measure will be determined by its type and orientation. Figure 2.1 shows the general structure of a DEA model as well as the most widely used efficiency measures in E&E studies, which will be discussed in the next section.

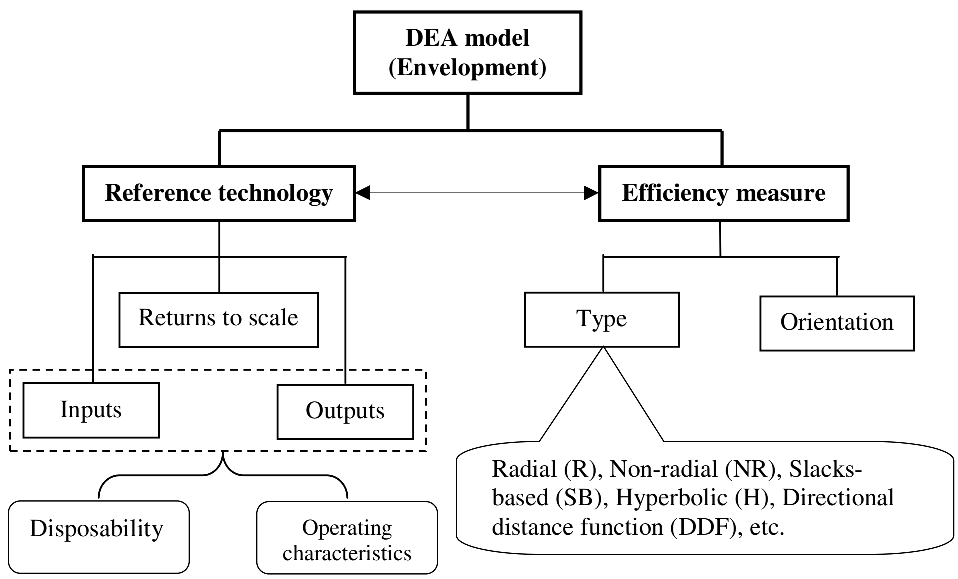

Fig. 2.1 The general structure of a DEA model (envelopment form)

2.1.2 Extensions to basic DEA models

As was described by Ramanathan (2003) and Cooper et al. (2006), a large number of extensions to basic DEA models have appeared in the literature. We shall limit our discussions to the most widely used extensions in E&E studies based on our survey and the general structure of DEA models (see Fig. 2.1).

2.1.2.1 Reference technology

In traditional DEA models including the CCR, the inputs and outputs are assumed to be strongly or freely disposable. That is to say, their reference technologies satisfy that if $(\mathbf{x},\mathbf{y}) \in T$ and $\mathbf{x}' \geq \mathbf{x}$ (or $\mathbf{y}' \leq \mathbf{y}$) then $(\mathbf{x}',\mathbf{y}) \in T$ (or $(\mathbf{x},\mathbf{y}') \in T$). However, this may not always be true in the real production process. For instance, in a fossil-fuel-fired electricity generation plant the generation of electricity is always accompanied by the production of undesirable outputs such as sulfur dioxide. In such cases, the reduction of undesirable outputs would likely be costly. It is therefore not appropriate to use the strong disposability reference technology.

Many methods have been proposed to incorporate undesirable outputs into DEA models (Scheel, 2001). Generally, these methods can be divided into two groups. One is based on data translation and the utilization of traditional DEA models, e.g., Seiford and Zhu (2002). The other uses the original data but is based on the concept of weak disposability reference technology as proposed by Färe et al. (1989). In the DEA framework, the weak disposability reference technology, also called the environmental DEA technology (Färe and Grosskopf, 2004), can be characterized as follows

$$
\begin{aligned}
T_e = \{(\mathbf{x},\mathbf{y},\mathbf{u}): & \sum_{k=1}^{K} z_k x_{nk} \le x_n,\ n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_m,\ m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = u_j,\ \ j = 1,2,\cdots,J \\
& z_k \ge 0,\ k = 1,2,\cdots,K\}
\end{aligned}
\tag{2.4}
$$

where $\mathbf{u} = (u_1, u_2, \cdots, u_J)$ represents the vector of undesirable outputs.

The difference between T and T_e is that in T_e the reduction of only undesirable outputs is impossible but the proportional reduction of both desirable and undesirable outputs is feasible. In addition, T_e also satisfies the desirable null-jointness property, i.e., if $(\mathbf{x},\mathbf{y},\mathbf{u}) \in T$ and $\mathbf{u} = 0$, then $\mathbf{y} = 0$. It implies that the only way to eliminate all the undesirable outputs is to end the production process. Therefore, T_e should be a better representation of the real production process when both desirable and undesirable outputs are simultaneously produced. It has been widely applied to such E&E studies as estimating productivity with pollutants considered and modeling environmental performance. See, for example, Färe et al. (1996, 2001, 2004), Chung et al. (1997), Boyd and McClelland (1999), Boyd et al. (2002), Zaim (2004), Arcelus and Bogetoft (2005), Picazo-Tadeo et al. (2005) and Zhou et al. (2006b, 2007c, 2008-b).

Although the derivation of the environmental DEA technology is based on the weak disposability of outputs, a similar idea can be generalized to the case of inputs (Färe et al., 1994a). This generalization is particularly useful when DMUs consume undesirable inputs such as carbon dioxide (Oude Lansink and Bezlepkin, 2003; Oude Lansink and Silva, 2003).

In addition to the disposability property of inputs and outputs, their operating characteristics, i.e., whether there exist non-discretionary or categorical or environmental variables, sometimes will also play an important role in characterizing the form of a reference technology. Two well-known examples are the DEA models with non-discretionary and categorical variables as formulated by Banker and Morey (1986a, b). In E&E studies, such kinds of models can be used to measure the efficiency of energy utilities when environmental regulations are imposed or there are external non-controllable factors, e.g., Korhonen and Sarjanen (2003), Agrell and Bogetoft (2005) and Hattori et al. (2005).

Another major characterization of the reference technology is its property on returns to scale (RTS). It is known that the reference technology T for the CCR model exhibits constant returns to scale (CRS). If an additional constraint $\sum_{k=1}^{K} \lambda_k = 1$ is appended to T, the resulting reference technology will permit the existence of variant returns to scale (VRS) and the CCR model (2.2) becomes the classical BCC model (Banker et al., 1984). In addition to CRS and VRS, non-increasing returns to scale (NIRS) reference technology, which can be derived by appending $\sum_{k=1}^{K} \lambda_k \leq 1$ to T, is also very useful because it is helpful to investigate the RTS properties of DMUs (Ramanathan, 2003). Although previous discussions are based on the strong disposability reference technology, various RTS conditions can also be integrated with the weak disposability reference technology in appropriate ways (Färe et al., 1994a; Zhou et al., 2008-b).

2.1.2.2 Efficiency measures

Efficiency measure will completely determine a DEA model once the reference technology is given (see Fig. 2.1). From the orientation point of view, efficiency measures used in E&E studies mainly consist of inputs, outputs and undesirable outputs oriented measures. In the case of the type, many different efficiency measures have been proposed with their respective advantages. Here we shall only introduce those which have been widely adopted in E&E studies.

The radial efficiency measure, which adjusts inputs or outputs proportionally, is probably the most widely used in DEA models. By combining radial efficiency measure with various reference technologies, we can obtain various DEA models including the CCR and BCC. If T_e is used and radial efficiency measure for adjusting undesirable outputs is adopted, we will get such a model as $\min\{\theta : (\mathbf{x}_o, \mathbf{y}_o, \theta\mathbf{u}_o) \in T_e\}$ that can be used to measure the environmental performance of DMU$_o$, e.g., Tyteca (1996, 1997) and Färe et al. (2004).

A non-radial efficiency measure allows for the non-proportional adjustment of different inputs/outputs. It usually has a higher discriminating power than radial efficiency measure in comparing DMUs. A well-known non-radial efficiency measure is the Russell efficiency measure $\min\{\frac{1}{N}\sum_{n=1}^{N}\theta_n : (\mathbf{x}_o\boldsymbol{\theta}, \mathbf{y}_o) \in T\}$ where $\boldsymbol{\theta}$ is a diagonal matrix consisting of θ_1 to θ_n (Färe et al., 1994a). If the weights for θ_n ($n = 1,2,\cdots,N$) are given, the weighted non-radial efficiency measure reflecting the preference structure of decision makers can also be obtained (Zhu, 1996).

A slacks-based efficiency measure is constructed directly from the slacks in inputs and outputs. There are various slacks-based efficiency measures, e.g., the additive measure and the Tone's measure (Tone, 2001; Cooper et al., 2006). Since slacks-based efficiency measure can identify all the economic inefficiencies, its discriminating power is relatively high.

The hyperbolic efficiency measure, also called graph measure, attempts to simultaneously reduce inputs and expand outputs at the same rate (Färe et al., 1994a). Technically, it can be characterized as $\min\{\theta : (\theta \mathbf{x}_o, \mathbf{y}_o / \theta) \in T\}$ if T is the reference technology used. This measure is particular useful when there are both desirable and undesirable outputs.

The directional distance function (DDF) efficiency measure allows us to simultaneously expand desirable outputs and reduce inputs and/or undesirable outputs based on a given direction vector (Chung et al., 1997). It represents a more general concept since traditional radial efficiency measure is a special case of it (Färe and Grosskopf, 2004).

2.1.2.3 Nonparametric Malmquist productivity index

In the foregoing the use of DEA is restricted to cross-sectional analysis, i.e., multilateral comparisons among different DMUs at the same point in time. However, in the case of energy sectors, there is generally a great interest in investigating their productivity change over time.

The nonparametric Malmquist productivity index (MPI) is such a formal time-series analysis method for conducting performance comparisons of DMUs over time by solving some DEA-type models (Malmquist, 1953; Caves et al., 1982; Färe et al., 1994b). Although MPI is defined based on the concept of distance functions, it can also be directly represented by DEA efficiency measures. Assume that $\theta^t(\mathbf{x}_o^t, \mathbf{y}_o^t)$ and $\theta^{t+1}(\mathbf{x}_o^t, \mathbf{y}_o^t)$ are the input-oriented efficiency measures of DMU$_o$ based on its inputs and outputs at period t for the reference technology at t and t+1. Further assume that $\theta^t(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})$ and $\theta^{t+1}(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})$ are the input-oriented efficiency measures of DMU$_o$ based on its inputs and outputs at period t+1 for the reference technology at t and t+1. The output-oriented MPI can be defined as

$$MPI_o = \left[\frac{\theta^t(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})}{\theta^t(\mathbf{x}_o^t, \mathbf{y}_o^t)} \frac{\theta^{t+1}(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})}{\theta^{t+1}(\mathbf{x}_o^t, \mathbf{y}_o^t)} \right]^{1/2} \tag{2.5}$$

We can then use MPI_o to measure the productivity change of DMU$_o$ over time. $MPI_o > 1$, $MPI_o = 1$ and $MPI_o < 1$ respectively indicate that the productivity of DMU$_o$ has improved, remained unchanged, and deteriorated from period t to t+1.

Following Färe et al. (1994b), MPI_o can also be written as

$$MPI_o = \left[\frac{\theta^t(\mathbf{x}_o^t, \mathbf{y}_o^t)}{\theta^{t+1}(\mathbf{x}_o^t, \mathbf{y}_o^t)} \frac{\theta^t(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})}{\theta^{t+1}(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})} \right]^{1/2} \times \frac{\theta^{t+1}(\mathbf{x}_o^{t+1}, \mathbf{y}_o^{t+1})}{\theta^t(\mathbf{x}_o^t, \mathbf{y}_o^t)} \tag{2.6}$$

In such a way, the productivity change can be decomposed into two parts, namely technological change and efficiency change. The technological change component, i.e., the terms enclosed by the square brackets, reflects the shift in the best practice frontier from t to t+1. The efficiency change component, i.e., the terms outside the brackets, measures the change in relative efficiency over time.

Other aspects of MPI have been explored in a variety of studies. For more details, see the excellent MPI survey by Färe et al. (1998).

2.1.2.4 Miscellaneous

In addition to those covered above, there are many other theoretical extensions to basic DEA models. Among these extensions, some are based on the envelopment version of DEA models, e.g., the non-separating approach proposed by Scheel (2001) to dealing with undesirable outputs, while others favour DEA models in the multiplier form. In the latter, the incorporation of weight restrictions into DEA, e.g., the Absolute Weights Restrictions approach initiated by Dyson and Thanassoulis (1988), should represent one of the most significant developments in DEA (Allen et al., 1997). The DEA models with weight restrictions, which are dual to the slacks-based DEA models proposed by Tone (2001), not only have higher discriminating power in performance comparisons but also are important for understanding the nature of the reference technology (Podinovski, 1999, 2001; Dyson et al., 2001). More discussion on these developments can be found in Allen et al. (1997) and Cooper et al. (2006).

To a certain extent, the popularity of DEA in empirical applications owes to the availability of many specialized DEA software packages. The study by Ramanathan (2003) has listed a collection of useful internet sites and popular DEA software. In E&E studies, two widely used free software packages are the DEAP developed by Coelli (1996) and the EMS developed by Scheel (2000).

2.1.3 Main features and findings of past studies

The 100 studies listed in Table A.1 in Appendix A have been collected primarily from major operations research/management science journals such as

European Journal of Operational Research, as well as some major E&E and economics journals. They are classified according to the following attributes: type of study, country/region, methodological aspect, and application scheme. The third column of Table A.1 shows that the 100 studies cover a wide spectrum of countries. To study possible changes over time, we divide the time frame into three 8-year periods, 1983-1990, 1991-1998 and 1999-2006. As shown in Fig. 2.2, the total number of publications has increased significantly, from 7 in 1983-1990 to 72 in 1999-2006. In the following sections, we present our main findings on the features of past studies in terms of application scheme and methodological aspect.

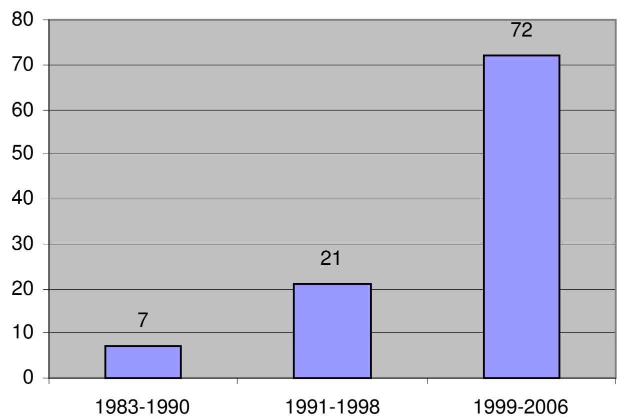

Fig. 2.2 Trends by number of studies

2.1.3.1 Application scheme

Application scheme refers to the main application issue studied, which is shown in the last column of Table A.1. If the purpose of a DEA study is to measure the productive efficiency of a sample of energy utilities, we then use the name of DMUs, e.g., electricity distribution utilities, to represent the application scheme.

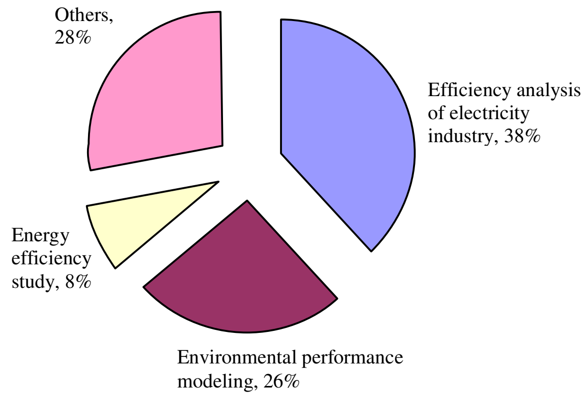

Fig. 2.3 Breakdown of studies by application scheme

Figure 2.3 shows the breakdown of the 100 studies by application scheme. It is found that 38% of studies deal with issues in electricity industry. Prior to 1990, the use of DEA in electricity industry mainly focused on electricity generation plants, e.g., Färe et al. (1983, 1985, 1990). Since the earlier 1990s, DEA has gradually become a popular benchmarking tool for studying the efficiency of electricity distribution utilities. The study by Weyman-Jones (1991), in which the technical efficiency of the UK electricity distribution industry was studied, is probably the first publication in this area. Since then, many studies have appeared in the literature and the study scope has also expanded from a single country case to a cross-country case (also called international benchmarking). Examples of such studies include Hjalmarsson and Veiderpass (1992), Bagdadioglu et al. (1996), Yunos and Hawdon (1997), Førsund and Kittelsen (1998), Edvardsen and Førsund (2003), Jamasb and Pollitt (2003) and Giannakis et al. (2005). Temporally, the shares taken up by the studies on electricity generation plants and the studies on electricity distribution utilities have, respectively, increased from 5% and 7% in 1991-1998 to 10% and 13% in 1999-2006. This could be explained by the electricity sector reforms that have occurred in many countries since the late 1980s and regulators have chosen appropriate benchmarking techniques such as DEA to quantify the efficiency improvements of electricity utilities.

Modeling environmental performance, which mainly includes environmental performance measurement and estimation of environmental regulation impacts, is another popular application area of DEA in E&E studies. Of the 100 studies, about a quarter deal with this area. Although a few studies were reported before 1990, e.g., Färe et al. (1986, 1989), most of them appeared in the latter two time periods, especially in 1999-2006. It should be attributed to the world-wide concern on environmental issues and sustainable development, as well as the ability of DEA in providing a standardized and aggregated environmental performance index (Tyteca, 1996; Allen, 1999). In some studies, e.g., Tyteca (1997, 1998), Boyd and McClelland (1999), Hernandez-Sancho et al. (2000) and Boyd et al. (2002), DEA was used to model environmental performance at firm level. Nevertheless, it seems that there is an increasing tendency of applying DEA to model environmental performance at the macro level. Particularly, regional/national carbon dioxide emissions have been widely studied. See, for example, Zaim and Taskin (2000a, 2000b), Zofio and Prieto (2001), Rmanathan (2002, 2005a), Färe et al. (2004) and Zhou (2006b, 2007c, 2008-b). This might be the result of the growing concern with climate change due to carbon dioxide emissions in recent years.

Energy efficiency measurement and monitoring has evolved as an important topic in E&E studies (Ang, 2006). Recently, the potential of DEA in energy efficiency study has also been widely investigated by researchers. The study by Boyd and Pang (2000) discussed the relationship between productivity and energy intensity, while Ramanathan (2000) applied DEA to study the energy efficiencies of alternative transport modes. More recently, Hu and Wang (2006) and Hu and Kao (2007) developed a total-factor energy efficiency index by using DEA, which provides a useful alternative to the traditional energy efficiency indicators such as the aggregated energy intensity. Within a joint production framework, Zhou and Ang (in press) proposed several DEA models for measuring economy-wide energy efficiency performance. Considering the importance of energy efficiency study and the ability of DEA in combining multiple factors, it is reasonable to believe that DEA would play a more important role in energy efficiency studies in future.

In addition to the three application areas discussed, DEA has also been applied to study the productive efficiency of some specific energy sectors, e.g., district heating plants (Raczka, 2001; Agrell and Bogetoft, 2005; Munksgaard et al., 2005), oil and gas industries (Thompson, 1995, 1996; Price and Weyman-Jones, 1996; Hawdon, 2003; Kashani, 2005a, 2005b) and coal mines (Byrnes, 1984, 1988; Thompson, 1992; Kulshreshtha and Parikh, 2002). Besides, as illustrated in Brännlund et al. (1998), DEA is also a useful tool for studying the issue of emissions permit allocations. Among these studies, several recent publications are worth highlighting because they may provide new directions for future research. One was by Ramanathan (2005b) who applied DEA to forecast energy consumption and carbon dioxide emissions. The others were by Pasurka Jr. (2006) and Zhou and Ang (2008b) who established a linkage between DEA and another popular E&E modeling technique called index decomposition analysis (Ang and Zhang, 2000; Ang, 2004).

2.1.3.2 Methodological aspect

As shown in Table A.1, the methodological aspect is further characterized by the disposability of inputs and outputs, the RTS property of reference technology, efficiency measure type and the use of MPI as described in Section 2.1.2. However, for those studies dealing with DEA models in multiplier form, which take up 17% of the 100 studies, we only present the models used without further characterizing their reference technologies and efficiency measures. As a result, these studies are not accounted for in discussing reference technology and efficiency measure.

Not surprisingly, almost all the studies assume that inputs are strongly disposable. This is determined by the "the less the better" property of inputs. However, the studies by Oude Lansink and Bezlepkin (2003) and Oude Lansink and Silva (2003) are two exceptions, in which carbon dioxide is used as an input of greenhouse firms. Several other studies assumed both strong disposability and weak disposability of inputs in order to measure the congestion of inputs, e.g., Byrnes et al. (1984, 1985) and Färe et al. (1985).

As to the disposability of outputs, strong disposability is still the most widely used one. Nevertheless, over a quarter of the studies assumed that outputs are weakly disposable, i.e., they dealt with the environmental DEA technology concept. Of these studies, most pertain to such issues as productivity estimation with pollutants considered, environmental performance measurement and estimation of environmental regulation impacts. Examples of such studies include Färe et al. (1986, 1989, 1996), Chung et al. (1997), Hernandez-Sancho et al. (2000), Tyteca (1997), Zaim and Taskin (2000a,b), Zofio and Prieto (2001), Zaim (2004) and Zhou et al. (2006b, 2007c, 2008-b). A common feature of these studies is that both desirable outputs and undesirable outputs are simultaneously considered. In such cases, the environmental DEA technology is particularly attractive because it has good theoretical properties and could characterize the real production process better.

For the RTS property of reference technology, it is found that about a half of the studies assumed that the reference technology exhibits CRS, although VRS might be a more appropriate assumption (Ramanathan, 2003). One possible reason is that the output-oriented radial efficiency measure is just the reciprocal of the input-oriented radial efficiency measure under the CRS assumption. As a result, the choice between input-oriented and output-oriented DEA model becomes indifferent. In addition, this could be partially explained by the popularity of MPI and the fact that the MPI based on the CRS assumption can be interpreted as a total productivity index (Førsund and Kittelsen, 1998). It is also noted that 30% of the studies adopted both the CRS and the VRS reference technologies. This might be a standardized application mode of DEA because in such cases the scale efficiency of each DMU can be estimated. Examples of such studies include Raczka (2001), Pacudan and de Guzman (2002), Chien et al. (2003) and Ramanathan (2005). If the CRS, VRS and NIRS reference technologies are used together, the RTS properties of DMUs can be further investigated (Färe et al., 1983, 1984, 1994a; Ramanathan, 2003).

From Table A.1 we can find that radial efficiency measure, adopted in over three-quarters of the studies, has all along been the most commonly used one among the various types of efficiency measures. Nevertheless, in some cases other efficiency measures may be more meaningful and practical. For instance, if both desirable and undesirable outputs are considered simultaneously, the DDF efficiency measure may provide a more reasonable productivity index because it considers the output of pollution abatement activities (Chung et al., 1997; Färe et al., 2001; Picazo-Tadeo et al., 2005). Compared with radial efficiency measure, slacks-based efficiency measure provides a more practical index with higher discriminating power for measuring energy efficiency and modeling environmental performance (Hu and Wang, 2006; Zhou et al., 2006b; Hu and Kao, 2007).

In addition, as shown in Table A.1, there has been a growing interest on the use of MPI in E&E studies in recent years. Particularly, in 1999-2006, the share taken up by MPI applications is 21%. A majority of MPI applications deal with the study of productivity growth over time in electricity utilities, e.g., Färe et al. (1990), Hjalmarsson and Veiderpass (1992), Yunos and Hawdon (1997), Førsund and Kittelsen (1998), Sueyoshi and Goto (2001), Giannakis et al. (2005), Abbott (2006) and Pombo and Taborda (2006). The popularity of MPI is likely due to the deregulation of electricity sectors worldwide and the interests of regulators in national/international benchmarking of electricity utilities under the new regimes.

2.1.3.3 Other features and findings

Table A.1 has shown that many studies dealt with both the theoretical and application aspects of DEA. This should attribute to the flexibility and ability of DEA in allowing for varying situations. Since various application studies have their individual characteristics, practitioners and researchers may have to present new DEA versions for their use. Another possible reason is that such popular software packages as EXCEL and MATLAB offer researchers huge flexibility to construct and apply their own models. In addition, we have also found that many OR/MS researchers favor DEA models in the multiplier form while E&E researchers and economists favor DEA models in the envelopment form. This is likely due to the interdisciplinary nature of DEA and its historical diffusion patterns (Førsund and Sarafoglou, 2005).

A majority of past studies dealt with the input-oriented DEA models rather than the output-oriented ones, which is not specified in Table A.1. To a large extent, it should be attributed to the characteristic of energy sectors that higher priority has often been given to the goal of meeting demand (Färe et al., 1994a). As a result, input conservation for given outputs seems to be a reasonable logic. Another possible reason is that in many empirical studies, particularly at the macro level, there is only one output such as GDP but multiple inputs are often used. Nevertheless, the undesirable outputs orientation DEA models seem to be more popular in modeling environmental performance.

2.1.4 Model selection and related issues

Since a large number of DEA models are available, researchers using DEA to study E&E issues will inevitably face the problem of deciding a specific DEA version to apply and selecting the appropriate inputs and outputs. Although the general application procedure of DEA has been discussed in previous studies (e.g., Golany and Roll, 1989; Dyson et al., 2001; Ramanathan, 2003), a systematic summary and reconsideration of these guidelines with particular reference to the use of DEA in E&E studies is still useful.

In general, input-orientated DEA models might be suitable for most E&E issues in which outputs are decided by the requirement of demand. When undesirable outputs are not considered, the incorporation of radial efficiency measures with the ordinary CRS and VRS reference technologies, e.g., the CCR and BCC models, would be appropriate since such a setting can provide the information on not only technical efficiency but also scale efficiency. If the RTS property of some specific

DMU is of interest, the NIRS reference technology can be used as an auxiliary tool to investigate this property. If the performance of DMUs over time is of interest, the nonparametric MPI based on the CCR model is highly recommended because the index obtained can be interpreted as a total factor productivity index.

However, when undesirable outputs are considered, the incorporation of environmental DEA technology with DDF or hyperbolic efficiency measure might be more appropriate for estimating the productive efficiency of DMUs. If a composite economic-energy-environmental index is expected, as illustrated by Zhou et al. (2006b), the slacks-based efficiency measure might be more appropriate because of its higher discriminating power. In addition, the nonparametric MPI can also be integrated with environmental DEA technology for time-series analysis.

As to the selection of inputs and outputs, the first step is to establish a list of possible inputs and outputs that may be related to the study. These inputs and outputs can be further examined by some screening procedures such as preliminary judgment and statistical analysis in order to retain only the most relevant ones (Golany et al., 1994). Besides, the selection of inputs and outputs also depends on data availability and the number of DMUs. In empirical applications, two widely adopted rules of thumb are to let the number of DMUs be larger than the product and be at least two times larger than the sum of the number of inputs and outputs (Dyson et al., 2001; Ramanathan, 2003; Cooper et al., 2006).

Once the DEA models used are specified and the inputs and outputs are determined, the DEA efficiency scores of DMUs can be calculated by some specialized software packages such as EMS and DEAP or by self-coded user programs built upon the EXCEL/MATLAB platforms. These efficiency scores can be further analyzed by using such techniques as regressions analysis in order to obtain more information.

Despite its various strengths, DEA was treated in most application studies as a deterministic technique and the results obtained are therefore very sensitive to even small permutations on the data used. To deal with the issue, Banker (1993) provided a statistical foundation by which hypothesis tests can be carried out based on the DEA efficiency scores. A number of statistical tests have so far been developed to address such issues as comparing the efficiency of two groups of DMUs, examining the existence of scale economics and testing the shift of efficiency frontier (Banker, 1996; Kittelsen, 1999; Banker and Natarajan, 2004). Another alternative, as suggested by Simar and Wilson (1998), is to use the bootstrap technique to conduct a sensitivity analysis on the DEA efficiency scores. In E&E studies, the usefulness of the bootstrap DEA approach has been empirically demonstrated by Hawdon (2003) and Sanhueza et al. (2004).

2.2 DA in E&E studies

DA usually refers to a set of formal quantitative methods for analyzing complex decision problems (Olson, 1996). It integrates traditional techniques of operations research, management science and systems analysis into a unified framework, which can help decision makers to tackle complex situations and then make better decisions (Keeney, 1982). In general, DA provides a systematic and effective methodology for structuring complex problems, identifying and representing uncertainties, dealing with multi-criteria situations and evaluating alternatives (Clemen and Reilly, 2001).

Early application studies of DA, carried out in the 1960s, dealt with decision making problems in oil and gas exploitation. Thereafter, the applications of DA were greatly expanded from industry to the public sector such as government policy making and medical decision making, as reflected in the excellent literature surveys by Corner and Kirkwood (1991) and Keefer et al. (2004). In the two publications, it is found that over a quarter of DA application studies dealt with E&E issues, which fully demonstrates the applicability of DA in E&E systems.

Some literature surveys on the application of DA in E&E studies have been reported. Hobbs and Meier (2000) provided a literature review of MCDA applications to energy planning and policy with an emphasis on sketching different points about the theory and practice of MCDA. Greening and Bernow (2004) reviewed the applications of MCDA methods to the analysis and formulation of E&E policies. Pohekar and Ramachandran (2004) reviewed more than 90 MCDA studies in sustainable energy planning.

So far, the most comprehensive survey of DA in E&E studies was conducted by Huang et al. (1995), which reported a total of 95 studies that appeared before 1995. Since 1995, the interest in E&E issues has risen as a result of the growing emphasis on environmental protection and sustainable development worldwide. The literature has expanded substantially with at least 150 new journal publications. There is, therefore, a need to revisit the area and do an up-to-date literature survey. In the following sections, we present the results of our update on the application of DA methods to E&E studies.

2.2.1 Decision analysis methods

There are a fairly large number of DA methods and they can be grouped into several different categories depending on the classification criteria adopted. For example, they can be classified into deterministic decision making methods (or decision making under certainty) and probabilistic decision making methods (or decision making under uncertainty) according to the information in hand. Also, single decision-maker methods and group decision making methods are two major categories of DA methods. Here they are classified into two main groups followed by some commonly used DA methods in E&E studies as shown in Fig. 2.4, which are single objective decision analysis (SODA) methods and multiple criteria decision analysis (MCDA) methods. A brief description of each is given below.

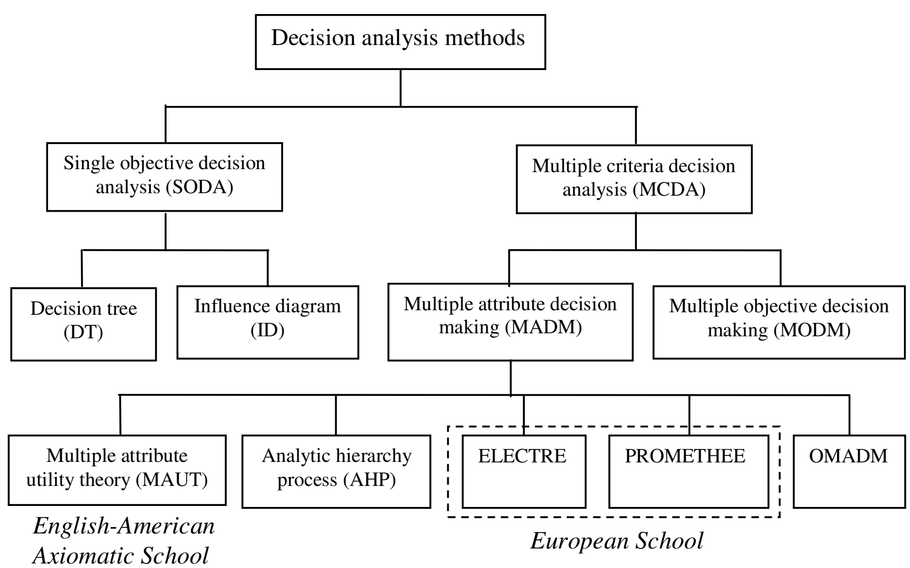

Fig. 2.4 Classification of DA methods

SODA comprises a class of methods which helps decision makers to evaluate the available alternatives with uncertain outcomes under single objective situation. Decision tree (DT) is a classical and well established approach. Another approach, the influence diagram (ID), provides a simpler and more compact representation and more effective analysis procedure of decision problems (Howard and Matheson, 1981).

MCDA allows decision makers to choose or rank alternatives on the basis of an evaluation according to multiple criteria (Stewart, 1992). Decisions are made based on trade-offs or compromises among a number of criteria which are in conflict with each other. Multiple objective decision making (MODM) and multiple attribute decision making (MADM) are two main branches of MCDA (Yoon and Hwang, 1995).

MODM methods usually refer to methods related with multiple objective mathematical programming models in which a set of conflicting objectives are optimized simultaneously subject to a set of constraints. In general, MODM methods have three main purposes (Cohon, 1978). The first is to generate the noninferior set for a multiple objective mathematical programming problem. The second is to iteratively interact with users to teach them the tradeoffs and help guide them to a recommendation. Finally, a few MODM methods including goal programming attempt to use a MCDA-type objective function to find the ideal solution. A special case of MODM is the multiple objective linear programming (MOLP), where the objective functions and constraints are linear functions.

MADM refers to making preference decisions by evaluating and prioritizing all the predetermined discrete alternatives which are usually characterized by multiple conflicting attributes. Many MADM methods have been developed by researchers and Fig. 2.4 shows the more popular ones in the context of E&E studies. Multiple attribute utility theory (MAUT) allows decision makers to consider their preferences in the form of multiple attribute utility function (Keeney and Raiffa, 1976). In this thesis, MAUT is interpreted in a broader manner than what Keeney and Raiffa (1976) discussed. A special case of MAUT is multiple attribute value theory (MAVT) where there is no uncertainty in the consequences of the alternatives. The analytic hierarchy process (AHP) is essentially a methodology consisting of structuring, measurement and synthesis, which can help decision makers to cope with complex situations easily (Satty, 1980, 1990). The elimination and choice translating reality (ELECTRE) methods, including ELECTRE I, II, III and IV methods, are intrinsically a family of outranking methods (Roy and Vincke Ph, 1981). The preference ranking organization method for enrichment evaluation (PROMETHEE) methods are also a class of outranking methods combined with the features of simplicity, clearness and stability (Brans and Vincke Ph, 1985; Brans et al., 1986). As Belton and Stewart (2001) stated, ELECTRE and PROMETREE are both part of the European School of MCDA while MAUT constitutes the English-American Axiomatic School. The differences between English-American Axiomatic School, AHP and European School are discussed in Belton and Stewart (2001). Other multiple attribute decision making (OMADM) methods include conjunctive or disjunctive methods, TOPSIS, and so on (Yoon and Hwang, 1995). However, these methods have not been widely adopted in E&E modeling and as such are lumped together as OMADM.

2.2.2 Classification of studies

A total of 227 studies are surveyed and classified according to the following attributes: source of publication, country/region, problem level, application area, energy type, and DA method. Table B.1 shows all the studies surveyed with their attributes specified. The last attribute, the "DA method", is based on the classification presented in Section 2.2.1. Since some studies use more than one DA method, we further classified the methods used into major or minor, where the minor method was often used as the auxiliary tool of the major method. If several DA methods appear in a study and the main purpose of the study is method comparison, we shall then indicate "Meta" in the column "Major". The definitions of the other attributes are described below.

In the case of "source of publication", we define six sources and the notations used are as follows. Source 1 is journals focusing primarily on energy or natural resources issues, e.g., *Energy*, *Energy Policy*, *Energy Economics*, and *Energy Sources*. Source 2 is journals focusing primarily on energy engineering issues, e.g., *Energy Conversion and Management*, *Electric Power Systems Research*, *IEEE Transactions on Power Systems*, and *Electric Power and Energy Systems*. Source 3 is journals covering the broad areas of environment, ecology or climate change, e.g., *Ecological Economics*, *Journal of Environmental Management*, *Environmental Modeling and Assessment*, and *Journal of Industrial Ecology*. Source 4 includes operations research, management science, and decision science journals, e.g., *Management Science*, *Operations Research*, *European Journal of Operational Research*, and *Decision Sciences*. Source 5 refers to journals that cannot be classified under any of the above four sources, such as *Fuzzy Sets and Systems*. Source 6 is non-journal publications such as conference papers and book chapters. It should be noted that the surveyed studies after 1995 are primarily journal papers.

In terms of "application level" the publications are broadly divided into two big groups: the strategic/policy (S/P) and the operational/tactical (O/T). The S/P level mainly deals with issues related to macro issues or long-term development goals such as energy policy analysis, energy investment planning and energy conservation strategies. The O/T level deals with issues which are operational, related to short-term development goals such as bidding, pricing and technology choice.

The following seven "application areas" are specified: energy policy analysis (I), electric power planning (II), technology choice and project appraisal (III), energy utility operations and management (IV), energy-related environmental policy analysis (V), energy-related environmental control and management (VI), and a miscellaneous category (VII). A short description on each area is given below.

Energy policy analysis (I) is concerned with the evaluation of the prospective energy policy or the current energy systems with the purpose of guiding the development and formulation of energy policy. The area covers national or regional energy systems assessment, public debate on energy policy, energy conservation strategies and energy resource allocation issues.

Electric power planning (II) mainly deals with strategic planning issues during the course of power generation, transmission and distribution, such as power generation expansion planning, electrical transmission network expansion planning and power distribution planning.

Technology choice and project appraisal (III) often involves the evaluation and selection of energy technologies and appraisal of energy-related investment project. Where a study specifically deals with the evaluation, appraisal or selection of projects in electricity supply, it shall be classified under electric power planning (II) mentioned above instead of this area.

Energy utility operations and management (IV) is concerned with the operational issues in energy industry such as energy bidding and pricing, power plant siting and the management of energy companies. It covers all energy sources, including not only electricity but also gases and renewables. In the case of power plants, this area also includes the development of DSS aiding the management of electricity utilities. Occasionally, there may be interactions between this area and the area of technology choice and project appraisal (III). When this occurs, we give a higher priority to Area III in order to explicitly determine the category of a study.

Energy-related environmental policy analysis (V) deals with the policy level of energy-related environmental problems such as assessment of climate policy, public debate on green-house warming and air pollution control policy. It is closely related to Area I except that energy related environmental issues are studied.

Energy-related environmental control and management (VI) mainly deals with areas such as solid waste management, evaluation of waste storage sites and environmental impact analysis related to major development projects. To a large extent, its coverage is similar to that of Areas II-IV except that the focus is now on environmental rather than energy issues.

The miscellaneous category (VII) includes rather unique and specialized areas which could not be included in any of the above six areas. An example is the prediction of world oil prices (Saaty and Gholammehad, 1981).

We break down “energy type” into six categories: energy in general (EG), coal (C), oil and gas (O/G), nuclear energy (N), renewable energy (RE) and electricity (Elec). The category energy in general (EG) refers to studies that treat energy supply and demand in general terms without focusing specifically on any single energy type. The category renewable energy (RE) includes all renewable energy sources, such as hydro, solar, wind and geothermal energy, and biomass. For simplicity, a study is classified based on the primary energy type studied. For example, a study dealing primarily with the operation of nuclear power plants would be classified under the category nuclear energy (N). However, if the study deals with the issues of electricity generation or distribution, it would be classified under the category electricity (Elec). If a study involves several specific energy types and yet is inappropriate to be classified under energy in general (EG), it would be specified as “Mix”. An example would be the evaluation of different energy resources for lighting in households (Ramanathan and Ganesh, 1995a).

2.2.3 Main features observed

The information presented in the sections that follow is obtained based on the data presented in our classification table, which includes some main characteristics observed based on the 227 studies when all of them are considered together and some changes that have taken over time.

2.2.3.1 Non-temporal features

Figure 2.5 shows the breakdown of the 227 studies by source of publication. Operations research, management science and decision science journals (Source 4) and energy and natural resource journals (Source 1) together account for almost two thirds (64%) of the surveyed studies. The remaining one third is fairly evenly shared by the other four sources. From the breakdown, one may conclude that the area of DA in E&E modeling is truly multi-disciplinary.

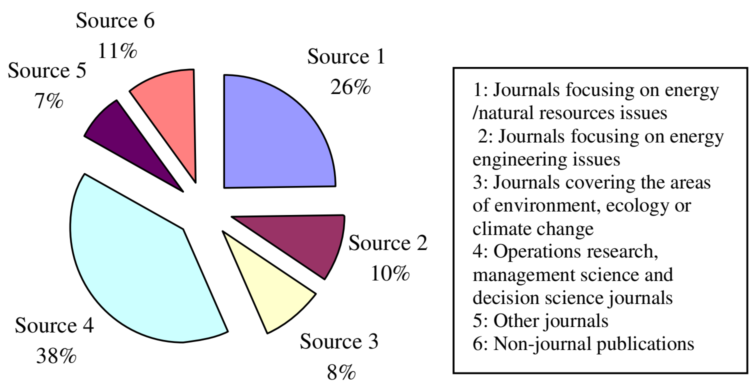

Fig. 2.5 Breakdown of publications by source of publication

Figure 2.6 shows the breakdown by energy type. Not surprisingly, the largest number of studies deals with electricity. Ignoring the category of energy in general, renewable energy has also been widely studied. Application to renewable energy studies includes exploitation of renewable energy resources such as geothermal potential (Capros et al., 1988; Georgopoulou et al., 1998; Goumas et al., 1999; Goumas and Lygerou, 2000; Haralambopoulos and Polatidis, 2003), allocation of renewable energy resources (Iniyan and Sumathy, 2000; Nigim et al., 2004; Suganthi and Williams, 2000) and evaluation of national renewable energy systems (Chedid, 2002; Mamlook et al., 2001b; Mohsen and Akash, 1997).

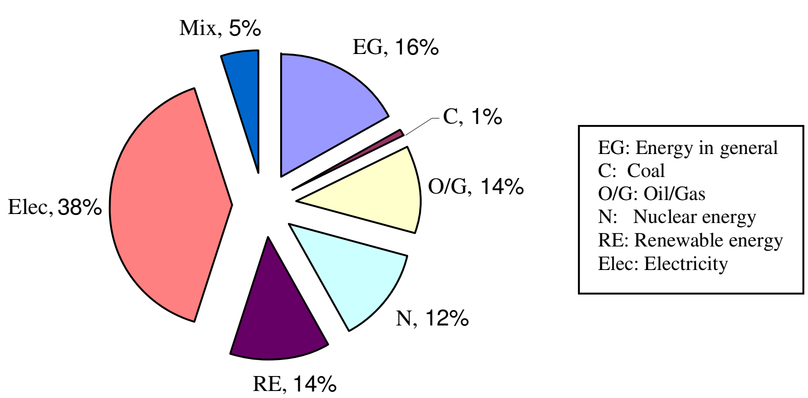

Fig. 2.6 Breakdown of publications by energy type studied

Table 2.1 Number of studies classified by application area and DA method

Application area	SODA		MCDA					Others	Total number
	DT	ID	MODM	MAUT	AHP	ELEC TRE	PROME THEE		
I	1	0	18	8	20	3	2	11	56
II	2	1	13	4	6	0	0	5	25
III	11	4	1	7	7	2	3	2	31
IV	19	4	6	13	4	3	2	2	46
V	3	0	2	4	9	1	2	7	24
VI	4	4	1	11	4	5	1	10	38
VII	1	0	0	1	2	0	0	3	7
Total number	41	13	41	48	52	14	10	40	

I: Energy policy analysis; II: Electric power planning; III: Technology choice and project appraisal; IV: Energy utility operations and management; V: Energy-related environmental policy analysis; VI: Energy-related environmental control and management; VII: Miscellaneous.

Table 2.1 shows the breakdown of studies by DA method and application area. Since more than one DA method may be applied in a study, the sum of studies by DA method exceeds that by application area. The last column of Table 2.1 gives the number of studies in each of the seven application areas. Of the 227 studies, 63% deal with strategic/policy issues and the remaining 37% operational/tactical issues. This demonstrates the suitability of DA methods to deal with both operational and strategic problems, as has been reported earlier (Corner and Kirkwood, 1991; Keefer et al., 2004). More specifically, 23% and 21% of studies deal with energy policy analysis and energy utility operations and management, respectively. Energy-related environmental control and management accounts for 18% of the studies. It is followed by the area technology choice and project appraisal (13%), electric power planning (11%) and energy-related environmental policy analysis (10%). Over a quarter of the studies deal with energy-related environmental studies. Examples of such studies include those on environmental impact assessment (Allett, 1986; Marttunen and

Hämäläinen, 1995; McDaniels, 1996; Miettinen and Hämäläinen, 1997; Mirasgedis and Diakoulaki, 1997; Ramanathan, 2001; Pineda-Henson et al., 2002), nuclear waste management (Gregory and Lichtenstein, 1987; Jackson et al., 1999; Kirkwood and Sarin, 1985; Lathrop and Watson, 1982; Merkhofer and Keeney, 1987; Saaty and Gholammehad, 1982) and the analysis of climate change and assessment of greenhouse gas mitigation options (Georgopoulou et al., 2003; Hobbs, 1997; Hobbs et al., 1997; Keeney and McDaniels, 2001; Loulou and Kanudia, 1999; Ramanathan, 1998, 1999; Ridgley, 1996; Vaillancourt and Waaub, 2004).

Table 2.1 shows that MCDA methods are the most commonly used DA methods. Specifically, the last row of the table shows that AHP (18%) is the most popular DA method, which is followed by MAUT (17%), MODM (14%) and DT (14%). In some MCDA applications at macro-level, it is found that MCDA methods have often been used to develop an E&E related composite indicator (CI) for the use of decision making. For instance, Afgan et al. (2000) applied the weighted arithmetic mean method to construct a sustainability index for energy systems assessment. Wang and Feng (2004) used the AHP method to develop an index system for evaluating sustainable development of rural energy in China.

From Table 2.1 we can find that most DT and ID applications involve technology choice and project appraisal or energy utility operations and management, while only a few of DT applications and no ID applications deal with energy or energy-related environmental policy analysis. The reason may be that the problems in the former two areas are more technical and the corresponding uncertainties can be more easily modeled by DA representation tools as compared to those in the latter two areas.

2.2.3.2 Temporal features

We divide the time frame into three ten-year periods, 1975-1984, 1985-1994, and 1995-2004. The total numbers of publications are respectively 33, 64 and 130 in the three periods which indicate a doubling in the number every 10 years.

Figure 2.7 shows the changes that have taken place by source of publication with non-journal publications (Source 6) excluded. The breakdown did not change much from 1975-1984 to 1985-1994, with operations research, management science, and decision science journals (Source 4) dominating these two periods. The shares taken up by energy/natural resource journals (Source 1), energy engineering journals (Source 2) and environmental, ecology, and climate change journals (Sources 3), however, increased markedly from a combined share of 30% in 1985-1994 to 64% in 1995-2004. Correspondingly, the share taken up by Source 4 dropped from 62% to 28% although in absolute terms, the number of publications had a slight increase. This shift might show the changes in the preferred outlets for researchers that could also be influenced by the launch of several new journals in the areas represented by Sources 1-3 after 1985. Also, it could be the result of wider penetration of DA methods to different E&E application problems.

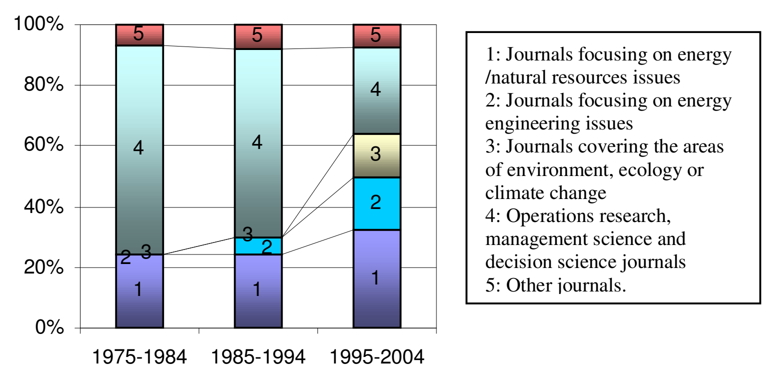

Fig. 2.7 Breakdown of publications by source of publication over time

By application level, slightly over 65% of studies deal with strategic/policy (S/P) issues while the remaining deal with operational/tactical (O/T) issues, and these shares have remained virtually unchanged over time. The higher share for studies on strategic/policy issues are likely because these issues are more complex, which makes the application of DA more meaningful.

By application area, energy-related environmental studies (V and VI in Fig. 2.8) have been steadily increasing, from 15% of total publications in 1975-1984 to 34% in 1995-2004, which is consistent with the growing concern on environmental issues. Another interesting feature is that the share of studies in electric power planning (II) has been increasing, taking up 5.9%, 9.5% to 13.1% in the three periods respectively. Most of these studies deal with power generation expansion planning (Levin et al., 1985; Therdyothin et al., 1992; Climaco et al., 1995; Martins et al., 1996; Pan and Rahman, 1998; Kalika and Frant, 1999; Mavrotas et al., 1999; Antunes et al., 2004). It might be the result of the wave of privatization in the electricity sector in recent years.

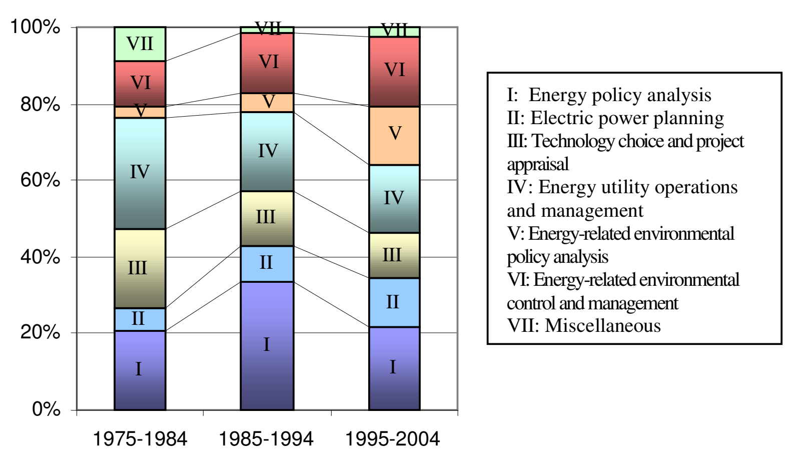

Fig. 2.8 Breakdown of publications by application area over time

By energy type, DA has most often been applied to electricity (Category "Elec" in Fig. 2.9). Its share in total publications increased from 30% in 1975-1984 to 46% in 1995-2004. Not surprisingly, studies related to nuclear energy (Category "N") have decreased substantially, from 30% in 1975-1984 to 7% in 1995-2004. Although the share taken up by renewable energy studies (Category "RE") remained little change at about 7% from 1975-1984 to 1985-1994, it increased to 22% in 1995-2004.

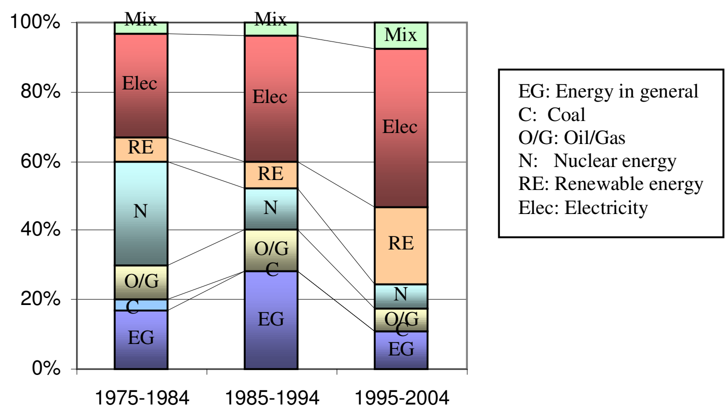

Fig. 2.9 Breakdown of publications by energy type studied over time

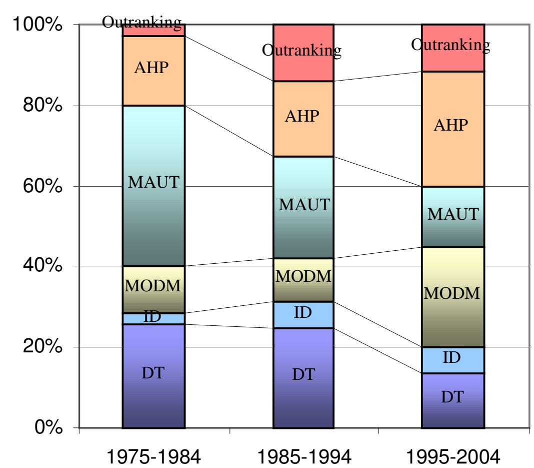

Fig. 2.10 Breakdown of publications by DA method used over time

The breakdown by DA method is shown in Fig. 2.10. The share taken up by DT has decreased from 26% in 1975-1984 to 13% in 1995-2004. A declining trend has also been observed for MAUT whose share decreased from 40% in 1975-1984 to 15% in 1995-2004. This may be due to the difficulties in formulating utility functions as have been pointed out by Pohekar and Ramachandran (2004). Conversely, the outranking methods including ELECTRE and PROMETHEE have become more popular. It is also noted that AHP accounts for a significant proportion in each of the periods. Many AHP applications deal with energy policy and energy-related environmental policy issues, such as assessment of solar heating systems (Chedid, 2002; Mohsen and Akash, 1997), evaluation and allocation of energy resources (Ramanathan and Ganesh, 1995a, b), prioritization of public transportation plans (Poh and Ang, 1999; Tzeng et al., 2005), and environmental cost analysis (Huang et al., 1996, 1997). The popularity of AHP in E&E modeling is likely due to its simplicity, ease of understanding and suitability for the evaluation of qualitative criteria. Although there is a small decrease in MODM applications from 1975-84 to 1985-94, which is consistent with the findings of Huang et al. (1995), the method has become more popular after 1995. A large number of MODM applications deal with energy policy analysis and electric power planning. To a large extent, the popularity of MODM is due to its flexibility in creating alternatives and the availability of many user-friendly computational aiding tools (Greening and Bernow, 2004; Pohekar and Ramachandran, 2004).

2.2.3.3 Comparisons with the earlier survey

There are a number of differences between this study and Huang et al. (1995) in terms of scope and definitions. Firstly, the study by Huang et al. covered 95 studies from 1960 to 1995 and almost two thirds of them are journal and conference papers. We have included these papers in our study but excluded the others which are mainly technical reports. We have also included in our study some journal papers published before 1995 that were not captured in Huang et al. Secondly, in the classification of DA methods, Huang et al. divided DA methods into three groups, i.e., decision making under uncertainty (DMUU), MCDA, and decision support system (DSS), while we divide them into SODA and MCDA because there are some interactions between DMUU and MCDA which may lead to confusion. DSS is dropped from our study because it is not an alternative to other DA methods. Thirdly, we have refined the classification of application areas in Huang et al. Despite the above, the differences in findings between the two studies reported below are mainly caused by the new developments of DA in E&E modeling.

Firstly, after 1995, the share of studies on renewable energy has increased while that on nuclear energy has decreased. Secondly, the share taken up by energy-related environmental studies has also increased significantly after 1995. Thirdly, we have found that the MCDA group of methods is the most widely used while in Huang et al.'s study it was found to be the DMUU group of methods. Fourthly, although MAUT, AHP and DT have been found to be the most commonly used DA methods both in Huang et al.'s study and this study, their popularity in the two studies are different. In our study AHP has been found to be the most popular and the DT the least, while in Huang et al.'s study MAUT has been found to be the most popular and the AHP the least. Fifthly, it is observed that MODM has become more popular in our study while few studies deal with it in Huang et al.'s study.

In some respects, the findings in the two studies are similar. For instance, the largest number of studies deal with electricity (Elec) and energy in general (EG), energy policy analysis is the most common application area, energy-related environmental studies account for a large number of studies, and MAUT, AHP and DT are the most popular DA methods. One possible reason for the popularity of these DA methods is that some specialized software packages for these methods have been developed, e.g., Logical Decisions (MAUT-based), Expert Choice (AHP-based), HIPRE 3+ (MAUT&AHP-based) and Precision Tree (DT-based).

2.2.4 Statistical tests

These findings presented earlier are based primarily on the journal papers in English surveyed. Other sources of publications in English, such as technical reports and theses, and non-English publications are not covered. It is appropriate to treat the data as a sample of all studies or the research interest in this field. However, the data may not necessarily reflect the frequency of application of MCDA methods in practice. For instance, some MADM methods are widely used in siting as a routine but few get published. If we make the assumption that the sample is representative of the interests of researchers, it is useful to conduct appropriate statistical testing on some findings.

There have been new developments and trends in the application of DA to E&E modeling after 1995. It is therefore reasonable to use 1995 as a demarcation for hypothesis testing. In our study a total of 97 studies before 1995 and 130 studies after 1995 (including publication in 1995) are sampled. The data for these two periods will be used to test the following hypotheses:

H1: There has been a greater emphasis on energy-related environmental issues.

H2: There has been less emphasis on nuclear energy while more on renewables.

H3: There is no significant difference in the share of application level.

H4: The preferred publication outlet for researchers has changed.

H5: The application of SODA has decreased while that of MCDA increased in importance.

The above hypotheses essentially involve the inferences on two proportions, before 1995 and after 1995. For example, in the case of H1, let p_1 and p_2 respectively be the share of energy-related environmental studies before 1995 and that after 1995. Then the hypothesis might be verified by testing the null hypothesis $p_1=p_2$ versus the alternative hypothesis $p_2>p_1$. Hence the procedure of statistical inference on two population proportions could be used to perform this task (Montgomery and Runger, 2002). The precondition for the testing procedure is that the two sample proportions should have approximate normal distributions. Our tests using normal probability plots show that this condition is satisfied. We have conducted the tests for H1 to H5 and the results show that all the above hypotheses could be accepted. Despite its simplicity and limitations, the statistical study conducted is more or less helpful in providing some formal evidence on our findings. Given the sufficiency of sample data, the same procedure might be used to test some other explicit or implicit hypotheses.

2.2.5 A multiple attribute analysis

To determine the suitability of different DA methods in each application area, we conducted a multiple attribute analysis similar to that in Huang et al. (1995) and compared the results with the actual practices revealed by our survey. The six attributes used in our study are as follows. The first is “complexity” which gives the relative complexity of a problem measured in terms of low, medium and high. The second is “uncertainty” which is the level of uncertainty involved in a problem also measured in terms of low, medium and high. The third is “multiple criteria” which is how often the problems in an application area involve multiple criteria, either frequently or rarely. The fourth is “alternative sets” which is divided into two categories namely design and selection, reflecting whether the alternatives of one problem are pre-determined or not. The fifth is “data availability” which refers to the relative difficulty in obtaining the required data for a DA method and it is given by easy, normal or difficult. The last is “recurring type” which is specified by common, periodic or seldom, depending on how often a problem occurs.

Table 2.2 shows our subjective evaluation of each of the application areas with respect to the above six attributes. The attributes are partially based on those used in the study by Huang et al. (1995). These evaluations are then used to determine the suitability of different DA methods for each of the application areas, which is indicated by “a”, “b” and “c” in Table 2.3. Here “a” indicates that the method is very suitable, “b” the method is not so suitable, and “c” the method is not suitable. The actual level of usage of different DA methods in each application area as revealed in our survey is shown by uppercase letters “A”, “B” and “C”. The criteria for determining the usage level of a DA method in a particular application area is given by the percentage of studies using the method in relation to the total number of studies in the area. It is given “A” if the percentage is more than 20%, “B” if the percentage is between 5% and 20%, and “C” if the percentage is less than 5%.

Table 2.2 Multiple attribute analysis of the application areas

Application area	Complexity	Uncertainty	Multiple criteria	Alternative sets	Data availability	Recurring type
I	High	High	Frequently	Selection	Difficult	Seldom
II	Medium	Low	Frequently	Design	Easy	Periodic
III	Medium	High	Rarely	Selection	Normal	Periodic
IV	Low	Medium	Frequently	Selection	Easy	Common
V	High	High	Frequently	Selection	Difficult	Seldom
VI	High	Medium	Frequently	Selection	Normal	Periodic

I: Energy policy analysis; II: Electric power planning; III: Technology choice and project appraisal; IV: Energy utility operations and management; V: Energy-related environmental policy analysis; VI: Energy-related environmental control and management; VII: Miscellaneous.

Table 2.3 Comparisons between multiple attribute analysis results and the actual usage revealed by this survey

Application area[a]	SODA		MCDA			
	DT	ID	MODM	MAUT	AHP	Outranking Methods[b]
I	c/C	c/C	b/A	a/B	b/A	b/B
II	c/C	c/C	a/A	b/B	b/B	c/C
III	b/A	a/B	c/C	a/A	b/A	b/B
IV	b/A	b/B	b/B	a/A	b/B	a/B
V	c/B	c/C	c/B	a/B	b/A	b/B
VI	c/B	c/B	b/C	a/A	b/B	a/B

[a] I: Energy policy analysis; II: Electric power planning; III: Technology choice and project appraisal; IV: Energy utility operations and management; V: Energy-related environmental policy analysis; VI: Energy-related environmental control and management; VII: Miscellaneous.
[b] Including ELECTRE and PROMETHEE.

In general, for problems with high complexity, AHP and influence diagram are preferred. For problems with high uncertainty, decision tree, influence diagram and MAUT are preferred. But for problems with medium uncertainty and high complexity, the outranking methods are preferred. If a problem involves multiple criteria, MCDA should be used. In the case of high uncertainty and multiple criteria, MAUT is preferred. For design problems, MODM should be used. If data are not easily available, AHP and the outranking methods should be preferred.

We can obtain a great deal of information from the results shown in Table 2.3. In the area of energy policy analysis, the most widely used methods were MODM and AHP. However, our analysis indicates that the combination of MAUT with AHP may be more suitable because high complexity and uncertainty are general features in this area. In the area of electric power planning, the popularity of MODM is consistent with our analysis. In the area of technology choice and project appraisal, decision tree, MAUT and AHP have been most widely used. However, our analysis shows that MAUT in conjunction with influence diagram may be more suitable. In the area of energy utility operations and management, the popularity of MAUT is consistent with our analysis. In the area of energy-related environmental policy analysis, the usage level of MAUT in conjunction with AHP is consistent with our analysis in general. Finally, in the area of energy-related environmental control and management, the popularity of MAUT is consistent with our analysis. In addition, although the outranking methods have not been so widely used, our analysis shows that the outranking methods including ELECTRE and PROMETHEE might be very suitable in this area, which was not reported in Huang et al. (1995).

2.3 Concluding comments

In this chapter, we have presented the results of our survey on DEA and DA applications in E&E modeling. In the case of DEA in E&E studies, we found that DEA has recently gained great popularity in environmental performance measurement because of its ability in combining multi-dimensional data into an environmental performance index. However, most previous studies often adopted the radial efficiency measures and the environmental DEA technology exhibiting constant returns to scale in developing an environmental performance index, which has some theoretical and practical limitations as we discussed in Chapter 1. It is therefore necessary to further characterize different environmental DEA technologies and develop alternative efficiency measures to modeling environmental performance, which are the objectives of Chapters 3 to 5 of this thesis.

Our survey on DA applications to E&E modeling has shown that MCDA methods have been widely explored in E&E studies in the past. In some application areas at macro-level, e.g., energy policy analysis, MCDA methods have often been applied to develop an E&E related composite indicator (CI) which is very useful to analysts and decision makers dealing with E&E issues. It justifies the usefulness of MCDA methods in constructing E&E related CIs. Nevertheless, as we discussed in Chapter 1, it is still worthwhile to further investigate some key methodological issues relevant to the applications of MCDA methods to CI construction. The results of our study on these issues are presented in Chapters 6 to 8 of this thesis.

CHAPTER 3 ENVIRONMENTAL DEA TECHNOLOGIES AND THEIR RADIAL IMPLEMENTATIONS[2]

DEA has recently gained in popularity in environmental performance measurement due to its ability in combining multi-dimensional data into an environmental performance index (EPI). As was discussed in Chapter 2, the representation manners of efficiency measure and the characterization of reference technology are two major foundation stones of DEA. In the case of reference technology, the commonly used one is the so-called environmental DEA technology in the context of environmental performance measurement (Färe and Grosskopf, 2004), in which outputs are assumed to be weakly disposable.

Most previous studies follow the original characterization of environmental DEA technology by assuming that the production technology exhibits constant returns to scale (CRS). However, cases such as variant returns to scale are likely to be observed in actual situations (Tyteca, 1996). These situations cannot be simply treated by imposing some additional constraints in the same manner as the traditional DEA models because this may violate the basis of environmental DEA technology. Scheel (2001) and Färe and Grosskopf (2004) have briefly described how to deal with variant returns to scale in environmental DEA technology. Nevertheless, further work is still needed on its characterization and application, including the characterization of environmental DEA technologies under different situations and their radial implementations for measuring environmental performance.

[2] The work presented in this chapter has been published as Zhou et al. (2008b).

In this chapter, we introduce the concept of environmental DEA technology and characterize the environmental DEA technologies exhibiting non-increasing returns to scale (NIRS) and variant returns to scales (VRS). The resulting radial DEA type models for measuring environmental performance under different situations are then presented. For the measures dealing with nonlinear programming models, we give their linear equivalents. We then present an application study on measuring carbon emission performance of world regions.

3.1 Environmental DEA technologies

It is known that most pollution problems arise from the joint production of undesirable outputs when desirable outputs are produced. For instance, the emissions of sulphur dioxide are inevitable when electricity is generated by burning coal. We now consider a production process in which desirable outputs and undesirable outputs are jointly produced. Assume that $\mathbf{x} \in \mathbf{R}_+^N$, $\mathbf{y} \in \mathbf{R}_+^M$ and $\mathbf{u} \in \mathbf{R}_+^J$ are the vectors of inputs, desirable outputs and undesirable outputs respectively. The production technology can be described as

$$T = \{(\mathbf{x}, \mathbf{y}, \mathbf{u}) : \mathbf{x} \text{ can produce } (\mathbf{y}, \mathbf{u})\} \tag{3.1}$$

In production theory T is often 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. Also, inputs and desirable outputs in T are assumed to be strongly or freely disposable. That is to say, if $(\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T$ and $\mathbf{x}' \geq \mathbf{x}$ (or $\mathbf{y}' \leq \mathbf{y}$) then $(\mathbf{x}', \mathbf{y}, \mathbf{u}) \in T$ (or $(\mathbf{x}, \mathbf{y}', \mathbf{u}) \in T$). For more details on production theory, see Färe and Primont (1995).

In order to reasonably model a production technology that produces both desirable and undesirable outputs, the following two assumptions proposed by Färe et al. (1989) are imposed on T.

P3.1 Outputs are weakly disposable, i.e.,, if $(\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T$ and $0 \le \theta \le 1$, then $(\mathbf{x}, \theta\mathbf{y}, \theta\mathbf{u}) \in T$.

P3.2 Desirable outputs and undesirable outputs are null-joint, i.e.,, if $(\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T$ and $\mathbf{u} = 0$, then $\mathbf{y} = 0$.

Assumption **P3.1** says that considered together, desirable and undesirable outputs are weakly disposable. It implies that the reduction of undesirable outputs is not free and the proportional reduction in desirable outputs and undesirable outputs is feasible. Assumption **P3.2** states that some undesirable outputs must also be produced when desirable outputs are produced. That is to say, the only way to eliminate all the undesirable outputs is to end the production process.

Up to now, the weak disposability reference technology, also called the polluting technology in Färe et al. (2005), has been well modeled conceptually for the simultaneous production of both desirable and undesirable outputs. In fact, it can also be described by the following output set:

$$P(\mathbf{x}) = \{(\mathbf{y}, \mathbf{u}) : (\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T\} \tag{3.2}$$

Obviously, $P(\mathbf{x})$ consists of all the technologically feasible outputs when the vector of inputs is $\mathbf{x}$. It can be shown that $(\mathbf{x}, \mathbf{y}, \mathbf{u}) \in T \Leftrightarrow (\mathbf{y}, \mathbf{u}) \in P(\mathbf{x})$ (Färe and Primont, 1995). If $P(\mathbf{x})$ is a bounded and closed set and its equivalent production technology

T satisfies the two properties **P3.1** and **P3.2**, it can be regarded as an "environmental output set" (Färe and Grosskopf, 2004).

Although the production technology T has been well defined conceptually, it cannot be directly used in empirical application. A common practice is to first establish the equivalent relationships between T and the Shephard distance function or the directional distance function, which can be regarded as the generalizations of the traditional single-output production functions (Färe and Primont, 1995; Färe et al. 2005). The distance functions used can then be calculated based on their parametric or nonparametric specifications. See, for example, Lee et al. (2002) and Färe et al. (2005, 2006).

In the case of nonparametric specification, the piecewise linear production technology exhibiting constant returns to scale (CRS) was first constructed by Fare et al. (1989). As Färe and Grosskopf (2004) argued, this kind of production technology could be termed as environmental DEA technology because it is formulated in the DEA framework. Assume that there are $k = 1,2,\cdots,K$ DMUs and for DMU$_k$ the observed data on the vectors of inputs, desirable outputs and undesirable outputs are $\mathbf{x}_k = (x_{1k}, x_{2k}, \cdots, x_{Nk})$, $\mathbf{y}_k = (y_{1k}, y_{2k}, \cdots, y_{Mk})$ and $\mathbf{u}_k = (u_{1k}, u_{2k}, \cdots, u_{Jk})$ respectively. Further assume that $\sum_{j=1}^{J} u_{jk} > 0\ (k = 1,2,\cdots,K)$ and $\sum_{k=1}^{K} u_{jk} > 0\ (j = 1,2,\cdots,J)$. Then the environmental DEA technology exhibiting CRS can be expressed as

$$
\begin{aligned}
T_{CRS} = \{(\mathbf{x},\mathbf{y},\mathbf{u}) : & \sum_{k=1}^{K} z_k x_{nk} \le x_n, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_m, m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = u_j, j = 1,2,\cdots,J \\
& z_k \ge 0, k = 1,2,\cdots,K\}
\end{aligned}
\tag{3.3}
$$

where $\mathbf{x} = (x_1, x_2, \cdots, x_N)$, $\mathbf{y} = (y_1, y_2, \cdots, y_M)$, $\mathbf{u} = (u_1, u_2, \cdots, u_J)$, and ($\mathbf{x}$, $\mathbf{y}$, $\mathbf{u}$) denotes a possible production combination of inputs, desirable and undesirable outputs.

The construction of T_{CRS} offers analysts and researchers a solid foundation in doing empirical studies such as developing environmental performance index when the production technology exhibits or approximately exhibits CRS. It can be shown that T_{CRS}, i.e., (3.3), satisfies all the properties discussed in the forgoing, e.g., the weak disposability of outputs and the null-jointness between desirable outputs and undesirable outputs (Färe and Primont, 1995).

Figure 3.1 shows a simple graphical illustration of the CRS environmental DEA technology by means of the output set, in which 3 DMUs use the same amounts of inputs to produce one desirable output y and one undesirable output u. The three outputs pairs are labeled A, B and C respectively. The environmental DEA technology represented by output set $P^w(\mathbf{x})$ is bounded by OABCD, which consists of all the possible combination of desirable and undesirable outputs satisfying P3.1 and P3.2. If the strong disposability of undesirable output is allowed, the corresponding output set $P^s(\mathbf{x})$ becomes the region OEBCD as it is possible to reduce the amount of u produced by B to zero without decreasing the amount of its desirable output.

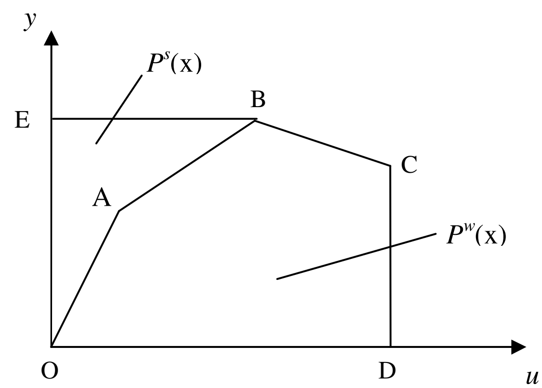

Fig. 3.1 An illustration of the CRS environmental DEA technology

In application, the CRS environmental DEA technology T_{CRS} can be used when it is reasonable or there are evidences to assume that the production technology exhibits CRS. Many researchers have explored the usefulness of the CRS environmental DEA technology in various fields, including in productive efficiency evaluation with consideration of undesirable outputs (Chung et al., 1997; Yu, 2004) and in environmental performance measurement (Tyteca, 1997; Färe et al., 2004; Zhou et al., 2006b, 2007c).

Nevertheless, in actual situations the reference technology may not always exhibit CRS, and other cases such as VRS are likely to be observed (Tyteca, 1996). As to the estimation of the returns to scale property for a reference technology, many studies have been reported, e.g., Färe et al. (1994a) and Ramanathan (2003). It is therefore logical to characterize other environmental DEA technologies and the corresponding DEA-based models for measuring environmental performance. According to Färe et al. (1994a), the reference technology exhibiting CRS, NIRS or VRS is particularly interesting in empirical studies. Therefore, we shall characterize the environmental DEA technologies that exhibit NIRS and VRS in the sections that follow.

The NIRS environmental DEA technology T_{NIRS} can be formulated by imposing the restrictions of intensity variables on the CRS environmental DEA technology in the same manner as that in the traditional DEA framework.

$$
\begin{aligned}
T_{NIRS} = \{(\mathbf{x},\mathbf{y},\mathbf{u}) : & \sum_{k=1}^{K} z_k x_{nk} \le x_n, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_m, m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = u_j, j = 1,2,\cdots,J \\
& \sum_{k=1}^{K} z_k \le 1 \\
& z_k \ge 0, k = 1,2,\cdots,K\}
\end{aligned}
\tag{3.4}
$$

We can show that T_{NIRS} exhibits NIRS globally because $P_{NIRS}(\theta\mathbf{x}) \subseteq \theta P_{NIRS}(\mathbf{x})$ for $\theta \ge 1$, where $P_{NIRS}(\mathbf{x})$ is the output set corresponding to T_{NIRS}. For more details on NIRS, see Färe et al. (1994a) and Färe and Primont (1995).

In the case of the VRS environmental DEA technology, it cannot be simply treated in the same manner as that in the NIRS environmental DEA technology because the resulting technology may violate the basis of environmental DEA technology. It is necessary to have a tradeoff between the concept of environmental DEA technology and the traditional DEA forms. To deal with it, we first make a minor modification on **P3.1** and **P3.2** whereby

P3.1' If $(\mathbf{x},\mathbf{y},\mathbf{u}) \in T$ and $0 < \theta \le 1$, then $(\mathbf{x},\theta\mathbf{y},\theta\mathbf{u}) \in T$.

P3.2' If $(\mathbf{x},\mathbf{y},\mathbf{u}) \in T$ and $\mathbf{u} \to 0$, then $\mathbf{y} \to 0$.

Here **P3.1'** still characterizes the weak disposability of outputs except the exclusion of the points $(\mathbf{x},\mathbf{0}_M,\mathbf{0}_J)$ from the production technology T. **P3.2'** states that the desirable outputs must also be infinitesimal if undesirable outputs are infinitesimal. There is no essential difference between **P3.1**, **P3.2** and **P3.1'**, **P3.2'** except that the latter is somewhat weaker than the former. Hence the piecewise linear production technology satisfying **P3.1'** and **P3.2'** can still be treated as an environmental DEA technology.

According to Färe and Grosskopf (2004), the VRS environmental DEA technology may be obtained by multiplying the right hand side of undesirable outputs constraints by an adjusting parameter not less than 1. We follow this suggestion but multiply the right hand side of desirable outputs constraints by the same parameter. The resulting environmental output set becomes

$$
\begin{aligned}
T_{VRS} = \{(\mathbf{x},\mathbf{y},\mathbf{u}) : &\sum_{k=1}^{K} z_k x_{nk} \le x_n, n = 1,2,\cdots,N \\
&\sum_{k=1}^{K} z_k y_{mk} \ge \alpha y_m, m = 1,2,\cdots,M \\
&\sum_{k=1}^{K} z_k u_{jk} = \alpha u_j, j = 1,2,\cdots,J \\
&\sum_{k=1}^{K} z_k = 1 \\
&\alpha \ge 1, z_k \ge 0, k = 1,2,\cdots,K\}
\end{aligned}
\tag{3.5}
$$

There is little difference between (3.5) and the idea of Scheel (2001) except that (3.5) is more similar to DEA in form. It can be easily shown that T_{VRS} satisfies the properties **P3.1'** and **P3.2'** (See Appendix C.1 for the proof). Therefore, T_{VRS} characterizes the VRS environmental DEA technology. Note that T_{VRS} is not a closed set although it will become one if the set $(\mathbf{x},\mathbf{0}_M,\mathbf{0}_J)$ are added. This, however, does not affect its application in measuring environmental performance. The reason is that at the points $(\mathbf{x}, \mathbf{0}_M, \mathbf{0}_J)$ the production process has ceased, which would not be preferred by any DMU.

To illustrate the VRS environmental DEA technology graphically, we consider the situation of four DMUs that use equal inputs to produce a desirable output and an undesirable output. The four DMUs are labeled A, B, C and D in Fig. 3.2. The environmental output set corresponding to T_{VRS} is the region OABCDE except the origin. However, without the adjusting parameter α in T_{VRS}, the region will be FABCDE. We may conclude that the adjusting parameter α allows T_{VRS} to possess the two properties (**P3.1'** and **P3.2'**) of environmental DEA technology.

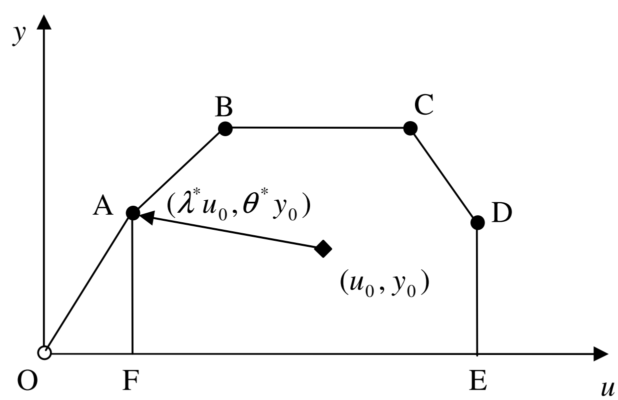

Fig. 3.2 An illustration of the VRS environmental DEA technology

3.2 Environmental performance measures

Earlier studies have shown that the aggregated environmental performance of industries can be measured from the standpoint of environmental efficiency by the use of undesirable outputs orientation DEA type models. We shall now introduce some new DEA type models for measuring environmental performance under the NIRS and

VRS environmental DEA technologies characterized in Section 3.1. Section 3.2.1 presents several pure EPIs while Section 3.2 proposes a mixed EPI under the VRS environmental DEA technology.

3.2.1 Pure environmental performance index

Many models for measuring environmental performance have been proposed under the CRS environmental DEA technology (Tyteca, 1996, 1997; Färe et al., 2004; Zaim, 2004; Zhou et al., 2006b, 2007c). Among these models, the undesirable outputs orientation model (3.6) highlighted by Tyteca (1996, 1997) is particularly attractive because it provides a pure environmental performance measure for DMU_0, i.e., PEI_C. Here PEI_C is called a pure EPI because in (3.6) only the adjustment of undesirable outputs is allowed.

$$
\begin{aligned}
PEI_C = \min\ & \lambda \\
\text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} \le x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0}, \quad m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda u_{j0}, \quad j = 1,2,\cdots,J \\
& z_k \ge 0, \quad k = 1,2,\cdots,K
\end{aligned}
\tag{3.6}
$$

Obviously, PEI_C is an aggregated and standardized EPI which lies in the interval (0,1]. If a specific DMU has a larger PEI_C, it has a better environmental performance under the CRS environmental DEA technology. The better environmental performance mainly results from its efficiency in controlling pollutants.

In the case of the NIRS and VRS environmental DEA technologies, we present the following two undesirable outputs orientation models for measuring environmental performance:

$$
\begin{aligned}
PEI_{NI} = \min \lambda & \\
\text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} \le x_{n0}, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0}, m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda u_{j0}, j = 1,2,\cdots,J \\
& \sum_{k=1}^{K} z_k \le 1 \\
& z_k \ge 0, k = 1,2,\cdots,K
\end{aligned}
\tag{3.7}
$$

$$
\begin{aligned}
PEI_{V} = \min \lambda & \\
\text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} \le x_{n0}, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge \alpha y_{m0}, m = 1,2\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda \alpha u_{j0}, j = 1,2,\cdots,J \\
& \sum_{k=1}^{K} z_k = 1 \\
& \alpha \ge 1, z_k \ge 0, k = 1,2,\cdots,K
\end{aligned}
\tag{3.8}
$$

Obviously, (3.7) can provide an aggregated and standardized index PEI_{NI} when the reference technology exhibits NIRS. If the reference technology exhibits VRS, we can also obtain a pure environmental performance measure by solving (3.8). (3.8) is a nonlinear programming model and we may use some well-established nonlinear programming algorithms to solve it. However, it seems logical if we transfer (3.8) into its equivalent linear programming problem (3.9) with the invariant optimal objective value:

$$
\begin{aligned}
PEI_V = \min \lambda & \\
\text{s.t.} \quad & \sum_{k=1}^{K} z_k x_{nk} \leq \beta x_{n0}, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \geq y_{m0}, m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda u_{j0}, j = 1,2,\cdots,J \\
& \sum_{k=1}^{K} z_k = \beta \\
& \beta \leq 1, z_k \geq 0, k = 1,2,\cdots,K
\end{aligned}
\tag{3.9}
$$

Theorem 3.1 *The optimal objective value of (3.9) is equal to that of (3.8).*

Proof. Dividing the two sides of each constraint in (3.8) by α and let $\frac{1}{\alpha} = \beta$ and $z_k \beta = z_k^{'} (k = 1,2,\cdots,k)$, we will obtain a new model equivalent to (3.8). Note that this new model is the same as (3.9) except for a difference in representation symbols.

As a result, we can obtain a pure EPI under the VRS environmental DEA technology by solving LP model (3.9) instead of NLP model (3.8). Since the optimal objective value of (3.9) lies in the interval (0,1], PEI_V is also an aggregated and standardized EPI. If a DMU has a larger PEI_V than another DMU, we may conclude that the former has a better environmental performance under the VRS environmental DEA technology.

In addition to the usefulness of PEI_C, PEI_{NI} and PEI_V in measuring environmental performance under different situations, they can be used together to investigate the returns to scale properties of a DMU with respect to the production of desirable outputs and undesirable outputs. Following the idea of the FGL approach (Färe et al., 1994a; Ramanathan, 2003), we may say that the reference DMU exhibits

CRS if PEI_C is equal to PEI_V. Otherwise, we should turn to PEI_{NI}. When PEI_{NI} is less than or equal to PEI_V, the reference DMU respectively exhibits increasing or decreasing returns to scale.

3.2.2 Mixed environmental performance index

Contrary to a pure EPI, an environmental performance measure considering the simultaneous adjustments of desirable and undesirable outputs can be called a mixed EPI. Under the VRS environmental DEA technology we present the following model for measuring environmental performance:

$$\begin{aligned}
MEI = \min \frac{\lambda}{\theta} & \\
\text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} \leq x_{n0}, n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \geq \theta\alpha y_{m0}, m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda\alpha u_{j0}, j = 1,2,\cdots,J \\
& \sum_{k=1}^{K} z_k = 1 \\
& \alpha \geq 1; \theta, z_k \geq 0, k = 1,2,\cdots,K
\end{aligned} \tag{3.10}$$

In (3.10) the removal of the adjusting parameter α would have no influence on its optimal objective value. In fact, the existence of α may bring great inconvenience in calculating a mixed EPI because (3.10) will have infinite optimal solutions. We therefore substitute (3.10) by the following model

$$
\begin{aligned}
MEI = \min \frac{\lambda}{\theta} & \\
\text{s.t.} \ \sum_{k=1}^{K} z_k x_{nk} & \leq x_{n0}, n = 1,2,\cdots,N \\
\sum_{k=1}^{K} z_k y_{mk} & \geq \theta y_{m0}, m = 1,2,\cdots,M \\
\sum_{k=1}^{K} z_k u_{jk} & = \lambda u_{j0}, j = 1,2,\cdots,J \\
\sum_{k=1}^{K} z_k & = 1 \\
\theta, z_k & \geq 0, k = 1,2,\cdots,K
\end{aligned}
\tag{3.11}
$$

Intuitively, (3.11) is very similar to the input-output orientation model used for determining the most productive scale size in the traditional DEA framework (Cooper et al., 1996). The difference is that in (3.11) the simultaneous adjustments of desirable and undesirable outputs are considered while in the traditional DEA framework the adjustments of inputs and outputs are considered. Therefore, (3.11) could be used to measure the efficiency of DMU_0 with respect to its production scale of desirable outputs to undesirable outputs. If $MEI = 1$, we may say that DMU_0 is at its most environmental scale size. If $MEI < 1$, it indicates that DMU_0 does not operate at its most environmental scale size.

Other implications of (3.11) can be illustrated by using the same simple example in Fig. 3.2. Assume that we wish to use (3.11) to compare DMU_B with DMU_C in terms of environmental performance. It can be easily verified that MEI_B / MEI_C is equal to $\frac{y_B / u_B}{y_C / u_C}$ or $\frac{u_C / y_C}{u_B / y_B}$. The first term denotes the ratio of "good" to "bad" between the two DMUs, which is consistent with the Hicks-Moorsteen EPI provided by Färe et al. (2004). The second may be described as the reciprocal of the ratio of their pollution intensities. For instance, if the desirable output and the undesirable output are gross domestic product (GDP) and carbon emissions respectively, then MEI_B / MEI_C is simply the reciprocal of the ratio of B's carbon intensity to C's carbon intensity. On the other hand, it can also be found that the projection of (u_0, y_0) to $(\lambda^* u_0, \theta^* y_0)$ for any DMU will reach point A in Fig. 3.2 since A has the maximal slope. That is to say, DMU_A is the most environmentally efficient performer used to evaluate other DMUs.

Since (3.11) is a nonlinear programming model, we transform (3.11) into its equivalent linear programming model (3.12) with the invariant optimal objective value:

$$\begin{aligned} MEI = \min \lambda & \\ \text{s.t.} \ & \sum_{k=1}^{K} z_k x_{nk} \leq \beta x_{n0}, n = 1,2,\cdots,N \\ & \sum_{k=1}^{K} z_k y_{mk} \geq y_{m0}, m = 1,2,\cdots,M \\ & \sum_{k=1}^{K} z_k u_{jk} = \lambda u_{j0}, j = 1,2,\cdots,J \\ & \sum_{k=1}^{K} z_k = \beta \\ & z_k \geq 0, k = 1,2,\cdots,K \end{aligned} \tag{3.12}$$

Theorem 3.2 *The optimal objective value of (3.11) is equal to that of (3.12).*

Proof. Divide the two sides of each constraint in (3.11) by θ and let $\frac{1}{\theta} = \beta$, $\lambda\beta = \rho$ and $z_k \beta = z_k^{'}$ ($k = 1,2,\cdots,k$). We then obtain a linear programming model equivalent to (3.11) which is the same as (3.12) except for a difference in representation symbols.

Theorem 3.2 indicates that a mixed EPI under the VRS environmental DEA technology can be obtained by solving linear programming model (3.12) instead of nonlinear programming model (3.11). Since $\lambda = \beta = 1$ is a feasible solution of (3.12), MEI lies in the interval (0, 1]. Thus MEI is also an aggregated and standardized EPI. If a DMU has a larger MEI than another DMU, we may conclude that the former has a better environmental performance than the latter under the VRS environmental DEA technology.

3.3 An application study

There has been a growing concern on global climate change due to carbon dioxide (CO_2) emissions worldwide (Tol, 2005). Several indicators, namely energy intensity (the ratio of energy use to GDP), carbon intensity (the ratio of carbon emissions to GDP) and carbon factor (the ratio of carbon emissions to energy use), are widely used to monitor or track a country/region's performance in CO_2 emissions over time (Choi and Ang, 2001; Ang and Choi, 2002). It has been shown that energy intensity is at least as useful as carbon factor in assessing the evolution patterns of industrialized and developing countries with regard to climate change (Ang, 1999). However, from the point of view of pure environmental performance, it seems that carbon intensity and carbon factor are adequate for gauging the carbon emission performance of a system. We shall apply the proposed environmental performance measures to study the carbon emission performances of eight world regions in 2002 under different reference technologies. The single input, desirable output and undesirable output are total energy consumption (Mtoe), GDP (billion 1995 US$ in PPP) and CO_2 emissions (Mt), respectively. The data and regions are shown in Table 3.1 and the data source is International Energy Agency (2004a).

Table 3.2 shows the three pure EPIs and the mixed EPI for measuring carbon emission performance of each region in 2002 obtained by using the proposed models in Section 3.2. The quantity on carbon intensity ($MtCO_2$/billion 95 US$), carbon factor ($MtCO_2$/Mtoe) and energy intensity (Mtoe/billion 95 US$) are also included in the table.

Table 3.1 The original data for eight world regions in 2002

DMU	**Energy consumption** (Mtoe)	**GDP** (billion 95 US $ in PPP)	**CO_2** (Mt)
OECD	3696.50	25374.85	12554.03
Middle East	290.90	1025.83	1092.84
Former USSR	610.17	1552.10	2232.17
Non-OECD Europe	63.86	358.26	252.84
China	823.02	5359.02	3307.42
Asia*	851.40	5507.94	2257.41
Latin America	354.75	2566.74	844.61
Africa	404.42	1668.75	743.12

* Asia excludes China.

Table 3.2 Comparisons between different EPIs and carbon intensity, carbon factor and energy intensity

DMU	PEI_C	PEI_{NI}	PEI_V	MEI	**Carbon intensity**	**Carbon factor**	**Energy intensity**
OECD	0.67	1.00	1.00	0.67	0.49	3.40	0.15
Middle East	0.31	0.31	0.32	0.32	1.07	3.76	0.28
Former USSR	0.23	0.23	0.23	0.23	1.44	3.66	0.39
Non-OECD Europe	0.47	0.47	1.00	1.00	0.71	3.96	0.18
China	0.53	0.66	0.66	0.53	0.62	4.02	0.15
Asia	0.80	1.00	1.00	0.80	0.41	2.65	0.15
Latin America	1.00	1.00	1.00	1.00	0.33	2.38	0.14
Africa	0.74	0.74	0.74	0.74	0.45	1.84	0.24

Not surprisingly, the EPI of a certain DMU may change under different environmental DEA technologies because different models are adopted under different situations. From Table 3.2 we can also find that the order ranks of two DMUs may also change if different technologies are specified. For instance, China has a better carbon emission performance than Non-OECD Europe if the reference technology exhibits CRS or NIRS. However, under the VRS environmental DEA technology the converse is the case, whichever of pure and mixed environmental performance measures is used. This indicates that it is necessary to characterize different environmental DEA technologies as well as the corresponding DEA-based models. If the CRS environmental DEA technology is always assumed in environmental performance measurement, the real position of a DMU in environmental performance may be distorted. As a result, the choice of a specific environmental DEA technology would play an important role in environmental performance measurement. For this case, the choice of a suitable EPI needs further investigations on the underlying production technology, which can be studied using the methods provided in Färe et al. (1994a) and Ramanathan (2003). However, since this application study is very aggregate and its main purpose is to illustrate the use of the proposed environmental performance measures, we shall not provide an in-depth analysis on the choice of a suitable EPI. Interesting readers may refer to Färe et al. (1994a) and Ramanathan (2003) for more discussions.

As shown in Table 3.2, carbon intensity is more highly correlated with environmental performance index than carbon factor and energy intensity. In particular, under the CRS environmental DEA technology the ranks on carbon intensity are completely consistent with the ranks of the eight regions on carbon emission performance. This indicates that carbon emission performance is mainly determined by carbon intensity. On the other hand, it can be observed from Table 3.2 that energy intensity may also affect the ranks of DMUs on carbon emission performance in some cases. For instance, if the pure EPI is chosen and the reference technology exhibits VRS, OECD has a better carbon emission performance than Africa although it has larger carbon intensity and carbon factor. This may be due to the fact that the energy intensity of OECD (0.15) is smaller than that of Africa (0.24). Thus we may conclude that it is not appropriate to determine the carbon emission performances of DMUs only by their carbon intensities and carbon factors.

Although a number of conclusions have been drawn from our application study, as mentioned above, the main purpose of this application is to illustrate the use of the proposed environmental performance measures and to demonstrate the advantages of DEA type models over some partial indicators in measuring carbon emission performance. Since DEA is a deterministic technique based on mathematical programming, the results obtained may be very sensitive to the uncertainty in the data. Therefore, if real cases are involved, as illustrated by Hawdon (2003), it is better to combine DEA models with such statistical techniques as bootstrap methods in order to produce a sampling distribution of EPI values and carry out statistical tests for decision making and policy analysis (Simar and Wilson, 1998). However, much larger samples are often required in combing DEA with bootstrap methods to provide relatively reliable estimations.

3.4 Conclusion

In this chapter we have further discussed the NIRS and VRS environmental DEA technologies, in which outputs are still weakly disposable essentially. The pure EPIs under different situations and a mixed EPI under the VRS environmental DEA technology for measuring environmental performance have also been proposed. For those measures dealing with nonlinear programming models, we also give their linear programming equivalents. An application study is finally presented to illustrate the use of proposed models in measuring environmental performance.

It should be pointed out that all the models proposed in this chapter follow the concept of radial efficiency measures. However, in some circumstances it may be difficult to compare some DMUs on environmental performance only by the proposed EPIs because of the weak discriminating power of radial DEA efficiency measures. Since non-radial DEA models usually have a higher discriminating power in evaluating the efficiencies of DMUs, in practice it may be more practical to incorporate the environmental DEA technologies with the non-radial DEA efficiency scores. This topic will be explored in the next chapter.

CHAPTER 4 NON-RADIAL DEA APPROACH TO MEASURING ENVIRONMENTAL PERFORMANCE[3]

In Chapter 3, we discussed different environmental DEA technologies and proposed their radial implementations for measuring environmental performance. A limitation of radial DEA type models is that they have weak discriminating power so that many DMUs with an EPI of 1 cannot be directly compared. In addition, these models always adjust all the undesirable outputs (or desirable outputs) by the same proportion to reach the efficient targets. However, the obtained efficient targets may not be preferred by decision makers or environmental analyst out of some realistic, economical or political considerations. Since non-radial efficiency measures may have higher discriminating power in comparing the performance of DMUs, non-radial DEA type models seem to be more effective in measuring environmental performance. Furthermore, when more information such as the preference structure of decision makers is available, non-radial DEA type models could incorporate the information by assigning different weights to different undesirable outputs. For instance, if climate change is the main focus, the reduction of CO_2 will be more important than the reduction of SO_2. The information can be easily incorporated into non-radial DEA models by imposing a larger weight to the reduction of CO_2.

In the traditional DEA framework, a series of non-radial DEA models have been well developed in the past. Examples of such studies include Banker and Morey (1986a), Thanassoulis and Dyson (1992), Zhu (1996) and Halme et al. (1999). More recently, the weighted non-radial DEA models were successfully applied to Chinese

[3] The work presented in this chapter has been published as Zhou et al. (2007c).

industrial productivity analysis by Seiford and Zhu (1998) and Chen (2003). Despite the existence of many non-radial DEA models, none of them consider the adjustment of both desirable and undesirable outputs together. It is therefore worthwhile to extend the traditional non-radial DEA models to the case when undesirable outputs exist for the purpose of measuring environmental performance. The purpose of this chapter is to develop a non-radial DEA approach to measuring environmental performance, which includes a non-radial DEA type model for multilateral environmental performance comparisons and a non-radial Malmquist environmental performance index for measuring the change of environmental performance over time. To illustrate the use of the proposed non-radial DEA approach, we also present a case study of modeling the environmental performance of OECD countries over time.

4.1 Background information

A large number of studies have been devoted to various theoretical and empirical aspects of DEA in the past several decades. Such developments in DEA can be found in Seiford (1996) and Cooper et al. (2004). Among these developments, the extension of traditional radial DEA models to non-radial DEA models especially DEA with preference structure is an important branch. See, for example, Banker and Morey (1986a), Thanassoulis and Dyson (1992), Zhu (1996), Halme et al. (1999), Chen and Sherman (2004), and Zhou et al. (2006d). In empirical application, the weighted CCR models (WCCR) developed by Zhu (1996) seemed to be very popular, e.g., Seiford and Zhu (1998) and Chen (2003).

Suppose that we want to measure the relative efficiency of $\mathrm{DMU}_{0,}$ $0 \in \{1,2,\cdots,K\}$. If the normalized preference weight ω_{ym} for adjusting the *m*-th output is available, then the output-oriented WCCR model can be written as

$$\begin{aligned} \phi_0^* = \max \sum_{m=1}^{M} \varpi_{ym} \phi_m & \\ \text{s.t. } \sum_{k=1}^{K} z_k x_{nk} \le x_{n0}, \quad n = 1,2,\cdots,N & \\ \sum_{k=1}^{K} z_k y_{mk} \ge \phi_m y_{m0}, \; m = 1,2,\cdots,M & \\ z_k \ge 0, \; k = 1,2,\cdots,K & \end{aligned} \tag{4.1}$$

According to Zhu (1996), DMU_0 is DEA efficient if $\phi_0^* = 1$ as well as the surplus and slacks in constraints are equal to zero. The popularity of this model in application owes to its flexibility, which is mainly due to the fact that the reduction of some outputs is permitted in order to reach the preferred target. Note that in (4.1) if ϖ_{ym} is equal to the proportion of the value of the *m*-th output to the total value of all the outputs, then the optimal objective value of (4.1) characterizes the maximal augmentation of DMU_0's revenues under the current production technology.

Similarly, the input-oriented WCCR model can be expressed as

$$\begin{aligned} \theta_0^* = \min \sum_{n=1}^{N} \varpi_{xn} \theta_n & \\ \text{s.t. } \sum_{k=1}^{K} z_k x_{nk} \le \theta_n x_{n0}, \quad n = 1,2,\cdots,N & \\ \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0}, \; m = 1,2,\cdots,M & \\ z_k \ge 0, \; k = 1,\cdots,K & \end{aligned} \tag{4.2}$$

where ϖ_{xn} represents the normalized preference weight for adjusting the n-th input. Also, if $\theta_0^* = 1$ as well as the surplus and slacks in constraints are equal to zero, DMU_0 is DEA efficient. Note that in this model the augmentation of some inputs is allowable in order to reach the preferred target. And if ϖ_{xn} is equal to the proportion of the costs of the n-th input to the total costs of all the inputs for DMU_0, the optimal objective value of (4.2) characterizes the maximal reduction of DMU_0's costs under the current production technology.

4.2 Non-radial DEA approach

4.2.1 Non-radial environmental performance measure

As was discussed in Chapter 3, many DEA type models for measuring environmental performance have been proposed in virtue of the environmental DEA technology concept. It is noted that most of them adopted radial efficiency measures. However, using radial efficiency measures often leads to the case where a lot of DMUs have the same efficiency score of 1 and hence difficulty in ranking and comparing these DMUs in terms of their environmental performance. In this section, we propose several non-radial DEA type models for measuring environmental performance. These models allow some undesirable outputs to increase so that other pollutants with higher priority can achieve greater decrease in the frontier of best practice. Although the proposed models in this section are only based on the CRS environmental DEA technology, they can be easily extended to other situations such as the VRS environmental DEA technology discussed in the last chapter.

Let $\varpi_{uj}(j=1,2,\cdots,J)$ be the normalized user-specified weights for adjusting the j-th undesirable output (or pollutant), i.e., $\sum_{j=1}^{J}\varpi_{uj}=1$, which reflects the desirability degree of decision makers in adjusting the current level of this pollutant. Following the spirit of the WCCR models described in Section 4.1, we propose the following non-radial undesirable outputs orientation DEA type model under the CRS environmental DEA technology for measuring environmental performance:

$$
\begin{aligned}
NREI(\mathbf{x}_0,\mathbf{y}_0,\mathbf{u}_0) = \min & \sum_{j=1}^{J}\varpi_{uj}\lambda_j \\
\text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} \le x_{n0},\ n=1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0},\ m=1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda_j u_{j0},\ j=1,2,\cdots,J \\
& z_k \ge 0,\ \ k=1,2,\cdots,K
\end{aligned}
\tag{4.3}
$$

The optimal objective value $NREI(\mathbf{x}_0,\mathbf{y}_0,\mathbf{u}_0)$ of (4.3) can be used to measure the environmental performance of DMU_0 relative to other DMUs. Obviously, $NREI(\mathbf{x}_0,\mathbf{y}_0,\mathbf{u}_0)$ is dimensionless and lies in the interval (0,1]. According to the characterization of standardized EPI (Tyteca, 1996), it is also a standardized EPI. The greater the $NREI(\mathbf{x}_0,\mathbf{y}_0,\mathbf{u}_0)$, the better the environmental performance of DMU_0.

Occasionally, some pollutants such as the j-th pollutant may not be expected to be adjusted for certain reasons, i.e., $\varpi_{uj}=0$. Then we should set $\lambda_j=1$ in order to properly characterize this situation. Note that if additional constraint $\lambda_1=\lambda_2\cdots=\lambda_J$ is added to (4.3), then it will collapse to the radial DEA type model (3.6) for measuring environmental performance. Therefore, (4.3) can be regarded as a generalization of model (3.6). If $\varpi_{u1} = \varpi_{u2} \cdots = \varpi_{uJ}$, (4.3) will become

$$\begin{aligned} \overline{NREI}(\mathbf{x}_0, \mathbf{y}_0, \mathbf{u}_0) = \min \frac{1}{J}\sum_{j=1}^{J}\lambda_j & \\ \text{s.t.} \sum_{k=1}^{K} z_k x_{nk} \le x_{n0},\ & n = 1,2,\cdots,N \\ \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0},\ & m = 1,2,\cdots,M \\ \sum_{k=1}^{K} z_k u_{jk} = \lambda_j u_{j0},\ & j = 1,2,\cdots,J \\ z_k \ge 0,\ & k = 1,2,\cdots,K \end{aligned} \tag{4.4}$$

Since (4.4) is basically a generalization of Russell DEA model in the context of environmental performance measurement, here we call $\overline{NREI}(\mathbf{x}_0, \mathbf{y}_0, \mathbf{u}_0)$ a Russell EPI.

In order to graphically compare radial and non-radial DEA models in environmental performance measurement, we shall use a simple numerical example of three DMUs (A, B and C), one input, one desirable output and two undesirable outputs to illustrate the use of (4.3) and (4.4). Assume that the input-output combinations for the three DMUs are (1, 1, 0.5, 2.2), (1, 1, 2, 1) and (1, 1, 2, 2), respectively. If the radial DEA model (3.6) is used, as shown in Fig. 4.1, the benchmark point for evaluating C's environmental performance is E. Accordingly, C's EPI value is OE/OC=0.722. If the non-radial DEA model with equal weights, i.e., (4.4), is used, the benchmark point for evaluating C's environmental performance becomes A. In order to become environmentally efficient, C needs to decrease its u_1 to 0.5 while increase its u_2 to 2.2. As a result, C's EPI value becomes 0.5×(0.5/2)+0.5×(2.2/2)=0.675. If (4.3) is used and the weights for u_1 and u_2 are respectively 0.2 and 0.8, then the benchmark point for evaluating C's environmental performance is B and C's EPI value is 0.2×(2/2)+0.8×(1/2)=0.6.

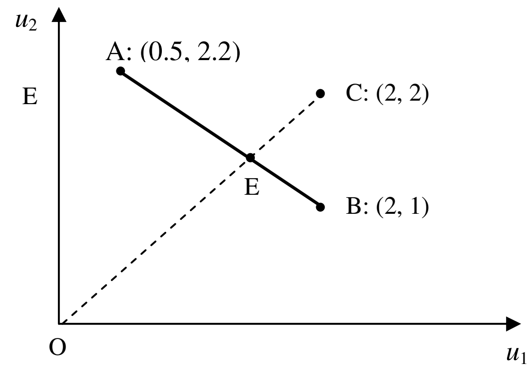

Fig. 4.1 A graphical comparison of radial and non-radial DEA models for measuring environmental performance

To further understand the implications of (4.3), we give its dual problem (after Charnes-Cooper transformation) as follows

$$
\begin{aligned}
& \max \frac{\sum_{m=1}^{M} u_m y_{m0} - \sum_{n=1}^{N} v_n x_{n0}}{\sum_{j=1}^{J} w_j u_{j0}} \\
& \text{s.t.} \ \frac{\sum_{m=1}^{M} u_m y_{mk} - \sum_{n=1}^{N} v_n x_{nk}}{\sum_{j=1}^{J} w_j u_{jk}} \le 1, \quad k = 1,2,\cdots,K \\
& \quad w_j u_{j0} = \varpi_{uj}, \quad j = 1,2,\cdots,J \\
& \quad u_m, v_n \ge 0, \ m = 1,2,\cdots,M;\, n = 1,2,\cdots,N
\end{aligned}
\tag{4.5}
$$

Model (4.5) can be interpreted as a generalization of the CCR model (in multiplier form) with preference structure when undesirable outputs are considered. It maximizes the ratio of net virtual desirable outputs (the difference between virtual desirable outputs and virtual inputs) to virtual undesirable outputs. The virtual multipliers of undesirable outputs are restricted by the user-specified weights.

Obviously, non-radial DEA type models (4.3) and (4.4) have higher discriminating power than radial DEA type model (3.6) in measuring environmental performance. Another advantage of (4.3) and (4.4) is that they allow some undesirable outputs to increase so that other pollutants with higher priority may achieve greater decrease in the frontier of best practice. Nevertheless, the application of (4.3) will inevitably involve the determination of preferred weights of undesirable outputs, which may bring difficulty to analysts and decision makers. A suggestion is that an undesirable output should be attached to a larger weight if it has a larger damage cost. Therefore, the expert information in environmental cost analysis, e.g., Huang et al. (1996, 1997), Tol (2005) and Färe et al. (2006), may be helpful in determining the weights for undesirable outputs. If we let the weights be proportional to the unit abatement costs of undesirable outputs, (4.3) is essentially to minimize the total abatement costs. Another suggestion is to determine the weights by utilizing the preference information of decision makers, which could be a topic for future research.

4.2.2 Non-radial Malmquist environmental performance index

The non-radial environmental performance measures described in Section 4.2.1 are primarily used to conduct multilateral comparisons on the basis of cross-sectional data, e.g., comparisons among different DMUs in environmental performance at the same point in time. However, in the case of DMUs, there is increasing interest in monitoring of their individual environmental performance changes between two periods. To serve this purpose, we extend the Malmquist productivity index given in Färe et al. (1994b, 1998) into a non-radial Malmquist environmental performance index. Although the original Malmquist productivity index is constructed on the basis of distance function, it can also be constructed by

DEA efficiency measures in virtue of the relationships between distance functions and efficiency measures. For instance, Chen (2003) defined an input-oriented non-radial Malmquist productivity index by non-radial DEA efficiency measures and applied it to evaluate the productivity changes of Chinese major industries.

Let t and s denote two time periods ($t < s$). Let $NREI^{t}(\mathbf{x}_0^t, \mathbf{y}_0^t, \mathbf{u}_0^t)$ and $NREI^{s}(\mathbf{x}_0^t, \mathbf{y}_0^t, \mathbf{u}_0^t)$ be respectively the non-radial EPIs of DMU_0 based on its inputs and outputs of period t for the reference technologies at t and s. Let $NREI^{t}(\mathbf{x}_0^s, \mathbf{y}_0^s, \mathbf{u}_0^s)$ and $NREI^{s}(\mathbf{x}_0^s, \mathbf{y}_0^s, \mathbf{u}_0^s)$ respectively denote the EPIs of DMU_0 based on its inputs and outputs of period s for the reference technologies at t and s. Following the spirit of Malmquist productivity index, we define the non-radial Malmquist environmental performance index of DMU_0 as follows:

$$NRMEI_0 = \left[\frac{NREI^{t}(\mathbf{x}_0^s, \mathbf{y}_0^s, \mathbf{u}_0^s)}{NREI^{t}(\mathbf{x}_0^t, \mathbf{y}_0^t, \mathbf{u}_0^t)} \frac{NREI^{s}(\mathbf{x}_0^s, \mathbf{y}_0^s, \mathbf{u}_0^s)}{NREI^{s}(\mathbf{x}_0^t, \mathbf{y}_0^t, \mathbf{u}_0^t)} \right]^{1/2} \tag{4.6}$$

We can then measure the environmental performance change of DMU_0 by $NRMEI_0$, where $NRMEI_0 > 1$, $NRMEI_0 = 1$ and $NRMEI_0 < 1$ respectively indicate that the environmental performance of DMU_0 has been improved, unchangeable and deteriorated. Like in the Malmquist productivity index, we can also investigate the mechanism of environmental performance changes by decomposing (4.6) into two components as follows:

$$NRMEI_0 = \frac{NREI^{s}(\mathbf{x}_0^s, \mathbf{y}_0^s, \mathbf{u}_0^s)}{NREI^{t}(\mathbf{x}_0^t, \mathbf{y}_0^t, \mathbf{u}_0^t)}$$

$$\times\left[\frac{NREI^{t}(\mathbf{x}_0^s,\mathbf{y}_0^s,\mathbf{u}_0^s)}{NREI^{s}(\mathbf{x}_0^s,\mathbf{y}_0^s,\mathbf{u}_0^s)}\frac{NREI^{t}(\mathbf{x}_0^t,\mathbf{y}_0^t,\mathbf{u}_0^t)}{NREI^{s}(\mathbf{x}_0^t,\mathbf{y}_0^t,\mathbf{u}_0^t)}\right]^{1/2} \tag{4.7}$$

where the first term of the right-hand side measures the change of relative environmental performance, i.e., technical efficiency change (EFFCH), and the second term measures the shift of environmental DEA technology, i.e., technological change (TECH).

4.3 Case study

We shall apply the non-radial DEA approach as described in Section 4.2 to measure the environmental performance of 26 OECD countries from 1995 to 1997. In this case study, labor force (LF) and primary energy consumption (PEC), are employed as two inputs. Capital stock, another commonly used input in efficiency and productivity analysis, is not included due to the lack of data. The only desirable output is gross domestic product (GDP). In the case of undesirable outputs, in addition to carbon dioxide (CO_2), sulphur oxides (SO_x) and nitrogen oxides (NO_x) frequently used by previous studies, we also chose carbon monoxide (CO) as a kind of undesirable output because it can cause adverse health effects. The data on these variables were collected from *Statistical Review of World Energy* (BP, 2003), *OECD Environmental Data* (OECD, 1999), *OECD Historical Statistics* (OECD, 2001) and *Energy Balances of OECD Countries* (OECD, 2003). Table 4.1 gives the descriptive statistics of the data collected.

The non-radial DEA model (4.3) is applied to calculate the EPIs of 26 OECD countries from 1995 to 1997. For a rigorous application study, as mentioned earlier, we suggest that the existing damage cost estimates of pollutants in literature are collected and used for derived the weights of undesirable outputs. As an example, Tol (2005) found that the mean damage cost estimate of carbon dioxide emissions given by a number of previous studies is \$93/tC. Since our application study is mainly for illustrate purpose, we arbitrarily specify the weight of every undesirable output (including CO_2, SO_x, NO_x and CO) is first specified as 0.25 that implies that the reductions of these undesirable outputs have the same degree of importance. Table 4.2 shows the obtained non-radial EPIs as well as the radial EPIs derived from model (3.6) of these countries.

Table 4.1 Summary statistics for 26 OECD countries in 1995-97

Year	Variable	Mean	S.D.	Min	Max
1995	LF (million workers)	17.16	28.08	0.15	133.64
	PEC (Mtoe)	180.21	413.16	1.9	2119.1
	GDP (Billion 95 US$)	891.02	1717.29	6.9	7338.4
	SO_x (thousand tons)	1475.70	3359.44	8.1	17407
	NO_x (thousand tons)	1673.27	4360.73	28	22725
	CO_2 (million tons)	421.58	996.69	2	5116
	CO (thousand tons)	6261.88	16289.95	49	83813
1996	LF	17.31	28.36	0.15	135.14
	PEC	186.12	426.81	1.9	2189.8
	GDP	916.46	1775.40	7.26	7603
	SO_x	1420.17	3298.80	8.3	17109
	NO_x	1708.23	4535.52	30	23635
	CO_2	434.96	1023.51	2	5255
	CO	6359.27	16942.62	50	87240
1997	LF	17.51	28.82	0.15	137.53
	PEC	187.09	429.83	2.1	2206.7
	GDP	945.00	1836.78	7.59	7943
	SO_x	1378.15	3386.99	8.8	17566
	NO_x	1707.04	4589.72	29	23907
	CO_2	442.31	1061.45	2	5460
	CO	6262.77	16681.88	39	85751

It can be seen from Table 4.2 that non-radial DEA type model has higher discriminating power than radial DEA type model in measuring environmental performance. Based on the radial DEA type model (3.6), over ten countries have the same EPIs of "1" and further comparisons among these countries are impossible. However, under non-radial DEA type model (4.3), only two countries (Japan and

Switzerland) have the environmental performance scores of “1”. Other countries with REI=1 can be easily compared in environmental performance by their non-radial EPIs. This should be attributed to the fact that non-radial DEA type models allow for the disproportional reduction of undesirable outputs. From Table 4.2 we can also find that Poland and Slovak Republic have smaller EPIs during the three years, whether radial or non-radial EPI is used. However, in the case of Australia and Hungary, although their radial EPIs have always been equal to one, their non-radial EPIs are relatively low during the three years.

Table 4.2 Radial and non-radial EPIs of 26 OECD countries in 1995-97

Country	REI			NREI		
	1995	1996	1997	1995	1996	1997
Australia	1.000	1.000	1.000	0.075	0.071	0.069
Austria	1.000	1.000	1.000	0.458	0.442	0.422
Canada	0.349	0.343	0.341	0.097	0.095	0.093
Czech Republic	1.000	1.000	0.216	0.046	0.045	0.045
Denmark	1.000	0.562	0.514	0.302	0.262	0.300
Finland	0.550	0.507	0.470	0.265	0.247	0.258
France	0.815	0.731	0.828	0.341	0.330	0.346
Germany	0.546	0.508	0.513	0.371	0.386	0.412
Greece	0.543	0.602	0.531	0.125	0.121	0.118
Hungary	1.000	1.000	1.000	0.072	0.070	0.071
Iceland	1.000	1.000	1.000	0.212	0.202	0.226
Ireland	0.536	0.555	0.596	0.211	0.216	0.228
Italy	0.436	0.464	0.462	0.227	0.227	0.229
Japan	1.000	1.000	1.000	1.000	1.000	1.000
Korea	1.000	1.000	1.000	0.201	0.199	0.197
Netherlands	1.000	1.000	1.000	0.400	0.403	0.436
New Zealand	1.000	1.000	1.000	0.168	0.157	0.147
Norway	1.000	1.000	1.000	0.416	0.424	0.420
Poland	0.096	0.106	0.116	0.035	0.034	0.037
Portugal	1.000	1.000	1.000	0.141	0.146	0.145
Slovak Republic	0.156	0.168	0.156	0.045	0.052	0.056
Spain	1.000	0.834	0.793	0.195	0.195	0.190
Sweden	0.762	0.775	0.905	0.405	0.388	0.411
Switzerland	1.000	1.000	1.000	1.000	1.000	1.000
United Kingdom	0.494	0.465	0.437	0.212	0.213	0.226
United States	0.240	0.255	0.261	0.123	0.119	0.118
Mean	0.751	0.726	0.698	0.275	0.271	0.277

Note: REI and NREI refer to radial and non-radial EPIs.

Table 4.3 shows the non-radial Malmquist EPIs as well as their components of these countries exclusive of Japan and Switzerland from 1995 to 1996 and from 1996 to 1997. As a whole, the environmental performance of OECD countries had been improved from 1995 to 1997 since the geometric mean of their non-radial Malmquist EPIs was always larger than 1 in 1995-1996 and 1996-1997. The improvement mainly came from the technological change although the technical efficiency change could also make a small contribution from 1996 to 1997. It should be pointed out that other factors such as recessions and exchange rate changes, which are not considered in this study, may also affect the change of environmental performance over time. How to separate these effects from technical efficiency and technological changes is a potential research topic that is worth investigating.

Table 4.3 Non-radial Malmquist EPIs and their components in 1995-97

Country	1995-1996			1996-1997		
	NRMEI	EFFCH	TECH	NRMEI	EFFCH	TECH
Australia	0.964	0.943	1.022	1.001	0.981	1.020
Austria	1.020	0.965	1.057	1.013	0.953	1.063
Canada	1.005	0.974	1.032	1.018	0.985	1.034
Czech Republic	1.024	0.995	1.029	1.008	0.983	1.025
Denmark	0.903	0.867	1.042	1.201	1.145	1.049
Finland	0.966	0.929	1.040	1.092	1.044	1.045
France	1.004	0.968	1.038	1.089	1.046	1.041
Germany	1.076	1.041	1.034	1.095	1.066	1.026
Greece	0.996	0.966	1.031	1.010	0.978	1.033
Hungary	1.014	0.979	1.036	1.047	1.007	1.039
Iceland	0.975	0.950	1.026	1.152	1.119	1.029
Ireland	1.054	1.024	1.029	1.080	1.054	1.025
Italy	1.037	0.998	1.038	1.051	1.009	1.042
Korea	1.025	0.989	1.036	1.015	0.987	1.028
Netherlands	1.050	1.009	1.040	1.110	1.080	1.027
New Zealand	0.981	0.940	1.043	0.974	0.931	1.046
Norway	1.070	1.020	1.050	1.046	0.991	1.056
Poland	1.003	0.967	1.037	1.111	1.067	1.041
Portugal	1.067	1.041	1.025	1.018	0.992	1.026
Slovak Republic	1.199	1.161	1.033	1.099	1.072	1.025
Spain	1.033	1.002	1.031	1.006	0.973	1.034
Sweden	0.999	0.958	1.042	1.108	1.060	1.045
United Kingdom	1.041	1.005	1.035	1.110	1.061	1.047
United States	1.006	0.969	1.037	1.029	0.989	1.040
Geometric mean	1.020	0.985	1.036	1.060	1.023	1.037

Note that the non-radial EPIs and non-radial Malmquist EPIs in Table 4.2 and Table 4.3 are calculated using $\varpi_{b1} = \varpi_{b2} = \varpi_{b3} = \varpi_{b4} = 0.25$. In order to determine the sensitivity of environmental performance ranks to the weights assigned, we attempts to calculate the non-radial EPIs using (4.3) under different weight combinations. We firstly define the low, middle and higher values of the weight for each undesirable output as 0.1, 0.25 and 0.4 respectively. If the weight of one undesirable output is determined, the remainder is then allocated to the other three undesirable outputs uniformly. We then obtain nine different weight combinations. Using these weight sets we can get nine sets of rank indexes in environmental performance for each country according to the non-radial EPIs derived. The corresponding box plots for the 26 countries in the sequence of mean rank values in 1997 are shown in Fig. 4.2.

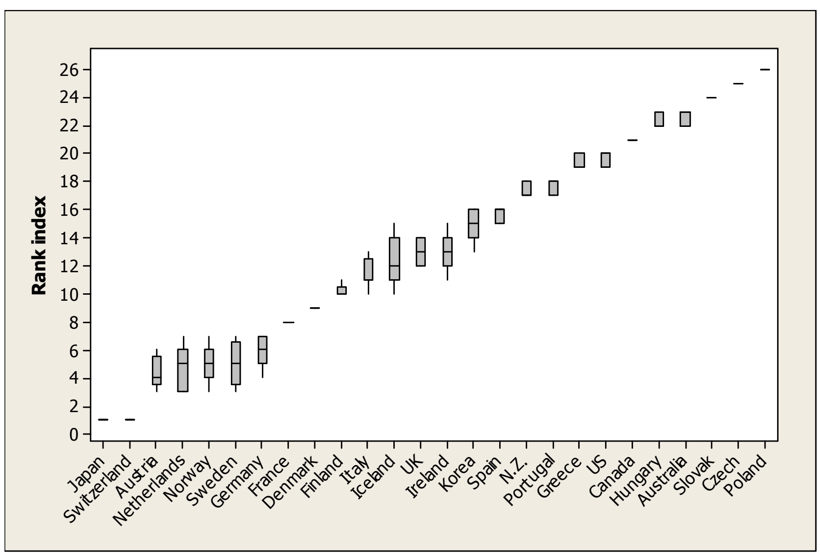

Fig. 4.2 Comparative box plots of environmental performance rank indexes in 1997

Generally speaking, the ranks of these countries in environmental performance are not very sensitive to the weight combinations of undesirable outputs. In particular, it is observed from Fig. 4.2 that the rank indexes of the countries at the two extremes, e.g., Japan, Switzerland, Slovak, Czech and Poland, remain the same for different weight combinations. Other countries with lower environmental performance such as Canada and Hungary also have little change in their ranks. On the other hand, the places of several countries with better or average environmental performances have wider fluctuating bands, e.g., Netherlands and Iceland. For instance, if the reduction of CO_2 is given a higher priority, Iceland ranks the tenth among the 26 countries. However, it ranks the fifteenth if the reduction of CO_2 is given a lower priority.

Although Fig. 4.2 gives a general overview of the 26 countries in environmental performance, it does not display the change of EPIs of individual countries with respect to changes of weights. Thus it is worthwhile to do further analysis in order to investigate the impacts of weight changes on environmental performances, especially for those countries with a wider fluctuating rank bands. Taking for example the Netherlands, we give one-way sensitivity analysis results for its EPI on the weight of each undesirable output as shown in Fig. 4.3. The results indicate that the EPI may also be quite insensitive to the weights of undesirable outputs.

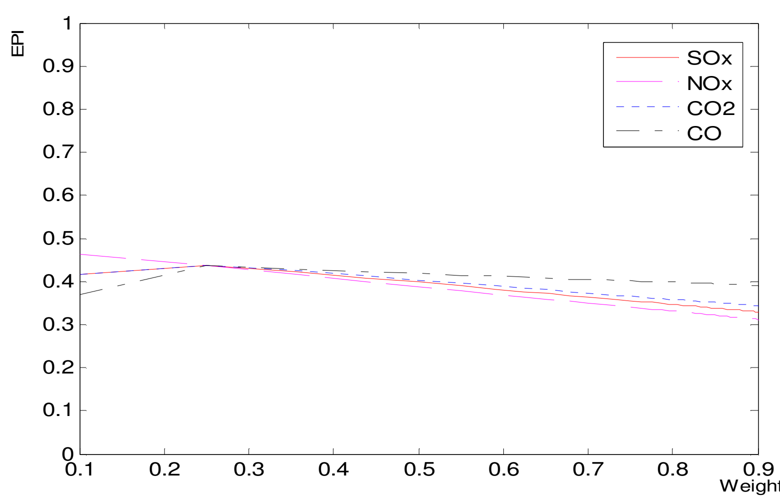

Fig. 4.3 Sensitivity analysis results for EPI of the Netherlands in 1997

4.4 Conclusion

In this chapter, we propose a non-radial DEA approach to measuring environmental performance, which consists of a non-radial DEA type model for multilateral environmental performance comparisons and a non-radial Malmquist environmental performance index for modeling the change of environmental performance over time. The non-radial DEA approach can be used to find a peer group that may provide a more rigorous standard in evaluating the environmental performance of the DMU concerned. Therefore, the non-radial DEA type models have higher discriminating power than radial ones in environmental performance comparisons. The proposed non-radial DEA approach has been applied to 26 OECD countries for modeling their environmental performance from 1995 to 1997. We have also conducted a sensitivity analysis of the proposed model with respect to the weights of undesirable outputs. The results show that not only the rank indexes of these countries but also the values of their EPIs are quite insensitive to the weights of undesirable outputs.

Despite the usefulness of the proposed non-radial DEA type model in environmental performance measurement, it does not consider the slacks in inputs and desirable outputs since the current focus is to model pure environmental performance. Nevertheless, in some cases decision makers may be more interested in modeling economic-environmental performance or sustainability. It is therefore meaningful to incorporate the slacks in inputs and desirable outputs into efficiency measures in appropriate ways, which will be dealt with in the next chapter.

CHAPTER 5 SLACKS-BASED EFFICIENCY MEAURES FOR MODELING ENVIRONMENTAL PERFORMANCE[4]

5.1 Introduction

In Chapter 4, we introduced a non-radial DEA approach to measuring environmental performance. Despite the usefulness of non-radial DEA approach in measuring pure environmental performance, it does not consider the slacks in inputs and desirable outputs. However, from the viewpoint of DEA, a DMU may not be fully efficient even if it has an efficiency score of 1. Furthermore, in some cases decision makers may be more interested in modeling economic-environmental performance or sustainability. Therefore, it is meaningful and worthwhile to incorporate the input excesses and desirable output shortfalls into DEA type models for modeling environmental performance.

In this chapter, we propose two slacks-based efficiency measures for modeling environmental performance which could be obtained by solving some DEA type models. The first measure is a composite index with very high discriminating power for measuring economic-environmental performance. The second measure could be used to estimate the impacts of environmental regulations. To illustrate the usefulness of the proposed measures, we also present an application study on modeling CO_2 emissions of 30 OECD countries from 1998 to 2002.

[4] The work presented in this chapter has been published as Zhou et al. (2006b).

5.2 Slacks-based environmental performance indexes

Many environmental performance indexes (EPIs) have been constructed by combining the CRS environmental DEA technology with different types of efficiency measures. For instance, Zaim and Taskin (2000a) apply the hyperbolic graph measure to construct an environmental efficiency index for comparing CO_2 emissions in OECD countries. Färe et al. (2004) provided a formal approach to constructing an EPI by using the theory of Malmquist quantity index number. Using the same idea as that in Färe et al. (2004), Zaim (2004) developed an aggregate pollution intensity index for measuring environmental performance of state manufacturing. More recently, Zhou et al. (2007c) proposed a non-radial DEA approach to measuring environmental performance of 26 OECD countries.

Among the previous studies, the undesirable outputs orientation DEA type model (3.6), i.e., (5.1), is particularly attractive (Tyteca, 1996, 1997). It provides an aggregated and standardized efficiency measure (greater than 0 but not more than 1) for measuring pure environmental performance.

$$
\begin{aligned}
PEI = \lambda^* = \min \lambda & \\
\text{s.t.} \quad & \sum_{k=1}^{K} z_k x_{nk} \le x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} \ge y_{m0}, \ m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda u_{j0}, \ j = 1,2,\cdots,J \\
& z_k \ge 0, \ \ k = 1,2,\cdots,K
\end{aligned}
\tag{5.1}
$$

Despite its many desirable properties, (5.1) does not consider the slacks in inputs and desirable outputs. This implies that even if a DMU dominates another in some inputs and desirable outputs, they might have the same EPI value of 1. However, of the two DMUs there at least exists one that is not fully efficient from the viewpoint of DEA. It is reasonable to identify these inefficiencies and integrate them into *PEI*. Following the concept of slacks-based measure of efficiency in traditional DEA framework proposed by Tone (2001) and using the optimal objective value λ^* derived from (5.1), we present

$$
\begin{aligned}
\rho^* = \min \ & \frac{1-\frac{1}{N}\sum_{n=1}^{N} s_n^- / x_{n0}}{1+\frac{1}{M}\sum_{m=1}^{M} s_m^+ / y_{m0}} \\
\text{s.t.} \ & \sum_{k=1}^{K} z_k x_{nk} + s_n^- = x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} - s_m^+ = y_{m0}, \ m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = \lambda^* u_{j0}, \ j = 1,2,\cdots,J \\
& z_k \geq 0, \quad k = 1,2,\cdots,K; s_n^-, s_m^+ \geq 0
\end{aligned}
\tag{5.2}
$$

Note that the set of constraints on undesirable outputs in (5.2) can guarantee that DMU_0 has now been an efficient practitioner in pure environmental performance. Therefore, (5.2) can be used to evaluate the economic inefficiency of DMU_0 by a slacks-based efficiency measure ρ^* after its pollutants are adjusted to their minimum levels. The slack variables s_n^-, s_m^+ ($n = 1,2,\cdots,N$; $m = 1,2,\cdots,M$) could be used to identify and estimate the causes of economic inefficiency. We can show that $0 < \rho^* \leq 1$ and satisfies the properties of units invariance and monotone. A larger ρ^* indicates that DMU_0 performs better in the aspect of pure economic performance. If there are no slacks in inputs and desirable outputs, i.e., $s_n^- = s_m^+ = 0$, then $\rho^* = 1$ and there are no economic inefficiencies. By integrating pure environmental and economic inefficiencies, we have the following slacks-based EPI:

$$SBEI_1 = \lambda^* \times \rho^* \tag{5.3}$$

Since $SBEI_1$ combines environmental and economic inefficiencies, it can be treated as a composite index for modeling economic-environmental performance. Note that $SBEI_1$ is also a standardized index because it lies in the interval (0, 1] and satisfies the property "the larger the better". In addition, (5.3) usually has a discriminating power higher than that of (5.1) in environmental performance comparisons. To a large extent, this index can reflect the standpoints of regulators and a portion of producers. For those producers with higher economic efficiencies, they prefer it because a punishing factor ρ^* is imposed on those producers with a lower economic efficiency. On the other hand, it can also stimulate those inefficient producers in economic performance to further improve their productivity, which is preferred by regulators and social managers.

Note that model (5.2) is a fractional programming problem that could lead to some calculation difficulties. We can transform it into an equivalent linear programming problem by using the theory of Charnes-Cooper transformation as described in Tone (2001). Let $z_k^{'} = tz_k, S_n^- = ts_n^-, S_m^+ = ts_m^+$, we then have

$$\begin{aligned}
\rho^* = \min \{ & t - \tfrac{1}{N}\textstyle\sum_{n=1}^{N} S_n^- / x_{n0} \} \\
\text{s.t. } & \sum_{k=1}^{K} z_k^{'} x_{nk} + S_n^- = t x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k^{'} y_{mk} - S_m^+ = t y_{m0}, \ m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k^{'} u_{jk} = t\lambda^* u_{j0}, \ j = 1,2,\cdots,J \\
& t + \tfrac{1}{M}\textstyle\sum_{m=1}^{M} S_m^+ / y_{m0} = 1 \\
& z_k^{'} \geq 0, \ \ k = 1,2,\cdots,K; S_n^-, S_m^+ \geq 0
\end{aligned} \tag{5.4}$$

As a result, we can easily obtain $SBEI_1$ for modeling economic-environmental performance of DMU_0 by solving (5.1), (5.4) and (5.3) in turn.

As a second possibility of defining an EPI, we shall not calculate the pure environmental efficiency index in the beginning as in the process of $SBEI_1$ derivation. Instead, we turn our attention to the so-called economic efficiencies under different situations. We first estimate the economic efficiency of DMU_0 and ignore the set of constraints on undesirable outputs by using the following slacks-based DEA model developed by Tone (2001):

$$\begin{aligned} \theta_1^* &= \min \frac{1-\frac{1}{N}\sum_{n=1}^{N} s_n^- / x_{n0}}{1+\frac{1}{M}\sum_{m=1}^{M} s_m^+ / y_{m0}} \\ \text{s.t. } & \sum_{k=1}^{K} z_k x_{nk} + s_n^- = x_{n0}, \quad n = 1,2,\cdots,N \\ & \sum_{k=1}^{K} z_k y_{mk} - s_m^+ = y_{m0}, \; m = 1,2,\cdots,M \\ & z_k \ge 0, \quad k = 1,2,\cdots,K;\, s_n^-, s_m^+ \ge 0 \end{aligned} \tag{5.5}$$

Model (5.5) can be used to identify all the economic inefficiencies when undesirable outputs are not considered in the production process. Although (5.5) is a fractional programming model, θ_1^* can be obtained from its equivalent linear programming problem as described in Tone (2001):

$$\begin{aligned} \theta_1^* &= \min \{t - \tfrac{1}{N}\sum_{n=1}^{N} S_n^- / x_{n0}\} \\ \text{s.t. } & \sum_{k=1}^{K} z_k^{'} x_{nk} + S_n^- = t x_{n0}, \quad n = 1,2,\cdots,N \\ & \sum_{k=1}^{K} z_k^{'} y_{mk} - S_m^+ = t y_{m0}, \; m = 1,2,\cdots,M \\ & t + \tfrac{1}{M}\sum_{m=1}^{M} S_m^+ / y_{m0} = 1 \\ & z_k^{'} \ge 0, \quad k = 1,2,\cdots,K;\, S_n^-, S_m^+ \ge 0 \end{aligned} \tag{5.6}$$

When undesirable outputs are considered, the production process can be well modeled by the CRS environmental DEA technology as described in Chapter 3. Then the economic inefficiency of DMU_0 can be identified by

$$\begin{aligned}
\theta_2^* = \min & \frac{1-\frac{1}{N}\sum_{n=1}^{N} s_n^- / x_{n0}}{1+\frac{1}{M}\sum_{m=1}^{M} s_m^+ / y_{m0}} \\
\text{s.t.} & \sum_{k=1}^{K} z_k x_{nk} + s_n^- = x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k y_{mk} - s_m^+ = y_{m0}, \; m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k u_{jk} = u_{j0}, \; j = 1,2,\cdots,J \\
& z_k \geq 0, \quad k = 1,2,\cdots,K; s_n^-, s_m^+ \geq 0
\end{aligned} \tag{5.7}$$

Similarly, θ_2^* can also be calculated by solving the equivalent linear programming problem of (5.7) as follows:

$$\begin{aligned}
\theta_2^* = \min & \{t - \tfrac{1}{N}\sum_{n=1}^{N} S_n^- / x_{n0}\} \\
\text{s.t.} & \sum_{k=1}^{K} z_k^{'} x_{nk} + S_n^- = t x_{n0}, \quad n = 1,2,\cdots,N \\
& \sum_{k=1}^{K} z_k^{'} y_{mk} - S_m^+ = t y_{m0}, \; m = 1,2,\cdots,M \\
& \sum_{k=1}^{K} z_k^{'} u_{jk} = t u_{j0}, \; j = 1,2,\cdots,J \\
& t + \tfrac{1}{M}\sum_{m=1}^{M} S_m^+ / y_{m0} = 1 \\
& z_k^{'} \geq 0, \quad k = 1,2,\cdots,K; S_n^-, S_m^+ \geq 0
\end{aligned} \tag{5.8}$$

After θ_1^* and θ_2^* are obtained, we define another slacks-based efficiency measure for modeling environmental performance as

$$SBEI_2 = \theta_1^* \Big/ \theta_2^* \tag{5.9}$$

Since θ_1^* and θ_2^* are respectively the economic efficiency scores when undesirable outputs are not and are considered, $SBEI_2$ could be used to model the impacts of environmental regulations on economic efficiency. Conceptually, this index is similar to the EPI proposed by Färe et al. (1996), which is based on the multiplicative separability assumption of the Shephard input distance function. However, our index deals with the slacks-based efficiency measures while in Färe et al. (1996) the input distance function concept is used.

Note that $SBEI_2$ would not take any positive value larger than 1. When $SBEI_2 = 1$, θ_1^* must be the same as θ_2^*. It implies that the transformation of production process from the traditional DEA technology to environmental DEA technology has no effects on the economic efficiency of the DMU concerned. If $SBEI_2$ is less than one, it indicates that environmental regulations result in the waste of inputs and (or) the loss of desirable outputs with respect to the hypothesized efficient DMU. That is to say, there is an opportunity cost due to environmental regulations. Quantitatively, the degree of regulatory impact can be measured by $1 - SBEI_2$. This idea can also be found in Boyd and McClelland (1999), Zaim and Taskin (2000b) and Picazo-Tadeo et al. (2005). The difference is that in these studies the hyperbolic distance measures are used while in our study the slacks-based efficiency measure is adopted.

So far, we have provided a series of EPIs in this and previous chapters. Although the application contexts have some differences, it could be helpful to give a summary on the strengths and weaknesses of each EPI. Table 5.1 gives a summary for the non-radial and slacks-based EPIs. The EPIs based on radial DEA models presented in Chapter 3 are not included in the table since they are mainly used to illustrate the use of different environmental DEA technologies.

Table 5.1 A summary of the strengths and weaknesses of different EPIs

Index	Strength	Weakness
NREI	High discriminating power in measuring pure environmental performance, can incorporate additional information	Need to determine the weights for undesirable outputs
NRMEI	Can measure environmental performance change over time	Need to determine the weights for undesirable outputs, involves solving more linear programs
$SBEI_1$	Can measure economic-environmental performance, high discriminating power	Involves solving more linear programs
$SBEI_2$	Can model the impact of environmental regulations	Involves solving more linear programs

5.3 An application study on carbon dioxide emissions

Many indicators, such as aggregate energy intensity (energy/GDP), carbon intensity (carbon/GDP), carbon factor (carbon/energy) and per capita CO_2 emissions, have been used to assess, measure or monitor national performances in CO_2 emissions and their mitigation. For instance, Ang (1999) compares aggregate energy intensity and carbon factor in the context of national CO_2 evolution patterns. Ang and Zhang (1999) study differences in total and per capita CO_2 emissions between world regions using several indicators. Despite the usefulness of these indicators, each of them can be seen as a partial indicator because only partial information is provided (Ramanathan, 2002). In contrast, DEA could give a composite index for measuring CO_2 emissions by combining all the relevant single indicators into a whole, as demonstrated in Zaim and Taskin (2000a, 2000b), Zofio and Prieto (2001) and Ramanathan (2002, 2005).

We apply the two proposed slacks-based efficiency measures to study the CO_2 emissions of thirty OECD countries from 1998 to 2002. Two inputs, one desirable output and one undesirable output are used here. They are total primary energy supply (TPES measured in petajoules), population (P measured in million), GDP (billion 1995 US$ in purchasing power parities) and CO_2 emissions (million tons), respectively. The main reason for choosing these four variables is that they are used to calculate the partial indicators mentioned above. Similar to the case study in Chapter 4, capital stock is not employed as an input in the study due to the lack of data. In real applications, it is suggested that all important factors should be considered in assessing efficiency. The data in our application study were collected from International Energy Agency (2004b). Table 5.2 shows the summary statistics of the data collected.

Table 5.2 Summary statistics for 30 OECD countries from 1998 to 2002

Variable	1998	1999	2000	2001	2002
TPES	7146.30 (16640.83)	7271.40 (17081.89)	7414.97 (17529.85)	7391.40 (17170.14)	7460.50 (17429.11)
P	37.17 (55.32)	37.45 (55.90)	37.68 (56.39)	37.92 (56.88)	38.17 (57.36)
GDP	767.96 (1559.70)	792.28 (1617.51)	823.06 (1676.56)	830.60 (1681.58)	845.83 (1717.78)
CO_2	403.65 (994.54)	406.56 (1002.92)	415.99 (1031.31)	415.42 (1017.94)	418.48 (1025.60)

Note: Sample means and standard deviations (in parentheses) are presented here.

Based on the cross-sectional data, we first calculate the proposed slacks-based efficiency measure $SBEI_1$ and the radial efficiency measure PEI of the respective countries to measure their CO_2 emission performances in 1998-2002. Table 5.3 shows the results obtained.

Table 5.3 PEI and $SBEI_1$ of 30 OECD countries in 1998-2002

Country	*PEI*					$SBEI_1$				
	1998	1999	2000	2001	2002	1998	1999	2000	2001	2002
Australia	0.316	0.320	0.304	0.306	0.307	0.059	0.061	0.054	0.055	0.056
Austria	0.701	0.729	0.714	0.683	0.686	0.174	0.187	0.179	0.161	0.165
Belgium	0.450	0.475	0.459	0.460	0.484	0.082	0.089	0.084	0.082	0.089
Canada	0.335	0.343	0.328	0.343	0.339	0.055	0.058	0.054	0.056	0.057
Czech Republic	0.259	0.268	0.242	0.250	0.258	0.031	0.033	0.028	0.029	0.031
Denmark	0.513	0.550	0.583	0.580	0.581	0.120	0.135	0.141	0.136	0.140
Finland	0.454	0.474	0.485	0.446	0.427	0.074	0.080	0.081	0.072	0.070
France	0.788	0.822	0.811	0.818	0.825	0.161	0.172	0.165	0.161	0.165
Germany	0.487	0.509	0.498	0.499	0.496	0.101	0.109	0.103	0.099	0.100
Greece	0.417	0.431	0.404	0.414	0.418	0.077	0.082	0.073	0.074	0.077
Hungary	0.417	0.406	0.444	0.458	0.470	0.055	0.056	0.062	0.062	0.067
Iceland	0.748	0.773	0.739	0.801	0.749	0.111	0.113	0.105	0.113	0.105
Ireland	0.511	0.537	0.540	1.000	1.000	0.119	0.134	0.138	0.529	0.522
Italy	1.000	1.000	1.000	1.000	1.000	0.411	0.409	0.407	0.387	0.409
Japan	0.613	0.583	0.557	0.572	0.540	0.136	0.129	0.119	0.120	0.113
Korea	0.344	0.345	0.332	0.333	0.340	0.042	0.044	0.042	0.041	0.044
Luxembourg	1.000	1.000	1.000	1.000	1.000	0.655	0.680	0.706	1.000	1.000
Mexico	0.484	0.507	0.488	0.494	0.481	0.069	0.074	0.071	0.069	0.066
Netherlands	0.496	0.525	0.503	0.501	0.491	0.104	0.114	0.105	0.101	0.099
New Zealand	0.535	0.523	0.495	0.486	0.487	0.084	0.084	0.076	0.074	0.078
Norway	0.753	0.711	0.797	0.856	0.914	0.166	0.148	0.166	0.181	0.210
Poland	0.246	0.262	0.269	0.275	0.282	0.028	0.032	0.033	0.032	0.034
Portugal	0.641	0.584	0.582	0.604	0.555	0.129	0.116	0.112	0.115	0.103
Slovak Republic	0.296	0.306	0.306	0.300	0.319	0.030	0.032	0.031	0.029	0.032
Spain	0.637	0.612	0.578	0.586	0.553	0.131	0.128	0.114	0.114	0.107
Sweden	0.884	0.942	0.945	1.000	0.969	0.160	0.178	0.181	0.180	0.180
Switzerland	1.000	1.000	1.000	1.000	1.000	0.266	0.270	0.262	0.250	0.253
Turkey	0.508	0.481	0.436	0.448	0.453	0.076	0.070	0.059	0.058	0.061
UK	0.548	0.563	0.556	0.556	0.565	0.114	0.120	0.116	0.115	0.121
United States	0.468	0.472	0.452	0.459	0.501	0.139	0.140	0.128	0.126	0.157
Mean	0.562	0.568	0.562	0.584	0.583	0.132	0.136	0.133	0.154	0.157

Interestingly, it can also be observed from Table 5.3 that in 1998-2000 none of the thirty countries have achieved a $SBEI_1$ value of 1. The best performer, i.e., Luxembourg, has $SBEI_1$ values of 0.655, 0.680 and 0.706. This shows that none of these countries could be taken as fully an efficient practitioner in both environmental and economic performances in the three years. For countries with *PEI* equal to 1, their inefficiencies mainly arise from excess usage of certain inputs or low production of desirable output (GDP) or both, which can be identified and estimated by the slack variables s_n^- and s_m^+ in model (5.2). For instance, Luxembourg should decrease its TPES by 32.1, 26.7 and 19.5 petajoules and increase its GDP by 5.5, 5.7 and 6.1 billion US$ in order to achieve $SBEI_1$ values of 1 in 1998-2000.

It should be pointed out that other non-efficiency factors may play certain roles in affecting their $SBEI_1$ values. For instance, trade and specialization among countries naturally let some countries specialize in more energy and pollution intensive industries while others specialize in services. As an example, Luxembourg's very good performance is also likely due to the fact that most of its GDP derives from services and it imports most of the manufactured goods and electricity it consumes. We therefore believe that a comparison of countries with regard to specific sectors, e.g., the electric power sector, should be more useful for policy making.

Table 5.3 provides some information on the trend of each country over time with respect to their economic-environmental performances. In general, most countries are fairly stable in $SBEI_1$ during the five years. However, Ireland is an exceptional case. In 1998-2000 its $SBEI_1$ value improves gradually and the ranks are respectively thirteenth, tenth and ninth. However, in 2001-2002 the country ranks second and its $SBEI_1$ values become larger than 0.5. The possible reason is that not only its pure environmental performance but also its economic efficiency has improved significantly in the two years.

We have also calculated the slacks-based efficiency measure $SBEI_2$ of each country, which can be used to model the impacts of transforming production process from one where all the outputs are freely disposable to the one where the CO_2 emissions are weakly (or costly) disposable as the result of hypothetical environmental regulations. As has been mentioned earlier, environmental regulations may result in an additional usage of inputs and (or) a loss of desirable outputs. If we assume in our application study that this impact would result in a loss of desirable output (GDP), by following Zaim and Taskin (2000), the opportunity cost due to the hypothetical environmental regulations can be approximately derived by using the formula $(1 - SBEI_2) \times GDP$.[5] Then the loss per tons of CO_2 emissions can be obtained by dividing the opportunity cost estimated by the amount of CO_2 emissions (Zaim and Taskin, 2000). Table 5.4 shows the estimated opportunity costs and the loss per ton of CO_2 emissions.

It can be seen from Table 5.4 that there exist zero opportunity costs due to the hypothetical environmental regulations in some countries, e.g., Belgium, Canada, Finland, Italy and Luxembourg. In 2002 almost two-thirds of the countries have zero opportunity costs and the average opportunity cost is very low. Roughly speaking, for countries with higher $SBEI_1$, e.g., Luxembourg, Italy and Switzerland, they have zero opportunity cost in most cases. In the case of Switzerland, since its $SBEI_1$ from 1998-2000 to 2001-2002 has a decreasing trend, its opportunity cost has correspondingly become larger than zero. It could be explained by the fact that the countries with a higher $SBEI_1$ are better practitioners in both environmental and economic performances. As a result, environmental regulation may have no impact on their

[5] It is also possible to interpret the opportunity cost of CO_2 emissions in an alternative manner. Since CO_2 emissions can be viewed as a proxy for environmental effects and regulation in general, the opportunity cost of CO_2 emissions could be treated as an indicator of the impact of environmental regulations in general, even though the US and most other countries have no CO_2 regulations in the time frame studied.

economic efficiency scores. This indicates that a larger $SBEI_1$ would likely lead to a larger $SBEI_2$ and therefore a lower opportunity cost.

Table 5.4 Estimated opportunity costs due to hypothetical environmental regulations of 30 OECD countries in 1998-2002

Country	Opportunity cost (billion 1995 US$)					Loss per tons of CO_2 ($/tons)				
	1998	1999	2000	2001	2002	1998	1999	2000	2001	2002
Australia	116.2	130.1	151.2	137.2	147.0	364.7	402.0	459.2	401.1	428.7
Austria	11.1	6.8	2.5	1.1	4.6	172.3	108.8	39.1	16.0	69.3
Belgium	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.4
Canada	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Czech Republic	15.3	10.3	15.4	3.4	1.4	134.7	94.5	130.1	28.9	12.2
Denmark	14.7	9.1	2.7	0.2	0.0	256.1	167.5	53.8	3.0	0.0
Finland	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
France	2.4	0.4	0.0	12.9	63.9	6.2	1.0	0.0	33.6	169.4
Germany	159.7	99.6	26.6	0.0	0.0	184.1	118.9	31.8	0.0	0.0
Greece	50.0	50.8	54.5	52.9	58.8	596.9	611.3	621.2	586.4	650.1
Hungary	4.0	5.1	1.5	0.0	0.0	70.3	83.6	27.8	0.0	0.0
Iceland	0.4	0.7	1.0	1.2	1.1	191.6	340.1	432.1	551.2	489.5
Ireland	10.5	7.2	2.7	0.0	0.0	277.1	181.9	65.8	0.0	0.0
Italy	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Japan	156.3	114.4	33.5	2.4	0.0	141.1	99.2	28.4	2.1	0.0
Korea	31.0	22.8	8.4	0.0	0.0	85.5	57.4	19.6	0.0	0.0
Luxembourg	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Mexico	17.0	23.1	15.9	0.0	0.0	48.1	67.2	43.8	0.0	0.0
Netherlands	23.0	11.5	3.0	0.1	0.6	132.5	68.0	17.4	0.4	3.3
New Zealand	0.5	0.2	0.0	0.0	0.0	15.9	5.4	0.0	0.0	0.0
Norway	0.6	2.8	5.8	6.6	6.3	15.4	73.4	169.6	196.9	191.4
Poland	198.9	199.8	202.4	201.1	209.9	629.7	654.0	690.8	690.0	741.8
Portugal	5.7	7.4	2.7	0.4	0.0	105.6	122.4	44.8	6.2	0.0
Slovak Republic	2.7	1.8	0.6	0.0	0.0	67.9	47.6	15.0	0.0	0.0
Spain	28.6	27.9	10.1	1.1	0.0	114.9	104.5	36.1	3.8	0.0
Sweden	0.8	6.1	9.9	64.4	14.2	14.4	118.6	196.3	1328.0	283.7
Switzerland	0.0	0.0	0.0	2.5	12.0	0.0	0.0	0.0	56.3	280.1
Turkey	4.2	11.9	10.7	0.7	0.0	22.9	65.6	52.8	3.6	0.0
UK	86.9	53.9	18.7	0.0	0.0	163.4	102.3	35.7	0.0	0.0
United States	1830.2	2084.5	2454.8	2309.7	614.4	333.6	377.0	431.6	411.4	108.7
Mean	92.4	96.3	101.1	93.3	37.8	138.2	135.7	121.4	144.0	114.3

However, if a country has a lower opportunity cost, it does not indicate that this country must have better economic-environmental performance. That is to say, a larger $SBEI_2$ may not lead to a larger $SBEI_1$. In particular, a country with zero opportunity cost may not have a $SBEI_1$ value of 1. It only means that the weak disposability of CO_2 emissions imposed has no impacts on the economic efficiency scores of these countries. For instance, Belgium has a $SBEI_2$ value of 1 in 1998-2002 because its opportunity cost has been zero all along. However, its economic efficiency scores before and after environmental regulations (θ_1^* and θ_2^*) are only around 0.7 during the five years.

5.4 Conclusion

We have developed two slacks-based efficiency measures for modeling environmental performance which could reasonably incorporate all the input excesses and output shortfalls in a standardized efficiency score. The first measure $SBEI_1$ can be treated as a composite index for modeling economic-environmental performance, while the second measure $SBEI_2$ can be used to estimate the impacts of environmental regulations.

We have also applied the two indexes $SBEI_1$ and $SBEI_2$ to study the CO_2 emissions of 30 OECD countries in 1998-2002. It is found that $SBEI_1$ has very high discriminating power in modeling CO_2 emission performance. Among the countries studied, Luxembourg always ranks first in $SBEI_1$ in the five years. However, in 1998-2000 none of these countries have achieved a $SBEI_1$ value of 1, which indicates that none of them are efficient practitioners in both economic and environmental performance during these three years. The causes for their economic inefficiencies can be identified and estimated by the slack variables obtained. Using the $SBEI_2$ values calculated we also estimated the opportunity costs due to environmental regulations and the losses per ton of CO_2 emissions. It is observed that zero opportunity costs due to environmental regulations occur in a few countries. In addition, we find that a larger $SBEI_1$ would likely lead to a larger $SBEI_2$ and therefore a lower opportunity cost. However, a lower opportunity cost does not necessarily imply a better economic-environmental performance.

In this chapter, country-level environmental issues are studied. The two measures proposed, however, could be applied to model the lower level environmental issues, such as at the firm level. It would also be useful to extend the current application study by including more countries and/or more years. If more attention is to be paid to the economic-environmental performance changes over time, we could combine $SBEI_1$ with the Malmquist productivity index approach in order to investigate the mechanisms of environmental performance changes. Finally, it should be pointed out that the two slacks-based environmental indexes proposed in the chapter are based on the CRS environmental DEA technology. Nevertheless, they can be easily extended to be integrated with other environmental DEA technologies as described in Chapter 3.

CHAPTER 6 COMPARING MCDA AGGREGATION METHODS IN CONSTRUCTING CIs[6]

6.1 Introduction

In addition to the DEA type models discussed in Chapters 3 to 5, there is another group of methods, namely MCDA, which can also be used to construct E&E related CIs. Examples of such studies include Diaz-Balteiro and Romero (2004), Ebert and Welsch (2004), Munda (2003, 2005), Nardo et al. (2005), Saisana et al. (2005), Zhou et al. (2006c) and Singh et al. (2007). Despite the usefulness of MCDA in CI construction, a problem in applying MCDA methods to construct CIs is the determination of an appropriate MCDA method. In literature, there exists many MCDA methods available, but none could be regarded as a 'super method' suitable for all the decision situations (Guitouni and Martel, 1998).

Researchers have developed a large number of criteria, e.g., theoretical foundation, understandability, ease of use and validity, which are helpful to analysts for the selection of an appropriate MCDA method. For instance, Duckstein et al. (1982) suggested that the selection of a MCDA method should be concerned with factors including data requirement, nature of decision problem, consistency of results between different models and computational complexity. Gershon and Duckstein (1984) developed a compromise programming procedure that can be used to select a MCDA technique based on a number of criteria. Subsequently, Hobbs (1986) and Hobbs et al. (1992) pointed out that ease of use, method appropriateness, validity and

[6] The bulk of the work presented in this chapter has been published as Zhou et al. (2006c).

sensitivity of results to choice of method need to be considered in comparing different MCDA methods.[7] Zanakis et al. (1998) carried out a simulation experiment to investigate the similarities and differences in the behavior of a number of MCDA methods. The comparative study by Salminen et al. (1998) showed that it is better to apply several methods to the same environmental problem. Using the criterion of prediction validity, Olson (2001) compared three MCDA methods based on baseball data and found that all have value for supporting decision making. Nevertheless, previous studies have shown that it is impossible to precisely determine a MCDA method that outperforms others in terms of all the criteria. As discussed in Triantaphyllou (2001), the problem of finding the best MCDA method will inevitably reach an unsolvable decision-making paradox.

In the context of CI construction, the selection of an appropriate MCDA aggregation method has also attracted a great deal of attention. For instance, Ebert and Welsch (2004) compared the simple additive weighting (SAW) method with the weighted product (WP) method in constructing a meaningful environmental index by using the theory of social choice. Munda (2003, 2005) highlighted the theoretical advantages of non-compensatory MCDA approach in constructing sustainability indicators. These studies are built upon the assumption that the only purpose for constructing CIs is to rank the systems compared. However, in some cases, more emphasis may be given to the cardinality of CIs. For instance, as a commonly used CI

[7] In terms of "validity", there is not a universally agreed upon definition of it. It is ambiguous when there is no objective measure of a "right" decision. Different researchers/analysts may refer to "validity" as different things, such as predictive validity, estimative validity, methodological validity, construct validity and convergent validity (Hobbs, 1986). The various definitions of "validity" arise from different purposes of MCDA methods in application. As discussed in Hobbs (1986), if a method is to be used to predict subjective judgment, predictive validity is more relevant. If one wishes to make judgment more rational, then estimative, methodological or construct validity are appropriate criteria. If one expects that choice of method won't affect the results, convergent validity is useful. For more discussions on the strengths and weaknesses of various MCDA methods with respect to validity criterion, please refer to Hobbs (1986) and Hobbs and Meier (2000).

for measuring the total value of goods and services produced by a country/region, GDP can provide information on not only the ranks but the absolute disparities for the countries/regions compared. Therefore, further comparisons among alternative MCDA aggregation methods in constructing CIs are both meaningful and necessary when the cardinality characteristic of CIs is highlighted.

Motivated by the above issues, in this chapter we introduce a novel criterion "information loss", and present an objective measure called the Shannon-Spearman measure (SSM) based on the information loss criterion for comparing alternative MCDA aggregation methods in constructing CIs. The effectiveness of the SSM is examined by the Monte Carlo approach-based uncertainty analysis and variance-based sensitivity analysis techniques. We then apply the SSM to evaluate several MCDA aggregation methods in constructing CIs by some case studies and present the results obtained.

6.2 The Shannon-Spearman measure

Assume that in the same time period there are m systems $S_i (i = 1,2,\cdots,m)$ whose CIs are to be calculated based on n sub-indicators $V_j (j = 1,2,\cdots,n)$. In MCDA, "systems" and "sub-indicators" are often termed as "alternatives" and "criteria", respectively. Let $I = (I_{ij})_{m\times n}$ be the original decision matrix, where I_{ij} is the value of system (or alternative) S_i corresponding to the sub-indicator (or criterion) V_j. Assume that V_j is ratio scaled and w_j is the standardized weight for sub-indicator V_j $(j = 1,2,\ldots,n)$. Further assume that $CI = (CI_1, CI_2, \cdots, CI_m)^T$ is the CI vector derived from a particular MCDA method.

It is well known that the main purpose for constructing CIs is to measure and compare the performances of the systems concerned. Evidently, the decision matrix I (or each sub-indicator) contains useful information for benchmarking purposes. Assume that the information in I could be precisely estimated in an appropriate way. After the CI vector is obtained by a certain aggregation method, the information in $CI = (CI_1, CI_2, \cdots, CI_m)^T$ could also be estimated. Then the discrepancy between the two pieces of information might be used to evaluate the aggregation method used because the same aggregation method would lead to the same CI values and then the same magnitude of discrepancy. Since the information in I acts as the base for evaluation, we term the discrepancy between the amount of information in CI and that in I as "loss of information". Intuitively, if an aggregation method would always result in less loss of information than other aggregation methods, it might be regarded as a better aggregation method with regards to the information loss criterion. If an aggregation method results in no loss of information, we may treat this method as a perfect method in terms of information loss.

To determine the information in I and CI, we first identify the sources of the information. A major source is the divergence of different systems with respect to each sub-indicator as well as CI. The Shannon's entropy, which is a measure of the amount of information conveyed by a given information source based on probability theory, could be used to measure this type of information (Shannon and Weaver, 1947). Following the procedure of using the Shannon's entropy to determine the objective weights in MCDA (Zeleny, 1982; Deng et al., 2000), we first normalize I and CI by

$$p_{ij} = \frac{I_{ij}}{\sum_{i=1}^{m} I_{ij}}, \quad i = 1,2,\cdots,m; j = 1,2,\cdots,n \tag{6.1}$$

$$p_k = \frac{CI_k}{\sum_{k=1}^{m} CI_k}, \quad k = 1,2,\cdots,m \tag{6.2}$$

The Shannon's entropy for measuring the divergence of different systems with respect to each sub-indicator and CI can be obtained by

$$e_j = -\frac{1}{\ln m} \sum_{i=1}^{m} p_{ij} \ln p_{ij}, \quad j = 1,2,\cdots,n \tag{6.3}$$

$$e = -\frac{1}{\ln m} \sum_{k=1}^{m} p_k \ln p_k \tag{6.4}$$

It can be shown that $0 \le e_j, e \le 1$ (Zeleny, 1982). Since p_{ij} and p_k are invariant with respect to ratio scaling, e_j and e are also invariant with respect to ratio scaling. The larger e_j or e is, the less divergence is observed among the systems with respect to V_j or CI. If all the systems have the same values in terms of V_j, $e_j = 1$ and sub-indicator V_j will provide no information for comparing these systems.

Other than the divergence of the systems with respect to $V_j (j = 1,2,\cdots,n)$ or CI, the conflict between ranking orders is another important source of information contained in I or CI. For instance, if V_i and V_j have the same elements with different sequences, the information conveyed by them are obviously different although their entropy measures are the same. This kind of information, which can be measured by the Spearman rank correlation coefficient, has been investigated in determining the objective weights of MCDA problems (Diakoulaki et al., 1995).

Without loss of generality, we may first set a reference rank sequence such as $r_0 = (m, m-1, \cdots, 1)^T$ and then calculate the Spearman rank correlation coefficient r_{sj} (r_s) between V_j (CI) and r_0.

In addition to the two types of information described above, there is still another type resulting from the weights assigned to sub-indicators before aggregation. The information in the weights may be treated as "exogenous one" and could reflect the preference of decision makers.

So far three major sources of information have been identified. We would like to develop two measures for the information in I and CI by combining these three types of information. According to the foregoing discussions, the two measures must satisfy (a) if $S_i (i = 1, 2, \cdots, m)$ have the same values with respect to one specific sub-indicator, this sub-indicator would play no role in estimating the information in I, (b) if the ranks of $S_i (i = 1, 2, \cdots, m)$ with respect to $V_j (j = 1, 2, \cdots n)$ and CI are the same, the amount of information provided by the ranks would be a common term for the two measures, and (c) the weights are only effective when the information in I is estimated. Based on these three prerequisites, we could use $\sum_{j=1}^{n} w_j (1 - e_j) r_{sj}$ and $(1 - e) r_s$ to represent the information in I and CI. Then we present the following measure of the loss of information before and after calculating the CI values, for the purpose of comparing different aggregation methods:

$$d = \left| \sum_{j=1}^{n} w_j (1 - e_j) r_{sj} - (1 - e) r_s \right| \tag{6.5}$$

In essence, d is the difference of the information in I and the information in CI. Since it is based on the concepts of the Shannon's entropy and the Spearman rank correlation coefficient, d is termed as the Shannon-Spearman measure (SSM) in this study. Despite its reasonableness in logic, the value of the SSM is not invariant with the reference rank sequence used to calculate the Spearman rank correlation coefficient, which should be treated as a limitation of the SSM. Note that (6.5) is an absolute difference measure of loss of information. When $\sum_{j=1}^{n} w_j (1-e_j) r_{sj}$ is not equal to zero, we may also use the Shannon-Spearman ratio measure as shown in (6.6) to compare different aggregating methods, which gives the relative degree of loss of information from I to CI.

$$d' = \left| 1 - \frac{(1-e) r_s}{\sum_{j=1}^{n} w_j (1-e_j) r_{sj}} \right| \tag{6.6}$$

6.3 Validity assessment of the SSM

Despite the logical reasonableness of the SSM, the following question may arise in its application: Is it really an effective measure in comparing alternative MCDA aggregation methods for constructing CIs? Intuitively, if the aggregation method is the only factor affecting the variation in the SSM, it is logical to believe that the SSM is a valid measure and could be used to compare alternative MCDA aggregation methods effectively in terms of the information loss criterion. If there are some other factors affecting its variation, the SSM may still be regarded as a valid measure as long as the major part of its variation could be explained by the uncertainty in the aggregation method. Along this line of reasoning, we shall assess the validity of the SSM by using the Monte Carlo approach-based uncertainty analysis and variance-based sensitivity analysis techniques.

6.3.1 Uncertainty analysis

Uncertainty analysis is the study of the overall uncertainty in the output values of a model resulting from the uncertainties in the model's inputs (Nardo et al., 2005; Saisana et al., 2005). It is essentially based on simulations of various factors that may affect the output values. In the followings, we shall apply it to quantify the overall uncertainty in the SSM due to the uncertainty in input factors.

We first identify the input factors that could affect the SSM values. Obviously, the decision matrix is one of these factors. Since the decision matrix varies from one problem to another, it is not practical to collect a large number of decision matrices for subsequent analysis. Therefore, we shall not consider the uncertainty due to decision matrix but choose the decision matrix in the *Technology Achievement Index* (TAI) example presented by Nardo et al. (2005) and Saisana et al. (2005) which consists of the data on 23 countries with respect to 8 sub-indicators.

Since different sub-indicators may have different measurement units, certain normalization procedure is usually implemented before data aggregation. It is known that different procedures could lead to different CI vectors. As a result, the normalization scheme may affect the SSM values. Here, we limit the uncertainty due to the normalization scheme to two commonly used normalization methods in MCDA, namely the linear normalization (LN) method and the vector normalization (VN) method (Yoon and Hwang, 1995). Their implementation functions for sub-indicators of the benefit type (the larger the better) are shown in Table 6.1. In the case of sub-indicators of the cost type (the smaller the better), as discussed in Yoon and Hwang (1995), I_{ij} can be first transformed to the benefit type by taking the inverse and then normalized by using the functions provided in Table 6.1.

Table 6.1 The implementation functions for the LN and VN normalization methods

Method	Implementation function
LN	$r_{ij} = I_{ij} \big/ \max_i \{I_{ij}\}$, $i = 1,2,\cdots,m$; $j = 1,2,\cdots,n$
VN	$r_{ij} = I_{ij} \Big/ \sqrt{\sum_{i=1}^{m} I_{ij}^2}$, $i = 1,2,\cdots,m$; $j = 1,2,\cdots,n$

Note: Despite its popularity, the MAUT normalization method, i.e., the linear scaling in the min-max range, is not consider here. The main reason is that the MAUT normalization method will cause the existence of zero in normalized sub-indicators, which may cause the problem of many CIs to be equal to zero if the WP method is adopted.

According to the definition of the SSM, the choice of the aggregation method also has influences on the SSM values. We restrict the uncertainty due to the aggregation scheme to five alternative MCDA aggregation methods, namely the simple additive weighting (SAW) method, the weighted product (WP) method, the weighted displaced ideal (WDI) method with parameters 2 (hereafter called WDI_2) and ∞ (hereafter called WDI_∞), and the TOPSIS method.

Table 6.2 The aggregation functions for five alternative MCDA methods

Method	Aggregation function
SAW	$CI_i = \sum_{j=1}^{n} w_j r_{ij}$, $i = 1,2,\cdots,m$
WP	$CI_i = \prod_{j=1}^{n} (r_{ij})^{w_j}$, $i = 1,2,\cdots,m$
WDI_2	$CI_i = \sqrt{\sum_{j=1}^{n} (w_j r_{ij})^2}$, $i = 1,2,\cdots,m$
WDI_∞	$CI_i = \min_j \{w_j r_{ij}\}$, $i = 1,2,\cdots,m$
TOPSIS	$CI_i = \dfrac{\sqrt{\sum_{j=1}^{n} (w_j r_{ij} - \min_i \{w_j r_{ij}\})^2}}{\sqrt{\sum_{j=1}^{n} (w_j r_{ij} - \min_i \{w_j r_{ij}\})^2} + \sqrt{\sum_{j=1}^{n} (w_j r_{ij} - \max_i \{w_j r_{ij}\})^2}}$, $i = 1,2,\cdots,m$

The SAW, WP, WDI_2 and WDI_∞ methods have been widely explored in CI construction, e.g., Diaz-Balteiro and Romero (2004), Ebert and Welsch (2004), Nardo et al. (2005), Esty et al. (2005), Saisana et al. (2005) and Zhou et al. (2006c). Although the TOPSIS method is rarely used to construct CIs, we include it because of its better properties (Yoon and Hwang, 1995; Deng et al., 2000; Opricovic and Tzeng, 2004). Table 6.2 shows the aggregation functions for the five alternative MCDA methods by which the CIs could be derived.

In addition to the normalization and aggregation schemes, the weights could also affect the variation in the SSM since different sets of weights might be assigned by different experts. As a result, we treat the weights as uncertain factors that are randomly determined within a certain range including the equal weight value.

Table 6.3 The 10 uncertain input factors and their descriptions

Input factor	Definition	PDF	Disposal rule
X_1	Trigger to select normalization method	Uniform [0, 1]	[0, 0.5) ≡ LN, [0.5, 1] ≡ VN
X_2	Trigger to select aggregation method	Uniform [0, 1]	[0, 0.2) ≡ SAW, [0.2, 0.4) ≡ WP, [0.4, 0.6) ≡ WDI_2, [0.6, 0.8) ≡ WDI_∞, [0.8, 1] ≡ TOPSIS
X_3	w_1	Uniform [1, 2]	$w_1 = X_3 \Big/ \sum_{k=3}^{10} X_k$
X_4	w_2	Uniform [1, 2]	$w_2 = X_4 \Big/ \sum_{k=3}^{10} X_k$
X_5	w_3	Uniform [1, 2]	$w_3 = X_5 \Big/ \sum_{k=3}^{10} X_k$
X_6	w_4	Uniform [1, 2]	$w_4 = X_6 \Big/ \sum_{k=3}^{10} X_k$
X_7	w_5	Uniform [1, 2]	$w_5 = X_7 \Big/ \sum_{k=3}^{10} X_k$
X_8	w_6	Uniform [1, 2]	$w_6 = X_8 \Big/ \sum_{k=3}^{10} X_k$
X_9	w_7	Uniform [1, 2]	$w_7 = X_9 \Big/ \sum_{k=3}^{10} X_k$
X_{10}	w_8	Uniform [1, 2]	$w_8 = X_{10} \Big/ \sum_{k=3}^{10} X_k$

So far, we have identified three types of uncertainties that could introduce uncertainty into the SSM values: (a) normalization scheme, (b) aggregation scheme, and (c) weights' values. More specifically, in the TAI example, there are ten input factors that can result in the variation in the SSM, as shown in the first two columns of Table 6.3.

We shall now use the Monte Carlo approach to evaluate the uncertainty in the SSM with 10 randomly selected input factors X_1-X_{10}. The procedure for Monte Carlo-based uncertain analysis is presented as follows:

Step 1. Randomly generate 10 independent input factors based on the PDF assigned to X_1-X_{10}, and repeat it for K times. Denote the K sets of input factors generated as $X_1(t)$, $X_2(t)$, …, $X_{10}(t)$ ($t = 1, 2, \ldots, K$).

Step 2. For each set of input factors $X_1(t)$-$X_{10}(t)$ ($t = 1, 2, \ldots, K$), use the disposal rule defined in Table 6.3 to select the corresponding normalization and aggregation methods, and determine the weights for the eight sub-indicators.

Step 3. For $t = 1, 2, \ldots, K$, use the normalization and aggregation methods assigned to derive the corresponding CI vector and then compute the SSM value $d(t)$.

Step 4. Analyze the resulting $d(t)$, $t = 1, 2, \ldots, K$.

Note that in Step 1 the input factors are generated by using the quasi-random sampling scheme that is implemented in the freely distributed software SIMLAB (Saltelli et al., 2004). The sample size K is set as 11264, which is required for using SIMLAB to carry out subsequent sensitivity analysis. In Step 2, every time the eight values from independent uniform [1, 2] distributions are to be scaled to a unit sum in order to obtain $w_1 - w_8$. As a result, the weight for each sub-indicator would be restricted to [1/15, 2/9] that includes 0.125 approximating its average. After the SSM values $d(t)$ (t = 1, 2, …, 11264) are obtained, they are used to build an empirical PDF of the SSM as shown in Fig. 6.1.

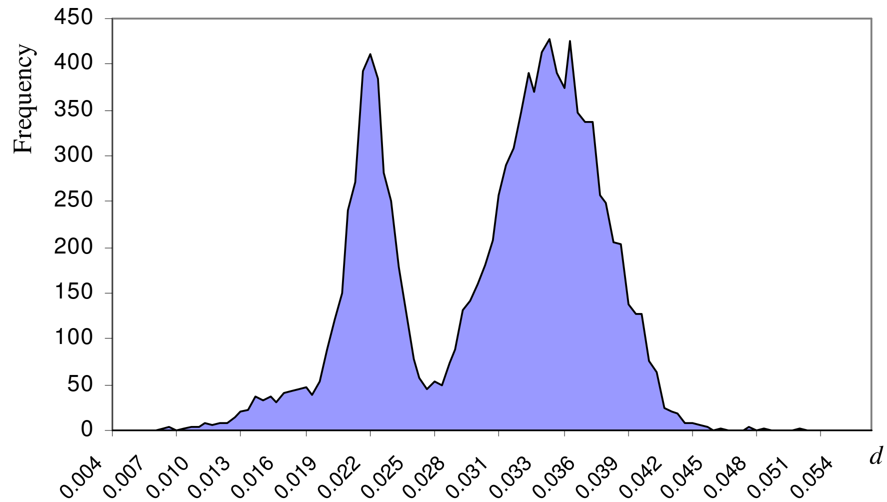

Fig. 6.1 The uncertainty analysis results for the SSM values in the TAI example

In summary, the coefficient of variation for d is about 24%, which indicates the uncertainty of the input factors could severely affect the SSM values. The higher standardized skewness (18.5) shows that the distribution for the SSM is significantly different from a normal distribution. It can also be seen from Fig. 6.1 that its empirical distribution has a distinct bimodal mode with a standardized kurtosis equal to -15.6. This may be an indication that certain input factor has severe impacts on the SSM values. It is therefore necessary to further investigate which is the most important factor affecting the variation in the SSM.

6.3.2 Sensitivity analysis

Sensitivity analysis is an effective tool for quantifying the contribution of each individual input factor to the uncertainty in a model's output values (Saltelli et al., 2004; Saisana et al., 2005). We shall conduct sensitivity analysis to investigate whether the variation in the SSM mainly arises from the uncertainty in aggregation scheme. Despite the existence of many techniques for sensitivity analysis, variance-based techniques seem to be the most suitable for the current study. The main reason is that the SSM is a complex non-linear model and variance-based techniques are model-free (Saltelli et al., 2004). In variance-based techniques, two sensitivity measures, namely the first-order sensitivity index S_l and the total effect sensitivity index S_{Tl}, are required to be estimated and they are given by

$$S_l = \frac{V_{\mathrm{X}_l}\{E_{\mathrm{X}_{-l}}(d|\mathrm{X}_l)\}}{V(d)}, \; l = 1,2,\cdots,10 \tag{6.7}$$

$$S_{Tl} = \frac{V(d) - V_{\mathrm{X}_{-l}}\{E_{\mathrm{X}_l}(d|\mathrm{X}_{-l})\}}{V(d)}, \; l = 1,2,\cdots,10 \tag{6.8}$$

where V and E are respectively the variance and expectation symbols, and X_{-l} denotes the input factors exclusive of X_l.

According to Saisana et al. (2005), S_l could be used to quantify the fractional marginal contribution of the uncertainty in X_l to the variation in the SSM. If the sum of S_l is equal to 1, there would be no interactions among input factors X_l (l=1,2,…,10) and the first-order sensitivity index S_l would capture the contributions of input factors completely. However, for a nonlinear model like the SSM, the contributions of higher order interactions among input factors are often expected to be estimated. This can be done by the total effect sensitivity index S_{Tl}, in which $V_{X_{-l}}\{E_{X_l}(d|X_{-l})\}$ is used to capture the total contribution to the variance of d due to non-X_l factors.

There are various methods available for estimating S_l and S_{Tl} (Chan et al., 2000). In our study, the method of Sobol', which can be implemented in the freely-distributed software SIMLAB (Saltelli et al., 2004), is chosen. The requirement of the method of Sobol' on sampling scheme and sample size has been considered when the input factors are generated. Table 6.4 shows the standard deviations of input factors and the sensitivity measures S_l and S_{Tl} obtained from the same set of data used in uncertainty analysis.

Table 6.4 The Sobol' first-order and total effect sensitivity indices

Input factor	Standard deviation	First-order effect (S_l)	Total effect (S_{Tl})	$S_{Tl} - S_l$
X_1	0.2885	0.00	0.08	0.08
X_2	0.2883	0.58	0.92	0.34
X_3	0.2880	0.02	0.10	0.08
X_4	0.2884	0.00	0.18	0.18
X_5	0.2883	0.00	0.04	0.04
X_6	0.2880	0.00	0.01	0.01
X_7	0.2882	0.00	0.01	0.00
X_8	0.2881	0.00	0.01	0.01
X_9	0.2881	0.00	0.01	0.01
X_{10}	0.2880	0.00	0.01	0.01
Sum	-	0.60	1.36	0.77

From Table 6.4 we can find that the input factor X_2, i.e., the trigger to select aggregation method, has the largest S_l value (0.58) while other input factors have negligible S_l values. It indicates that X_2 is the most important factor affecting the variation in d. That is to say, most of the variance in the SSM would be removed if the aggregation method is fixed. Since the sum of S_l (l=1,2,…,10), which represents the fraction of the variance in the SSM that is explained by all the input factors individually, is less than 1 (=0.60), 40% of the variance in *d* might be explained by interactions among input factors.

It can also be observed from Table 6.4 that X_2 has the largest S_{Tl} and $S_{Tl} - S_l$ values. This may be an indication that the trigger to select an aggregation method has a strong interaction with other factors, particularly with the weight for the second sub-indicator. This could be explained by the fact that different aggregation methods integrate the weights in different ways. If we fix the aggregation method, the variance due to interaction terms would also be reduced by much. Since most of the variation in the SSM arise from the uncertainty in the aggregation method, it is reasonable to believe that the SSM could be an effective measure for comparing alternative MCDA aggregation methods in constructing CIs in terms of information loss.

6.4 A comparison among alternative MCDA aggregation methods

In this section we shall apply the SSM to evaluate the five alternative MCDA methods in constructing CIs in a more comprehensive way. As was discussed in Section 6.3, the normalization scheme and the weights for different sub-indicators could be the unimportant factors affecting the variation in the SSM. According to Saisana et al. (2005), the unimportant factors in a model can be fixed at certain levels for evaluating this model. Therefore, we select the LN method as the normalization method used and set equal weights for different criteria for our subsequent analysis.

6.4.1 Case study 1: The composite air quality index

We first present the example of constructing the composite air quality index (CAQI) for 47 major cities in China in 2003 to evaluate the three most popular MCDA aggregation methods, i.e., the SAW, WP and WDI_{∞} methods. The data were collected from *China Environment Yearbook* (EBCEY, 2004). Following the practice of the State Environmental Protection Administration of China (SEPAC), we choose the yearly average concentrations of the three pollutants, namely sulfur dioxide (SO_2), nitrogen dioxide (NO_2) and particulate matter (PM_{10}), as the underlying environmental variables for constructing the CAQI. Table 6.5 presents the descriptive statistics of the three variables in 2003.

Table 6.5 Descriptive statistics of 47 China cities with respect to three environmental variables in 2003

Environmental variables	Mean	Standard Deviation	Min	Max
SO_2 (Mg/m^3)	0.048	0.030	0.002	0.152
NO_2 (Mg/m^3)	0.039	0.015	0.012	0.072
PM_{10} (Mg/m^3)	0.108	0.049	0.030	0.337

The SAW, WP and WDI_{∞} methods are then respectively used to aggregate the three environmental variables into the CAQIs for the 47 cities. After the CAQIs are calculated, the SSM values for the three MCDA methods can then be derived according to the procedure described in Section 6.2. It is found that the WP method has the least (0.00255) while the SAW method has the largest (0.00282) SSM value. However, since this is only a special case, we are not able to conclude that the WP method will always outperform the other two methods in terms of information loss criterion.

Next, we present another example using the simulated data based on the distribution of the data in the CAQI example. It is found that the observations on the three environmental variables are larger than zero and highly skewed, which could be fitted well by three independent log normal distributions with different parameters well. Thus we use the three log normal distributions to respectively generate the three sub-indicators where the number of hypothetical cities changes from 5 to 200. The SAW, WP and WDI_∞ methods are then respectively used to calculate the CAQIs of the simulated cities according to the simulated data. The SSM values for the three MCDA methods under different scenarios are calculated and shown in Fig. 6.2.

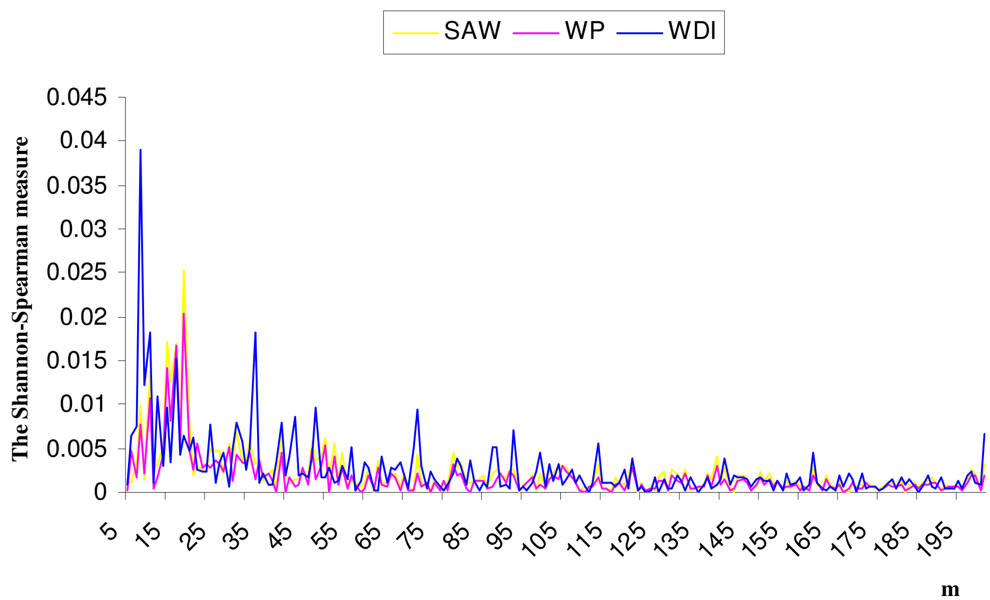

Fig. 6.2 The SSM values on the simulated data based on the collected data with the number of hypothetical cities (*m*) changing from 5 to 200

It is observed from Fig. 6.2 that the SSM values for the SAW and WP methods become very small when the number of cities is quite large. This might be an indication that the two MCDA methods always result in little information loss in constructing CIs when the number of sub-indicators is small and the size of the comparable systems is large. As to the WDI_∞ method, although the SSM value also becomes smaller when the number of cities is quite large, it appears to be somewhat unstable. In general, the WP method has the smallest (0.00172) while the WDI_∞ method has the largest (0.00258) average SSM value.

6.4.2 Case study 2: The TAI and random data examples

In this section, we shall first apply the SSM to evaluate the five MCDA methods based on the TAI example used in Section 6.3. The SSM values for the five MCDA methods are first calculated based on the decision matrix in the TAI example. As an individual value provides no information about the precision and reliability, the confidence intervals for the SSM values obtained are also expected to be given. Since the statistical property of the SSM is unknown, the nonparametric bootstrap technique (Efron and Tibshirani, 1993) is used to derive these confidence intervals. In our study, 100 bootstrap decision matrices are generated to derive the 95% confidence intervals for the SSM values. Figure 6.3 shows the SSM value and its bootstrap confidence interval for each MCDA method.

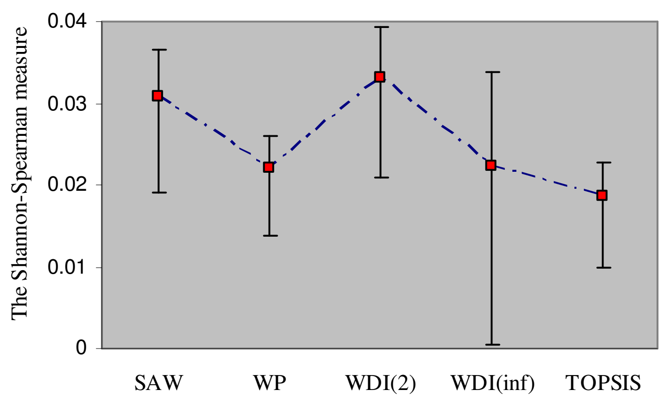

Fig. 6.3 The SSM values (red solid squares) and their 95% bootstrap confidence intervals for the five MCDA methods based on the TAI example

From Fig. 6.3, the TOPSIS method has the smallest while the WDI_2 method has the largest SSM value. This indicates that the TOPSIS method could result in the least loss of information for the TAI example. The bootstrap confidence interval for the WDI_∞ method is significantly wider than those for the other MCDA methods. This might indicate that the WDI_∞ method is not so stable with respect to the loss of information in constructing CIs. In contrast, the WP method seems to be a good choice because it has both a smaller SSM value and the narrowest confidence interval. Nevertheless, we are not able to judge which method would result in least information loss in most cases since these results are obtained based on a specific decision matrix.

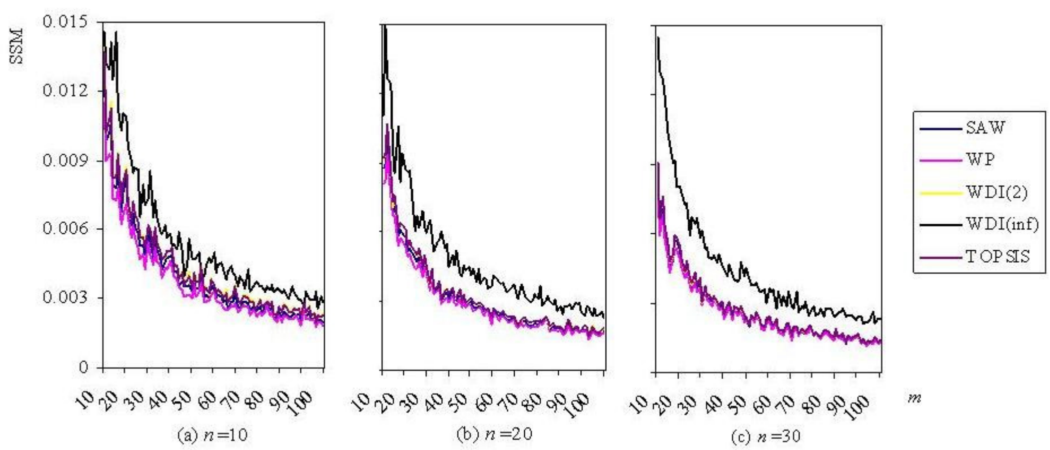

Fig. 6.4 The average SSM values with the number of sub-indicators (*n*) being fixed at 10, 20 and 30 and the number of systems (*m*) varying from 10 to 100

To further investigate the appropriateness of the five MCDA aggregation methods in constructing CIs, we next use the randomly generated decision matrices to calculate their SSM values. An $m \times n$ decision matrix is obtained by generating m numbers from each of n independent log normal distributions with parameters 0 and 1. The reason for choosing the log normal distribution is that the observations on each sub-indicator for constructing CIs tend to be larger than zero and highly skewed, which could be well modeled by the distribution (Zhou et al., 2006c). We first consider the cases in which the number of sub-indicators is respectively fixed at 10, 20 and 30 while the number of systems varies from 10 to 100. For each scenario, 100 decision matrices are randomly generated and used to derive 100 SSM values. The average of the 100 SSM values are then calculated and plotted in Fig. 6.4.

From Fig. 6.4 we can find that the WDI_∞ method always has the largest SSM value and therefore leads to the maximum loss of information among the five MCDA methods. The WP method has been found to be the best because it results in the least loss of information in most cases. The WP method is followed by the SAW method but it is difficult to compare the WDI_2 method and the TOPSIS method. In addition, the number of sub-indicators has practically no influence on the SSM value.

We have also considered cases where the number of alternatives is fixed at 20, 50 and 100 while the number of sub-indicators varies from 5 to 100. Similarly, for each scenario 100 decision matrices are randomly generated to derive 100 SSM values and then their average. Fig. 6.5 shows the results obtained.

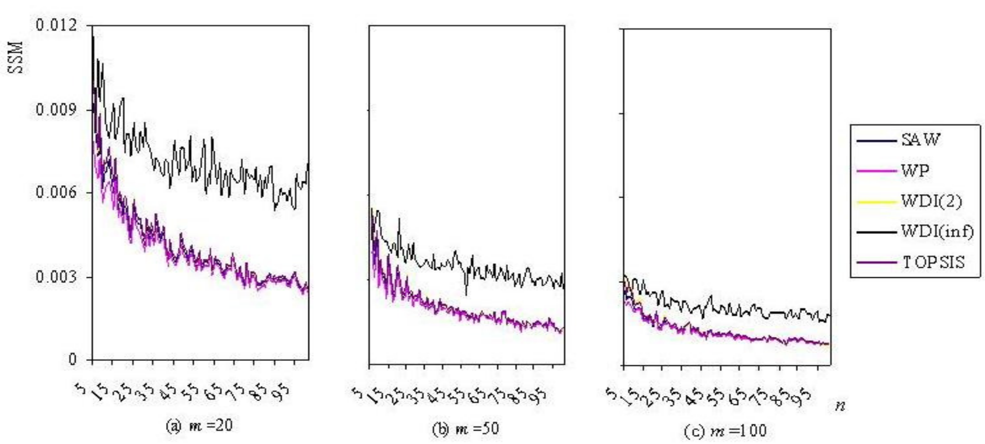

Fig. 6.5 The average SSM values with the number of systems (*m*) being fixed at 20, 50 and 100 and the number of sub-indicators (*n*) varying from 5 to 100

From Fig. 6.5 we can find that the relative positions of the five MCDA methods remain unchanged, as compared to Fig. 6.4. When the number of systems and the number of sub-indicators are quite large, the SSM values for the SAW, WP, WDI_2 and TOPSIS methods become fairly stable. Interestingly, it can also be observed that for each of the five methods the SSM value decreases as the number of systems increases.

Based on the above case studies, the WP method has been found to be the best among the five MCDA methods in constructing CIs in terms of the information loss criterion. This finding supports the conclusion drawn by Ebert and Welsch (2004) that the WP method has better properties. These case studies also show that the WDI_∞ method may not be a good choice for constructing CIs. It is likely due to the fact that only one of the underlying sub-indicators is used in the WDI_∞ method. However, this does not mean that the WDI_∞ method could be ignored because the CI given by it can provide some implications about the balances of the system studied (Diaz-Balteiro and Romero, 2004). In real situations, it might be better if two sets of CIs are constructed respectively by the WDI_∞ method and the WP method (or the SAW method). The first can be used to compare the balanced performance of a system while the second represents the aggregated performance of the system.

6.5 Conclusion

In this chapter, we present an objective measure called the Shannon-Spearman measure (SSM) based on the concept of “loss of information” which can be used to empirically compare alternative MCDA aggregation methods for constructing CIs. The Monte Carlo approach-based uncertainty analysis and variance-based sensitivity analysis techniques are applied to investigate the effectiveness of the SSM. It is found that most of the variation in the SSM arises from the uncertainty in aggregation scheme among all the factors considered, which demonstrates that the SSM could be an effective measure for comparing the information loss of alternative MCDA methods in constructing CIs.

The SSM has been applied to evaluate five popular MCDA aggregation methods in constructing CIs. The case studies presented show that the WP method may be a good choice with regards to information loss criterion because it results in the smallest SSM values in most cases. On the other hand, the WDI_∞ method may not be a good choice because it often results in the maximum loss of information. It is also found that the number of alternatives could affect the SSM value severely while the number of criteria has little influence on the SSM value.

CHAPTER 7 INFORMATION-THEORETIC AGGREGATION APPROACH TO CONSTRUCTING CIs[8]

In Chapter 6, we proposed the so-called Shannon-Spearman measure (SSM) for comparing alternative MCDA aggregation methods in constructing CIs based on the "minimum information loss" concept. Using the SSM, we empirically found that the weighted product (WP) method could be a better choice with regards to the information loss criterion. In this chapter, we apply the "minimum information loss" concept, to develop a new information-theoretic aggregation approach to constructing CIs. It is shown that the WP method highlighted in Chapter 6 is a special case of this approach. This provides further evidence for practitioners to adopt the WP method in empirical applications where the criterion of information loss is concerned by decision makers. Furthermore, the information-theoretic aggregation approach can incorporate additional information and deal with both quantitative and qualitative data, which therefore provides a more flexible way to construct CIs.

7.1 Background information

Assume that there are m entities, e.g., countries/regions, whose CIs are to be constructed based on n sub-indicators. Let I_{ij} and w_j respectively denote the value of entity i with respect to sub-indicator j after normalization and the standardized weight assigned to sub-indicator j. For simplicity, we further assume that all the sub-indicators are positive and of the benefit-type, i.e., they satisfy the property of "the

[8] The work presented in this chapter has been published as Zhou et al. (2007a).

larger the better". The problem is to aggregate $I_{ij}\,(j=1,2,\cdots,n)$ into CI_i for every entity *i*.

Among the existing aggregation methods such as those discussed in Chapter 6, the SAW method seemed to be the most commonly used aggregation method for constructing CIs. Related studies include Esty et al. (2005, 2006). Mathematically, the SAW method can be written as

$$CI_i = \sum_{j=1}^{n} w_j I_{ij}\ ,\ i=1,2,\cdots,m \tag{7.1}$$

The popularity of the SAW method is due to its transparency and ease of understanding (Hobbs et al., 1992). In addition, the SAW method would still yield an extremely close approximation to the ideal value function even if the assumption of preference independence among sub-indicators does not hold (Yoon and Hwang, 1995).

The weighted product (WP) method given by

$$CI_i = \prod_{j=1}^{n} I_{ij}^{w_j}\ ,\ i=1,2,\cdots,m \tag{7.2}$$

is another popular aggregation method with great promise in CI construction. It represents a concept that lies between the SAW method with full compensability and the non-compensatory MCDA approach (Triantaphyllou, 2000; Nardo et al., 2005). Ebert and Welsch (2004) have theoretically shown that the WP method has some good properties. More recently, Zhou et al. (2006c) found that the WP method may lead to the minimum information loss compared with some other MCDA aggregation methods, which further demonstrated the advantages of the WP method in constructing CIs.

In addition to the SAW and WP methods, there are some other aggregation methods for constructing CIs, such as the non-compensatory MCDA approach highlighted by Munda (2003, 2005). Further discussions on various aggregation methods can be found in Munda (2003, 2005), Diaz-Balteiro and Romero (2004), Nardo et al. (2005), Saisana et al. (2005) and Zhou et al. (2006c).

7.2 Information-theoretic aggregation approach

Information theory, founded by Shannon (1948), is a branch of mathematics that deals with the information content of messages. It is mainly concerned with the amount of information and the accuracy of its transmission. Entropy is the basic concept of information theory. Although entropy is initially defined as "*a measure of uncertainty of a random variable*", it is also suitable for measuring the relative contrast intensity of a set of deterministic values by which the amount of intrinsic information contained in these values can be represented (Deng et al., 2000; Zhou et al., 2006c).

The generic problem of constructing CIs, as described in the left-hand part of the symbol "~" in Fig. 7.1, may be interpreted as such an information transmission type problem: derive a CI vector that can transmit the same information to decision makers as the sub-indicator matrix does for performance comparisons. This is of course the ideal case which is expected. Nevertheless, it is logical to believe that a better aggregation method could lead to less information loss from the sub-indicator matrix to the CI matrix, provided that the information loss criterion is adopted. In the sections that follow, we shall use this principle to derive a new aggregation method rather than to compare the existing ones as done in Chapter 6.

$$\begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1n} \\ I_{21} & I_{22} & \cdots & I_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ I_{m1} & I_{m2} & \cdots & I_{mn} \end{bmatrix} \rightarrow \begin{bmatrix} CI_1 \\ CI_2 \\ \vdots \\ CI_m \end{bmatrix} \sim \begin{bmatrix} CI_1 & CI_1 & \cdots & CI_1 \\ CI_2 & CI_2 & \cdots & CI_2 \\ \vdots & \vdots & \ddots & \vdots \\ CI_m & CI_m & \cdots & CI_m \end{bmatrix}_{m\times n}$$

Fig. 7.1 Relationship between the sub-indicator matrix and the CI vector

7.2.1 Basic model

The main purpose for constructing CIs is to assess and compare the overall performance of various entities with respect to all the sub-indicators. If every entity has the same value with respect to all the sub-indicators, we may use this value to represent its overall performance for every entity. Therefore, as illustrated in Fig. 7.1, the CI vector is essentially equivalent to an $m\times n$ matrix with each column equal to the CI vector. As such, the problem for deriving the CI vector can be considered as a problem to derive the CI matrix. Based on the "minimum information loss" concept, we expect an aggregation method that could lead to the minimum loss of information from the sub-indicator matrix to the CI matrix. This requires us to first devise a measure for quantifying the information loss.

Cross-entropy, also known as the Kullback-Leibler entropy, could be used to serve our purpose for measure information loss (Kullback and Leibler, 1951; Kapur and Kesavan, 1992). Since in our case the weights for sub-indicators are assumed to be known, we define the following weighted cross-entropy for quantifying the information loss from sub-indicator matrix to the CI matrix:

$$WCE = \sum_{i=1}^{m} \sum_{j=1}^{n} w_j CI_i \ln \frac{CI_i}{I_{ij}} \tag{7.3}$$

The information loss is expected to be minimized and we therefore present the following entropy optimization problem for deriving the CI values:

$$\begin{aligned} &\min \sum_{i=1}^{m} \sum_{j=1}^{n} w_j CI_i \ln \frac{CI_i}{I_{ij}} \\ &\text{s.t. } CI_i \geq 0, i = 1,2,\cdots,m \end{aligned} \tag{7.4}$$

Model (7.4) is the basic model of our approach since only the basic information for constructing CIs is used. It matches the well-known "minimum cross-entropy principle" in information theory that has been widely applied to address the problem of information recovery from limited/incomplete data in various fields (Kapur and Kesavan, 1992; Golan et al., 1994; Golan et al., 1996; Robinson et al., 2001). By assumes that the constraint $CI_i \geq 0$ is not binding and solving its first-order conditions, we obtain the following optimal solution of model (7.4):

$$CI_i^* = e^{-1} \prod_{j=1}^{n} I_{ij}^{w_j} \text{ , } i = 1,2,\cdots,m \tag{7.5}$$

Interestingly, (7.5) is consistent with the WP method, i.e., (7.2), except for a constant difference. This implies that if no additional information is given, the WP method would likely result in the minimum information loss among all the alternative aggregation methods including those we have not explored.

In some circumstances experts or decision makers may provide some additional information, which cannot be easily incorporated by the WP method. For instance, when an entity has an extremely bad value with respect to an important sub-indicator, decision makers may reasonably believe that the CI value of this entity should be lower than those of some other entities. In such cases, the additional information can be easily incorporated into our basic model (7.4) by adding appropriate constraints. The resulting entropy optimization models, according to their specific structures, can be solved by different algorithms as described in Fang et al. (1997). Our approach therefore provides a more flexible way to construct CIs than what the WP method does.

7.2.2 An extension of basic model to deal with qualitative data

The basic model described in Section 7.2.1 is mainly used to deal with quantitative sub-indicators. We now extend this basic model to deal with qualitative data, as sub-indicators may be expressed qualitatively. For instance, if the information on sub-indicators comes from survey data, it may be more appropriate to represent each sub-indicator as the probabilities of an entity in a set of states such as good, satisfactory, neutral, unsatisfactory and bad. In such cases, it might be better to express the CI value of each entity as the probabilities of this entity in the same set of states with respect to its overall performance.

Suppose that there are still *m* entities to be evaluated based on *n* sub-indicators and each sub-indicator has *k* possible states. For the entity *i* with respect to sub-indicator *j*, we assume that its probabilities in status $1,2,\cdots,k$ are $p_{ij}^1, p_{ij}^2, \cdots, p_{ij}^k$ respectively. The purpose is to derive the probabilities of each entity in different states with respect to its overall performance, which are denoted by $p_i^1, p_i^2, \cdots, p_i^k$ ($i = 1,2,\cdots,m$).

Based on the "minimum cross-entropy principle", we present the following entropy optimization model:

$$
\begin{aligned}
&\min \sum_{l=1}^{k}\sum_{i=1}^{m}\sum_{j=1}^{n} w_j p_i^l \ln \frac{p_i^l}{p_{ij}^l} \\
&\text{s.t. } \sum_{l=1}^{k} p_i^l = 1, i = 1,2,\cdots,m \\
&\quad p_i^l \geq 0, i = 1,2,\cdots,m; l = 1,2,\cdots,k
\end{aligned}
\tag{7.6}
$$

Using the simple Lagrange multiplier method, we can derive the optimal solution of model (7.6) as

$$
\hat{p}_i^l = \frac{\prod_{j=1}^{n} (p_{ij}^l)^{w_j}}{\sum_{l=1}^{k} \prod_{j=1}^{n} (p_{ij}^l)^{w_j}}, \; l = 1,2,\cdots,k; i = 1,2,\cdots,m \tag{7.7}
$$

The probabilities given by (7.7) constitute the CI for every entity, which is not an individual value but a set of probabilities. Decision makers can use the information provided by this kind of CI to compare different entities. If all the possible states could be quantified in an appropriate way, we can use the information to further derive an expected CI value for each entity.

7.3 Illustrative examples

We use a simple numerical example with three entities (A, B and C) and three sub-indicators (I_1, I_2 and I_3) to illustrate the application of the information-theoretic aggregation approach described in Section 7.2. Columns 2 to 4 of Table 7.1 show the hypothetical data (dimensionless) and the remaining columns give the results obtained from alternative aggregation methods. As to the use of information-theoretic approach, Case I deals with the basic model (7.4) while in Case II the additional information that CI_B is not more than CI_A is given.

Table 7.1 A simple example for comparing various aggregation methods

Entity	I_1 (w_1=0.25)	I_2 (w_2=0.5)	I_3 (w_3=0.25)	CI			
				SAW	WP	Information-theoretic	
						Case I	Case II
A	40	20	10	22.5	20.0	7.4	8.5
B	100	50	2	50.5	26.6	9.8	8.5
C	100	40	5	46.3	29.9	11.0	11.0

When the additional information $CI_A \geq CI_B$ is given, the resulting entropy optimization model based on the data given by Table 7.1 can be formulated as

$$\begin{aligned}
\min\Big\{ & 0.25CI_A \ln\frac{CI_A}{40} + 0.5CI_A \ln\frac{CI_A}{20} + 0.25CI_A \ln\frac{CI_A}{10} \\
& + 0.25CI_B \ln\frac{CI_B}{100} + 0.5CI_B \ln\frac{CI_B}{50} + 0.25CI_B \ln\frac{CI_B}{2} \\
& + 0.25CI_C \ln\frac{CI_C}{100} + 0.5CI_C \ln\frac{CI_C}{40} + 0.25CI_C \ln\frac{CI_C}{5} \Big\} \\
\text{s.t. } & \mathrm{CI_A} \geq CI_B \\
& CI_A, CI_B, CI_C \geq 0
\end{aligned} \tag{7.8}$$

Model (7.8) can be further simplified as

$$\begin{aligned}
\min & \left\{ CI_A \ln\frac{CI_A}{20} + CI_B \ln\frac{CI_B}{26.6} + CI_C \ln\frac{CI_C}{29.9} \right\} \\
\text{s.t. } & \mathrm{CI_A} \geq CI_B \\
& CI_A, CI_B, CI_C \geq 0
\end{aligned} \tag{7.9}$$

To solve (7.9), we can first write its K.K.T. conditions as follows

$$
\begin{aligned}
&CI_A = 20\exp(-w + w_A - 1) \\
&CI_B = 26.6\exp(w + w_B - 1) \\
&CI_C = 29.9\exp(w_C - 1) \\
&w(CI_B - CI_A) = 0 \\
&CI_B \le CI_A,\ w \ge 0 \\
&w_j \cdot CI_j = 0,\ w_j, CI_j \ge 0 \quad (j = A, B, C)
\end{aligned}
\tag{7.10}
$$

By solving (7.10), we can easily obtain the optimal solution of (7.8) as shown in the last column of Table 7.1.

It can be seen from Table 7.1 that the SAW method and the WP method could give different CI values and rank orders. Whichever of the two methods is used, the CI value of B is larger than that of A. Nevertheless, the results from the SAW method seem to indicate that B is more than twice better than A, which is different from the WP method. It can be explained by the fact that A has a value far larger than that of B in I_3, and by the nature of the two methods, i.e., the full and half compensability of the SAW and WP methods (Nardo et al., 2005). In relation to the information-theoretic approach, as we expected, the CI values derived from model (7.4) are proportional to those derived from the WP method. If additional information $CI_A \ge CI_B$ is given, the CI values obtained are slightly different from those derived from the basic model (7.4). In particular, we observe that the CI value for C remains unchanged since the additional information has no relationship with C.

Table 7.2 presents another simple example to illustrate the use of the proposed approach to dealing with qualitative data. Assume that the sub-indicators of each entity can only be represented by the probabilities of this entity in the state space {satisfactory, neutral, unsatisfactory} since the data are collected from questionnaire. For instance, (0.8, 0.1, 0.1) in the first position of Table 7.2 indicates that 80% of people evaluate A as "satisfactory" while 10% of them evaluate A as "neutral" and "unsatisfactory" respectively with respect to I_1.

Table 7.2 An illustrative example for dealing with qualitative data

Entity	I_1 (w_1=1/3)	I_2 (w_2=1/3)	I_3 (w_3=1/3)	CI
A	(0.8, 0.1, 0.1)	(0.5, 0.4, 0.1)	(0.6, 0.1, 0.3)	(0.67, 0.17, 0.16)
B	(0.6, 0.1, 0.3)	(0.4, 0.3, 0.3)	(0.5, 0.1, 0.4)	(0.51, 0.14, 0.34)
C	(0.5, 0.4, 0.1)	(0.6, 0.2, 0.2)	(0.5, 0.3, 0.2)	(0.54, 0.29, 0.16)

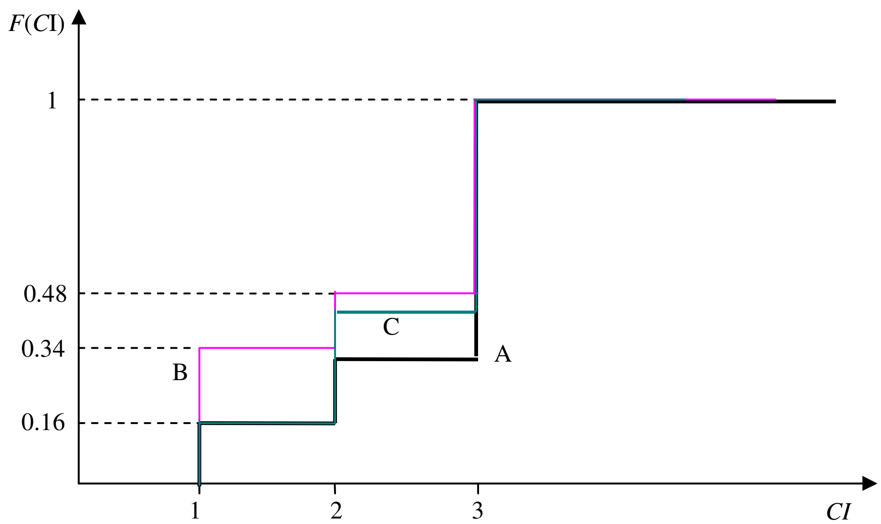

Fig. 7.2 Cumulative probability distributions of CIs for entity A, B and C

Based on the data given in columns 2 to 4 of Table 7.2, we derive the CIs of the three entities using models (7.6) and (7.7). The last column of Table 7.2 shows the results, also in the form of probability distributions. If let CI = 1, 2 and 3 respectively denote the cases where people feel unsatisfactory, neutral and satisfactory, we can plot the cumulative probability distributions of CIs for the three entities as shown in Fig. 7.2. From Fig. 7.2 we can see that the cumulative probability distribution of CI_A stochastically dominates (first order) that of CI_B, which in turn stochastically dominates (first order) that of CI_C. Therefore, A is the best while B is the worst performer in overall performance with respect to the three sub-indicators. However, this conclusion could not be drawn directly from the original data table. It demonstrates the applicability of the proposed approach in constructing CIs when only qualitative data are involved.

7.4 Conclusion

In this chapter, we propose an information-theoretic approach to constructing CIs by following the concept of "minimizing information loss". The proposed approach can deal with both quantitative and qualitative sub-indicators. The WP method highlighted in Chapter 6 has been found to be a special case of our proposed approach, which provides further evidence for practitioners to choose the WP method in empirical applications where the information loss criterion is concerned by decision makes. Two examples are presented to illustrate the application of the proposed approach in dealing with different situations.

CHAPTER 8 A LINEAR PROGRAMMING APPROACH TO CONSTRUCTING CIs[9]

8.1 Introduction

As was discussed in Chapters 6 and 7, MCDA methods have been widely investigated in the CI construction. A major problem in applying MCDA aggregation methods to construct a CI is the determination of the weights for the underlying sub-indicators. From the methodological viewpoint, there exist many weighting methods which can be used to derive the weights for sub-indicators. Nardo et al. (2005) have recently discussed the pros and cons of different weighting methods. In practice, expert judgment or public opinion poll results are often used to derive the weights for sub-indicators (Hope et al., 1992). When such information is unavailable, as illustrated in the Human Development Index, equal weights seem to be the norm. Nevertheless, not all the entities to be evaluated will agree with the equal weight assumption since every one of them has its own characteristics and preference (Lau and Lam, 2002). Fortunately, DEA can help us determine the weights for sub-indicators in CI construction.

The use of DEA in CI construction can be roughly divided into two groups. One follows the tradition of DEA by first identifying inputs and outputs and then constructing an aggregated index using the common DEA procedure. Examples of such studies include the construction of environmental performance index as we discussed in Chapters 2 to 4. In the other line, all the sub-indicators are firstly

[9] The work presented in this chapter has been published as Zhou et al. (2007b).

transformed into the same type of variables (benefit or cost type) and then aggregated into a CI by some DEA-like models. In recent years, much attention has also been focused on this line of research, e.g., Lovell et al. (1995), Mahlberg and Obersteiner (2001), Cherchye (2001), Lau and Lam (2002), Despotis (2005a, b) and Cherchye et al. (2007-a, b). This chapter also follows this line of research. More specifically, in this chapter we extend previous studies and present a simple linear programming approach to constructing CIs that combine ideas from MCDA and DEA. For the illustration purpose, we apply the proposed approach to develop a CI for modeling sustainable energy development of eighteen APEC economies.

8.2 Model development

Again consider the case where there are *m* entities, e.g., countries or regions, whose aggregated performance are to be evaluated based on *n* sub-indicators. These sub-indicators usually have no common measurable units. Let I_{ij} denote the value of entity *i* with respect to sub-indicator *j*. Without loss of generality, we further assume that all the sub-indicators are of the benefit type which satisfy the property of "the larger the better". As illustrated in Fig. 8.1, the problem is to aggregate $I_{ij}\,(j=1,2,\cdots,n)$ into a composite indicator CI_i that can be used to evaluate the aggregated performance of entity *i* with respect to all the underlying sub-indicators.

$$\begin{bmatrix} I_{11} & I_{12} & \cdots & I_{1n} \\ I_{21} & I_{22} & \cdots & I_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ I_{m1} & I_{m2} & \cdots & I_{mn} \end{bmatrix} \rightarrow \begin{bmatrix} CI_1 \\ CI_2 \\ \vdots \\ CI_m \end{bmatrix}$$

Fig. 8.1 Graphical representation of CI construction

8.2.1 An encompassing CI

As has been mentioned earlier, a critical issue in using MCDA aggregation methods to construct CIs is the subjectivity in assigning weights for sub-indicators. Since different weight combinations may lead to different ranking results, it is unlikely that all the entities would easily reach a consensus in determining an appropriate set of weights. In addition, it may not be easy to obtain the expert information for deriving the weights. Although the use of equal weights seems to be a relatively fair choice, some entities may still have different opinions since they have their particular preferences. To avoid these issues, a DEA-like model is given here for aggregation purpose:

$$
\begin{aligned}
gI_i = \max \sum_{j=1}^{n} w_{ij}^{g} I_{ij} & \\
\text{s.t.} \sum_{j=1}^{n} w_{ij}^{g} I_{kj} \le 1,\ k = 1,2,\cdots,m & \qquad (8.1)\\
w_{ij}^{g} \ge 0,\ j = 1,2,\cdots,n &
\end{aligned}
$$

Model (8.1) provides an aggregated performance score gI_i for entity i in terms of all the underlying sub-indicators. By solving (8.1) repeatedly for each entity, we will obtain a set of indices $gI_1, gI_2, \cdots, gI_m$ for these entities.

Note that the objective function in (8.1) is externally similar to the popular SAW aggregation method in MCDA. It implies that our approach adopts linear rather than nonlinear aggregation procedure. Although nonlinear aggregation, e.g., the WP method, may have some advantages as discussed in Chapters 6 and 7, we choose linear aggregation procedure here because of its simplicity and ease of understanding. In addition, linear aggregation is a common practice in DEA literature. Despite its similarity to the SAW method, in (8.1) the weights for sub-indicators are endogenous and changeable while in the SAW method they are exogenous and fixed. In essence, (8.1) is an output maximizing multiplier DEA model with multiple outputs and constant inputs, which measures how far the evaluated entity is from the best practice entity under the best possible weights. It should be pointed out that many MCDA researchers have attempted to use linear programming to help determine the weights and rank alternatives, e.g., Kirkwood and Sarin (1985), Salo and Hämäläinen (2001), and Mustajoki et al. (2005). In DEA literature, (8.1) is not a new model yet. For example, Despotis (2005a, b) recently proposed an approach to reassessing the Human Development Index which could be considered as an extension to (8.1). More recently, Ramanathan (2006) applied the same model to study a multi-criteria inventory classification problem.

In virtue of its DEA feature, (8.1) can help each entity select the "best" set of weights for use. It avoids the subjectiveness in determining the weights and therefore provides a relatively objective performance score for each entity. However, if an entity has a value dominating other entities in terms of a certain sub-indicator, this entity would always obtain a score of 1 even if it has severely bad values in other more important sub-indicators (see Appendix C.2 for the proof). If an entity is a strongly or weakly nondominated entity compared to the convex combinations of other entities, this entity will also always obtain a score of 1 (see Appendix C.3 for the related definitions and mathematical proof). Furthermore, only (8.1) may lead to the situation that a large number of entities have a performance score of 1 and further ranking among them becomes difficult. To address these issues, we extend (8.1) and propose a similar linear programming model as follows:

$$
\begin{aligned}
bI_i = \min \sum_{j=1}^{n} w_{ij}^{b} I_{ij} & \\
\text{s.t.} \sum_{j=1}^{n} w_{ij}^{b} I_{kj} \geq 1,\ k = 1,2,\cdots,m & \qquad (8.2) \\
w_{ij}^{b} \geq 0,\ j = 1,2,\cdots,n &
\end{aligned}
$$

Contrary to (8.1), (8.2) seeks the "worst" set of weights for each entity which are used to aggregate the sub-indicators into a performance score. Externally, (8.2) is very similar to an input minimizing multiplier DEA model with multiple inputs and constant outputs. However, in (8.2) all the sub-indicators are of the benefit-type and it is not appropriate to consider them as "inputs". Essentially, (8.2) measures how close the evaluated entity is to the worst practice entity under the worst possible weights. It provides a way for further comparison among those incomparable entities only based on (8.1). It is worth pointing out that (8.2) is not a brand-new model in the DEA literature. Conceptually, it is parallel to the minimum efficiency concept as discussed in Zhu (2004). The similar idea has also been applied to study a site selection problem by Takamura and Tone (2003) and a multi-criteria inventory classification problem by Zhou and Fan (2007). Nevertheless, as far as we know, it is the first time that (8.2) is applied to the field of CI construction.

So far we have provided two performance indexes for each entity which are derived from the data by two DEA-like models, i.e., (8.1) and (8.2). Since the two indexes are based on the weights that are most favourable and least favourable for each entity, they could only reflect partial aspects of an entity in terms of its aggregated performance. It is logical and reasonable to combine them into an overall index. Therefore, we combine the two indexes to form a CI in the following way:

$$CI_i(\lambda) = \lambda \cdot \frac{gI_i - gI^-}{gI^* - gI^-} + (1-\lambda) \cdot \frac{bI_i - bI^-}{bI^* - bI^-} \tag{8.3}$$

where $gI^* = \max\{gI_i, i = 1,2,\cdots,m\}$, $gI^- = \min\{gI_i, i = 1,2,\cdots,m\}$, $bI^* = \max\{bI_i, i = 1,2,\cdots,m\}$, $bI^- = \min\{bI_i, i = 1,2,\cdots,m\}$, and $0 \le \lambda \le 1$ is an adjusting parameter.

In (8.3), we use the linear scaling in the min-max range to let the two indexes become comparable (in the range of [0, 1]) and then use the linear aggregation to combine them together by the adjusting parameter λ, If $\lambda = 1$, CI_i will become a normalized version of gI_i. If $\lambda = 0$, CI_i will become a normalized version of bI_i. For other cases, (8.3) makes a compromise between the two indexes. If decision makers or analysts have no particular preference, $\lambda = 0.5$ seems to be a fairly neutral choice. Given these characteristics of (8.3), we may believe that (8.3) provides a more encompassing CI since it takes into account two extreme cases. Nevertheless, the indexes given by (8.1) and (8.2) should not be discarded since they can provide some other valuable information such as the "performance bound" information.

We can show that CI_i satisfies a number of desirable properties:

P8.1 $0 \le CI_i \le 1$;

P8.2 CI_i is units invariant;

P8.3 CI_i is invariant to the right hand sides of the constraints in (8.1) and (8.2).

The property **P8.1** indicates that (8.3) provides a standardized index which lies in the interval [0, 1]. If an entity has a larger value, we may say that this entity has better aggregated performance. If an entity has the largest values in terms of both gI_i and bI_i, it will give a CI of "1" no matter what λ is. If an entity has the smallest values in terms of both gI_i and bI_i, it will give a CI of "0" no matter what λ is. The property **P8.2** says that whatever units are chosen for sub-indicators, the value of CI_i will remain unchanged. As a result, we do not need to consider the normalization procedure before aggregation in applying the proposed approach to construct CIs. **P8.3** implies that if we replace "1" in the constraints of (8.1) and (8.2) by any other positive values, the value of CI_i would remain unchanged.

8.2.2 Restricting the weights for sub-indicators

Note that in the previous models no exogenous restrictions are imposed on the weights for sub-indicators. All the weights are generated from the data. Under these circumstances the weights used may be such that a number of sub-indicators would be ignored in aggregation. This is definitely not the case we expect since all the sub-indicators selected should be considered as "important" ones and it may not be appropriate to ignore many of them. To overcome this problem, we may consider restricting the flexibility of weights in an appropriate way by incorporating additional information. In principle, this can be done by a number of methods used in DEA studies as reviewed by Allen et al. (1997). In MCDA, many different kinds of methods have also been developed to incorporate partial information about the weights (Kirkwood and Sarin, 1985; Salo and Hämäläinen, 2001; Mustajoki et al., 2005). Mahlberg and Obersteiner (2001) and Cherchye et al. (2007-a, b) have recently given a few demonstrations on how to restrict the flexibility of weights in CI construction.

Although a number of studies highlight the direct restrictions on weights, we would suggest the use of "proportion constraints" proposed by Wong and Beasley (1990) in the DEA literature. Technically, we can revise (8.1) and (8.2) by respectively adding the following two sets of constraints:

$$L_j \leq \frac{w_{ij}^g I_{ij}}{\sum_{j=1}^n w_{ij}^g I_{ij}} \leq U_j,\ j = 1,2,\cdots,n \tag{8.4}$$

$$L_j \leq \frac{w_{ij}^b I_{ij}}{\sum_{j=1}^n w_{ij}^b I_{ij}} \leq U_j,\ j = 1,2,\cdots,n \tag{8.5}$$

where L_j and U_j are respectively denote the lower and upper limits for the contribution of the *j*-th sub-indicator in CI and satisfy $0 \leq L_j < U_j \leq 1$.

The main reason for using this way to restrict the flexibility of weights arises from some practical considerations. As Cherchye et al. (2007-b) argued, it is easier and more practical to let experts make a "limited agreement" on the determination of weights. Therefore, it is not a difficult task to derive the limits L_j and U_j in practice. Usually this can be done by making a consensus among decision makers or domain experts as to the relative importance of each sub-indicator. In the case that no consensus could be reached in terms of a certain sub-indicator, we can remove the corresponding weight restriction constraint. If no expert information is given, we can let $L_j = 0, U_j = 1\ (j = 1,2,\cdots,n)$ and the revised models will reduce to (8.1) and (8.2).

Another advantage of using "proportion constraints" is that it preserves the desirable units invariance property as pointed out by Cherchye et al. (2007-b).

8.3 Case study: sustainable energy index

Sustainable energy development, which consists of such elements as energy supply, energy efficiency and environmental protection, is a major concept in sustainable development (Jefferson, 2006). It is therefore very meaningful to gauge the sustainable energy development of a country/region relative to other countries/regions. In this section, we shall apply the proposed approach to develop a CI, namely sustainable energy index (SEI) for 18 APEC economies in 2002 for measuring and comparing their performance towards sustainable energy development. Using this application study, we can also illustrate what the general procedure for constructing CIs is and how the proposed approach can be used to construct CIs in practice.

The first step for constructing SEI is to select appropriate underlying sub-indicators. The International Atomic Energy Agency (IAEA) has recently published a total of thirty indicators related to sustainable energy development (IAEA, 2005). Despite its comprehensiveness, to include all of them is impossible due to the lack of data. Following Esty et al. (2006), we choose only energy efficiency indicator (EEI), renewable energy indicator (REI) and climate change indicator (CCI) as our sub-indicators for constructing SEI.

In the case of energy efficiency, various indicators, e.g., thermodynamic indicators, physical-based indicators and monetary-based indicators, have been used. According to Ang (2006), monetary-based indicators are more suitable for measuring energy efficiency at a high level of aggregation, which corresponds to our case here. We therefore choose the energy-GDP ratio, e.g., the ratio of total final energy consumption to GDP, as our EEI. The data on energy consumption and GDP are collected from APEC Energy Statistics 2003 (APEC, 2005). The REI is defined as the percentage of renewable energy in total final energy consumption. Renewable energy consumption includes such renewable sources as hydro-electricity, geothermal, solar and wind, and the data are collected from the US Energy Information Administration (2005). In the case of CCI, we follow Esty et al. (2006) and use the ratio of CO_2 emissions to GDP as its proxy. The data on CO_2 emissions are collected from the World Resources Institute (2005).

Note that according to our previous definitions EEI and CCI are cost-type indicators. So we first transform them into benefit-type indicators by taking their reciprocals before aggregation. We then apply (8.1), (8.2) and (8.3) to calculate the SEI values of the eighteen economies. Table 8.1 presents the results obtained as well as the data for the three sub-indicators.

It can be seen from Table 8.1 that all the economies can be compared with each other based on the SEI values while four of them have the same performance score of "1" by (8.1), which indicates that the proposed approach could lead to CIs with higher discriminating power. Ignoring the issue of data quality, Table 8.1 could also provide some useful information about sustainable energy development in APEC economies. It is observed from Table 8.1 that Peru has the highest SEI value (=1) although none of the three sub-indicators ranks first for the country. It is likely due to the fact that Peru not only has relatively high sub-indicator values but also has a better balance among different sub-indicators. From Table 8.1 we can also observe that

Russia has the least SEI value (=0) since Russia's two indexes given by Models (8.1) and (8.2) are the smallest compared to other economies. As a whole, it seems that the sustainable energy development of APEC economies is not so good since most economies have a very small SEI value and the average is below 0.4.

Table 8.1 Three sub-indicators and the SEI values of eighteen APEC economies in 2002

Economies	EEI (10^3 US$/toe)	REI (%)	CCI (10^3 US$/tons)	Model (1)	Model (2)	SEI ($\lambda = 0.5$)
Peru	13.825	53.6	4.510	1.000 (1.000)	5.159 (1.000)	1.000
Philippines	17.758	44.6	4.136	1.000 (1.000)	4.964 (0.953)	0.977
Papua New Guinea	12.381	23.5	5.039	1.000 (1.000)	3.577 (0.620)	0.810
New Zealand	5.473	56.9	2.281	1.000 (1.000)	2.231 (0.296)	0.648
Vietnam	10.790	30.0	2.478	0.642 (0.546)	3.134 (0.513)	0.529
Canada	4.286	46.8	1.608	0.822 (0.775)	1.747 (0.180)	0.477
Chile	6.950	32.2	2.542	0.597 (0.489)	2.817 (0.437)	0.463
Japan	8.647	8.2	2.522	0.558 (0.440)	2.103 (0.265)	0.353
Mexico	8.424	9.5	2.059	0.488 (0.351)	1.853 (0.205)	0.278
Indonesia	8.516	7.8	1.784	0.480 (0.340)	1.585 (0.141)	0.240
Thailand	8.204	4.8	1.891	0.462 (0.318)	1.511 (0.123)	0.220
China	8.178	11.1	1.372	0.461 (0.316)	1.467 (0.112)	0.214
United States	5.901	6.0	1.614	0.366 (0.196)	1.382 (0.092)	0.144
Australia	6.208	5.6	1.425	0.350 (0.176)	1.235 (0.057)	0.116
Malaysia	5.767	4.0	1.442	0.339 (0.162)	1.169 (0.041)	0.101
Taiwan, China	5.539	2.6	1.391	0.326 (0.146)	1.066 (0.016)	0.081
Korea	4.683	0.6	1.437	0.312 (0.128)	1.000 (0.000)	0.064
Russia	2.453	11.5	0.652	0.211 (0.000)	1.000 (0.000)	0.000
Mean	7.999	20.0	2.232	0.578 (0.466)	2.167 (0.281)	0.373
Standard Deviation	3.748	19.1	1.186	0.271 (0.343)	1.285 (0.309)	0.312

Note: The normalized values for the indexes given by (8.1) and (8.2) are shown in parentheses.

Note that in Table 8.1 we calculate the SEI values by fixing the adjusting parameter λ at 0.5. To investigate whether the adjusting parameter has severe effects on SEI, we further consider the cases that $\lambda = 0, 0.1, 0.2, \cdots, 1$. Using the eleven λ values we can get eleven SEI scores for each of the eighteen economies. Fig. 8.2 shows the comparative box plots of SEI values for the eighteen economies in the sequence of the mean SEI values, and Fig. 8.3 shows the comparative box plots of their SEI ranks in the same sequence. It can be seen from Fig. 8.2 that the SEI value is very insensitive to λ for most economies. In fact, as shown in Fig. 8.3, the ranks of over two thirds of economies in terms of their sustainable energy development are fairly consistent under different λ values. The Spearman ranking correlation coefficients between the SEI values for $\lambda = 0.5$ and the SEI values in other cases are all larger than 0.98.

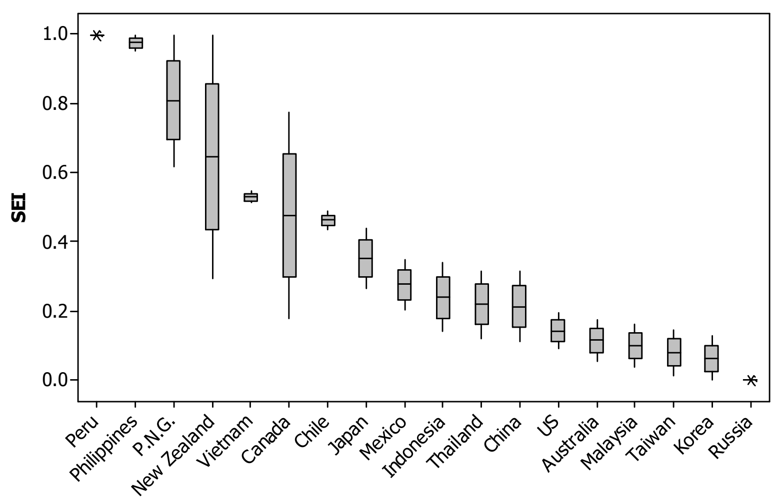

Fig. 8.2 Comparative box plots of SEI values for eighteen APEC economies in 2002

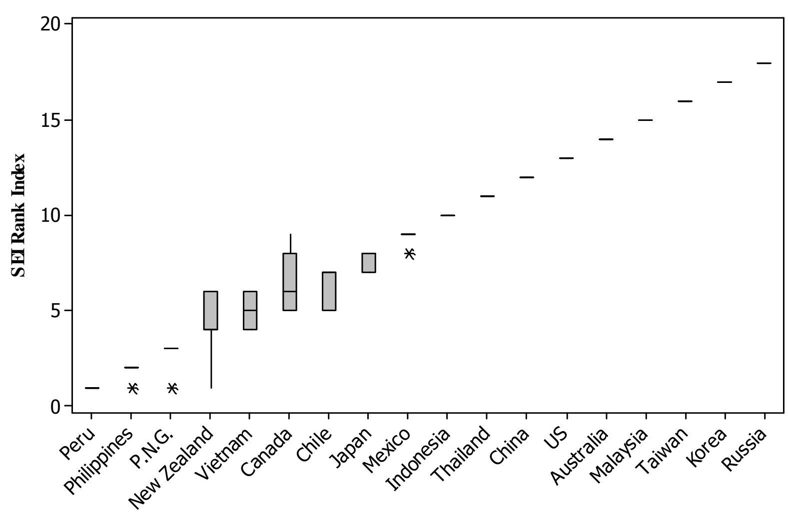

Fig. 8.3 Comparative box plots of SEI ranks for eighteen APEC economies in 2002

Previous discussions are based on the basic models of the proposed approach, i.e., (8.1), (8.2) and (8.3). In the following, we shall consider the case that the flexibility of weights is restricted in the form of (8.4) and (8.5). Since the current case study is mainly for illustration purposes, we arbitrarily choose $L_1 = L_2 = L_3 = 0.1$ and $U_1 = U_2 = U_3 = 0.5$ for use, which indicates that the contribution of each sub-indicator is not less than 10% but not larger than a half of the aggregated CI. We then apply the resulting models to recalculate the SEI values for these economies by using $\lambda = 0.5$. The results obtained, labeled as Scenario 2, as well as the SEI values without restricting the flexibility of weights (Scenario 1) are displayed in Fig. 8.4.

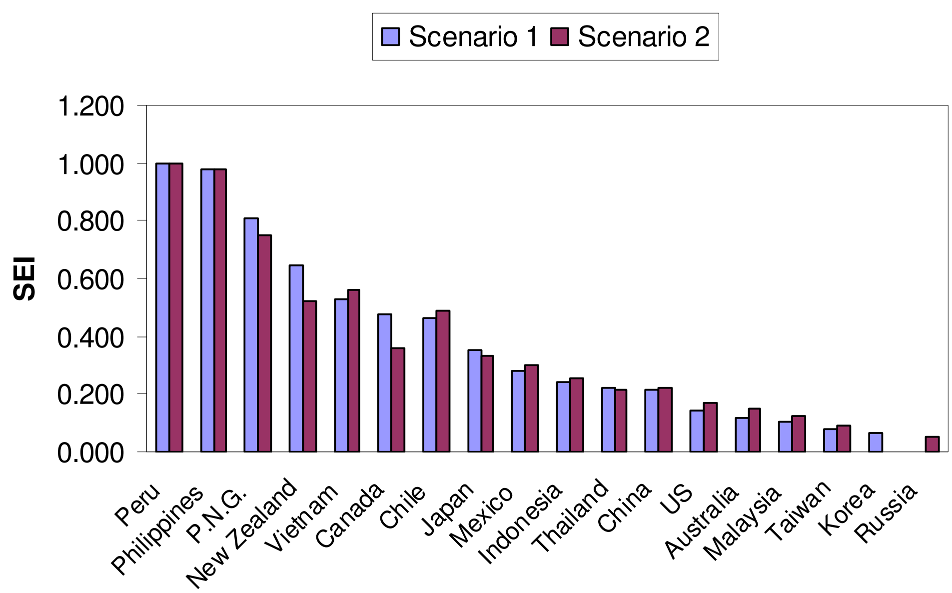

Fig. 8.4 Comparison between the SEI by basic models and that by models with weight restrictions

It can be seen from Fig. 8.4 that the SEI values of many economies, e.g., Peru, the Philippines, Thailand and China have no or little changes after weights for sub-indicators are restricted. On the contrary, in some economies there have been obvious changes. For instance, under Scenario 1 Russia has the least SEI value while under Scenario 2 Korea has the least SEI value. This could be explained by the fact that

Korea has a very small REI value and the weight for REI is zero by (8.1) under Scenario 1, while under Scenario 2 it is larger than zero.

Table 8.2 Correlation between sub-indicators and SEI

		EEI	REI	CCI	Scenario 1		Scenario 2	
					Model (8.1)	SEI	Model (8.1)	SEI
Scenario 1	Model (8.1)	0.660 (0.636)	0.876 (0.792)	0.832 (0.872)	1 (1)	0.961 (0.992)		
	SEI	0.800 (0.670)	0.841 (0.808)	0.910 (0.878)	0.961 (0.992)	1 (1)		
Scenario 2	Model (8.1)	0.836 (0.680)	0.803 (0.833)	0.911 (0.868)	0.929 (0.981)	0.987 (0.992)	1 (1)	
	SEI	0.852 (0.701)	0.794 (0.827)	0.918 (0.872)	0.910 (0.979)	0.987 (0.992)	0.995 (0.996)	1 (1)

Note: The Spearman rank correlation coefficient is included in parentheses

Table 8.2 shows the correlations of the two sets of SEI values under different scenarios with each other and with the three sub-indicators. The correlations of the two sets of indexes given by (8.1) with each other, with the two sets of SEI values, and with the three sub-indicators are also displayed in Table 8.2. It can be observed from Table 8.2 that the contributions of various sub-indicators in SEI are obviously different. It seems that SEI is strongly connected with CCI in both scenarios. When the weight restrictions are considered, the indexes given by (8.1) become more highly correlated with EEI, CCI and the SEI values under Scenario 1. It is likely due to the fact that the discriminating power of (8.1) becomes higher when considering weights restrictions. In the case of rank correlation, we can find that the SEI ranks under Scenario 2 are more consistent with the ranks of sub-indicators. We can also find that the two sets of SEI values are highly correlated with each other, which may be an indication of the robustness of the proposed approach in constructing CIs.

8.4 Conclusion

In this chapter, we propose a linear programming approach to constructing CIs. Compared with previous studies, the proposed approach requires no prior knowledge of the weights for sub-indicators. The weights used can be generated by solving a series of DEA-like models. Since the proposed approach uses two sets of weights that are most and least favourable for each entity, it may provide a more reasonable and encompassing CI. In addition, the proposed approach can easily incorporate additional information on the relative importance of sub-indicators when they are available.

The proposed approach has been applied to develop a CI for modeling the sustainable energy development of 18 APEC economies in 2002. We first apply the basic models of the proposed approach to construct a SEI for each economy. We then investigate whether the adjusting parameter used in the proposed approach has severe effects on the SEI values. It is found that the SEI value is very insensitive to this parameter. The scenario in which the flexibility of weights is restricted has also been investigated and the results obtained are compared with the scenario in which basic models are used. It is found that the two sets of SEI values are highly correlated with each other, which may be an indication of the robustness of the proposed approach in constructing CIs.

CHAPTER 9 CONCLUSIONS AND FUTURE RESEARCH

This thesis contributes to some methodological issues in applying DEA and MCDA to construct various E&E related composite indicators (CIs). In this chapter we shall summarize and discuss the main results of our research work as described in previous chapters. Possible future research will also be presented.

9.1 Summary of results

In Chapter 3, we discussed the NIRS and VRS environmental DEA technologies, which are important extensions to the traditional CRS environmental DEA technology and enrich the foundation of using DEA to development EPIs. We also proposed several DEA type models for measuring environmental performance under the NIRS and VRS technologies. For the models dealing with nonlinear programs, we gave their linear programming equivalents. The application study on modeling the carbon emission performances of world regions showed that different ranks could be obtained under different environmental DEA technologies, which demonstrates the relevance of this study. It also suggests that the choice of an appropriate DEA model for measuring environmental performance should depend on the underlying production technology.

Previous studies including the work we presented in Chapter 3 mainly dealt with the developments and applications of radial DEA type models, which have weak discriminating power in performance comparisons. We therefore developed a non-radial DEA approach to measuring environmental performance in Chapter 4, which includes a non-radial DEA type model for multilateral environmental performance comparisons and a non-radial Malmquist environmental performance index for measuring the change of environmental performance over time. We also presented an illustrative example of 26 OECD countries using both radial and non-radial DEA type models. The results offer clear evidence that the non-radial DEA type model has higher discriminating power than radial ones in measuring pure environmental performance.

Since the non-radial DEA approach proposed does not consider the slacks in inputs and desirable outputs, in Chapter 5 we developed two slacks-based efficiency measures for modeling environmental performance, which could incorporate all the input excesses and outputs shortfalls in a standardized efficiency score. The application study on CO_2 emissions of 30 OECD countries demonstrated that slacks-based efficiency measures have high discriminating power. In empirical applications, it is suggested that slacks-based efficiency measures should be put first when both economic and environmental inefficiencies are concerned.

In the scope of MCDA methods, we proposed the so-called Shannon-Spearman measure (SSM) for comparing alternative MCDA aggregation methods in constructing CIs based on the concept of "information loss" (see Chapter 6). The validity of the SSM was verified by the Monte Carlo approach-based uncertainty analysis and variance-based sensitivity analysis techniques. We have applied the SSM to empirically compare several popular MCDA methods in constructing CIs. It was found that in most cases the WP method would result in minimum loss of information. This finding is particularly important since it is consistent with the previous theoretical study by Ebert and Welsch (2004). From our results, we suggest that the WP method be chosen to construct E&E related CIs such as environmental sustainability index when the information loss criterion is concerned by decision makers.

Using the “minimum information loss” concept, in Chapter 7, we presented an information-theoretic approach to constructing CIs inclusive of E&E related CIs. This approach seems to be more general than the several commonly used MCDA aggregation methods for constructing CIs because it can deal with both quantitative data and qualitative data. Somewhat interestingly, we found that the WP method highlighted in Chapter 6 is a special case of our approach in dealing with quantitative data. This implies that the WP method may result in minimum information loss among all the alternative aggregation methods, including those that we have and have not explored. This offers practitioners further evidence in applying the WP method to construct CIs.

Our research in Chapters 6 and 7 is based on the assumption that the weights for sub-indicators have been given. However, in practice the assignment of weights to the underlying sub-indicators is always controversial. Therefore, in Chapter 8 we proposed a linear programming approach to constructing CIs in virtue of the idea of DEA and MCDA. Compared with previous studies, the proposed approach requires no prior knowledge of the weights for sub-indicators. Since the proposed approach uses two sets of weights that are most and least favourable for each entity, it may provide a more reasonable and encompassing CI. The proposed approach has been applied to develop a CI for modeling the sustainable energy development of 18 APEC economies in 2002, which shows the flexibility and robustness of the proposed approach in constructing CIs.

9.2 Possible future research

Despite the contributions described above, the work reported in this thesis has inevitably some limitations where further investigation may be conducted. Areas where further research would be fruitful are summarized below.

In applying non-radial DEA type models to construct the environmental performance index, we did not attempt to provide a way to determine the weights that would reflect decision makers' preference information. It would therefore be meaningful to conduct further investigation in this area, such as rank information. Alone this line, the representation form of preference information and the interpretation of the resulting model must be considered simultaneously, which would be a major research challenge.

As pointed out in earlier chapters, to determine the weights for sub-indicators has always been a controversial topic in applying MCDA methods to construct CIs. Our study has provided a linear programming approach to constructing CIs which may help to avoid the subjectiveness in determining the weights. This approach is closely related to DEA and the SAW method in MCDA. As far as the information loss criterion is concerned, our research in Chapters 6 and 7 has shown that the WP method could be a good choice. It is therefore meaningful to extend our proposed linear programming approach to constructing CIs by combining DEA and the WP method in order to make good use of the strengths of these two methods. On the other hand, since only the criterion of information loss has been examined in Chapters 6 and 7, the conclusions drawn from these two chapters cannot be easily generalized.

Future research directed at making the results to be more general by considering more criteria simultaneously would be a worthwhile endeavor.

This thesis is mainly about methodological developments. The case studies presented in various chapters are based on some public datasets at the macro level. Clearly, future research may be carried out to apply our proposed models to some lower-level and more industry-based E&E issues, e.g., comparing the environmental performances of different companies in the same industry sector. This line of work will involve major effort in data collection but it may lead to results which are useful and interesting.

Finally, a number of methods/models, including those we proposed, have been used to construct CIs. This may confuse practitioners, especially those who do not have in-depth knowledge, in selecting an appropriate method or model in a specific application. It would therefore be very meaningful to provide a set of guidelines on method/model selection, as well as on the strengths and weaknesses of each method/model in different application situations.

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APPENDIX A CLASSIFICATION TABLE OF STUDIES SURVEYED ON DEA IN E&E MODELING

Table A.1 Studies of DEA in E&E with their specific features

Study	Type	Country/Region	Reference Technology			Efficiency measure	MPI	Application scheme
			Inputs	Outputs	RTS			
Abbott (2006)	A	Australia	SD	SD	C,V	R	Yes	Electricity distribution utilities
Agrell and Bogetoft (2005)	T+A	Denmark	SD	SD+NC	C,V	SB	Yes	District heating plants
Arcelus and Arocena (2005)	A	14 OECD countries	SD	SD,WD	V	R, DDF	No	Productivity estimation with CO_2
Athanssopoulos et al. (1999)	T+A	UK	SD+B	SD+B	C	NR	No	Electricity generation plants
Bagdadioglu et al. (1996)	A	Turkey	SD	SD	C,V	R	No	Electricity distribution utilities
Barla and Perelman (2005)	A	12 OECD countries	SD	SD	C	R	Yes	Productivity and SO_2 emissions
Bevilacqua and Braglia (2002)	A	Italy	SD	SD	C	R	No	Environmental performance
Boyd and McClelland (1999)	T+A	US	SD	SD,WD	C	H	No	Impacts of environmental regulations
Boyd and Pang (2000)	A	US	SD	SD	C	R	No	Energy efficiency study
Boyd et al. (2002)	T+A	US	SD	SD,WD	C	DDF	Yes	Impacts of environmental regulations
Brannlund et al. (1998)	T+A	Sweden	SD	WD	NI	Profit	No	Profit estimation with emissions
Byrnes et al. (1984)	T+A	US	SD,WD	SD	C,V,NI	R	No	Coal mines
Byrnes et al. (1988)	T+A	US	SD,WD	SD	C,V,NI	R	No	Coal mines
Callens and Tyteca (1999)	T	-	CCR multiplier form with bad outputs				No	Environmental performance
Chauhan et al. (2006)	A	India	SD	SD	C,V	R	No	Energy use efficiency study
Chien et al. (2003)	A	China (Taiwan)	SD	SD	C,V	R	No	Electricity distribution districts
Chitkara (1999)	A	India	SD	SD	C	R	Yes	Electricity generation plants
Chung et al. (1997)	T+A	Sweden	SD	WD	C	DDF	Yes	Productivity estimation with
Claggett Jr. and Ferrier (1998)	A	US	SD	SD	C,V	Cost	No	Electricity distribution utilities
Cook and Green (2005)	T+A	-	CCR multiplier form + AR method				No	Electricity generation plants
Criswell and Thompson (1996)	A	US	CCR multiplier form + AR method				No	Comparison of different power
Dyckhoff and Allen (2001)	T	-	DEA + multi-attribute value theory				No	Environmental performance
Edvardsen and Førsund (2003)	T+A	5 Euro countries	SD	SD	C	R	Yes	Electricity distribution utilities
Färe et al. (1983)	T+A	US	SD,WD	SD	C,V,NI	R	No	Electricity generation plants
Färe et al. (1985)	T+A	US	SD,WD	SD	C,V,NI	R, Cost	No	Electricity generation plants
Färe et al. (1986)	T+A	US	SD	SD,WD	V	R	No	Impacts of environmental regulations
Färe et al. (1989)	T+A	US	SD	SD,WD	C	H	No	Impacts of environmental regulations

Table A.1 Studies of DEA in E&E with their specific features [continued]

Study	Type	Country/Region	Reference Technology			Efficiency measure	MPI	Application scheme
			Inputs	Outputs	RTS			
Färe et al. (1990)	T+A	US	SD	SD	C	R	Yes	Electricity generation plants
Färe et al. (1996)	T+A	US	SD	SD,WD	C	R	No	Environmental performance
Färe et al. (2001)	T+A	US	SD	WD	C	DDF	Yes	Productivity estimation with pollutants
Färe et al. (2004)	T+A	17 OECD countries	SD	WD	C	R	No	Environmental performance
Ferrier and Hirschberg (1992)	A	US	SD	SD	C	R	No	Climate control efficiency evaluation
Førsund and Kittelsen (1998)	A	Norway	SD	SD	C	R	Yes	Electricity distribution utilities
Giannakis et al. (2005)	A	UK	SD	SD	C,V	R	Yes	Electricity distribution utilities
Golany et al. (1994)	A	Israel	SD	SD	V	R	No	Electricity generation plants
Goto and Tsutsui (1998)	A	Japan & US	CCR/BCC multiplier form + AR method				Yes	Electricity generation plants
Hattori et al. (2005)	A	Japan & UK	SD	SD+N	C,V	R	Yes	Electricity distribution utilities
Hawdon (2003)	A	33 countries	SD	SD	C,V	R	No	Gas industry
Haynes et al. (1994)	T	-	CCR multiplier form				No	Environmental performance
Hernandez-Sancho et al. (2000)	T+A	Spain	SD	WD	C	H	No	Impacts of environmental regulations
Hjalmarsson & Veiderpass	A	Sweden	SD	SD	C	R	Yes	Electricity distribution utilities
Hu and Kao (2007)	T+A	17 APEC	SD	SD	C	R, SB	No	Energy efficiency study
Hu and Wang (2006)	T+A	China	SD	SD	C	R, SB	No	Energy efficiency study
Jamasb et al. (2004)	A	US	SD	SD	C	R	No	Electricity distribution utilities
Jamasb and Pollitt (2003)	A	6 European	SD	SD	C,V	R	No	Electricity distribution utilities
Kashani (2005a)	A	Norway	SD	SD	C,V	R	Yes	Petroleum industry
Kashani (2005b)	A	UK	SD	SD	C,V	R	Yes	Petroleum industry
Korhonen and Luptacik (2004)	T+A	Europe	CCR extensions with bad outputs considered				No	Environmental performance
Korhonen and Syrjanen (2003)	A	Finland	SD+NC	SD	C,V	R	Yes	Electricity distribution utilities
Kulshreshtha and Parikh (2002)	A	India	SD	SD	C	R	Yes	Coal mines
Kumar (2006)	A	41 countries	SD	WD	C	DDF	Yes	Productivity estimation with CO_2
Lam and Shiu (2001)	A	China	SD	SD	V	R	No	Electricity generation plants
Liang et al. (2004)	T+A	China	Extensions of CCR multiplier form				No	Environmental performance
Lo et al. (2001)	A	China (Taiwan)	SD	SD	C,V	R	No	Electricity distribution utilities

Table A.1 Studies of DEA in E&E with their specific features [continued]

Study	Type	Country/Region	Reference Technology			Efficiency measure	MPI	Application scheme
			Inputs	Outputs	RTS			
Miliotis (1992)	A	Greece	SD	SD	C	R	No	Electricity distribution utilities
Munksgaard et al. (2005)	A	Denmark	SD	SD	C,V	R	No	District heating production
Murllo-Zamorano (2005)	A	18 countries	SD	SD	C	R	Yes	Productivity and energy inputs
Nag (2006)	A	India	SD	SD	C	R	No	Electricity generation plants
Olatubi and Dismukes (2000)	A	US	SD	SD	V	Cost	No	Electricity generation plants
Onut and Soner (2006)	A	Turkey	SD	SD	C	R	No	Energy efficiency study
Oude Lansink&Bezlepkin	A	Netherland	WD+NC	SD	C,V	R	No	CO_2 and energy efficiency study
Oude Lansink and Silva (2003)	A	Netherland	WD+NC	SD	C,V	R	No	CO_2 and energy efficiency study
Pacudan and de Guzman	A	Philippines	SD	SD	C,V	R	No	Electricity distribution utilities
Pahwa et al. (2002)	A	US	SD	SD	C	R	No	Electricity distribution utilities
Park and Lesourd (2000)	A	Korea	SD	SD	V	R	No	Electricity generation plants
Pasurka Jr. (2006)	T+A	US	SD	WD	C	R	No	Decomposition of air emissions
Picazo-Tadeo et al. (2005)	T+A	Spain	SD	SD,WD	V	DDF	No	Impacts of environmental regulations
Pollitt (1996)	A	UK	SD+UC	SD	C,V	R, Cost	No	Nuclear electricity generation plants
Pombo and Taborda (2006)	A	Colombia	SD	SD	C,V	R	Yes	Electricity generation plants
Price and Weyman-Jones	A	UK	SD	SD	C	R	Yes	Gas industry
Raczka (2001)	A	Poland	SD	SD	C,V	R	No	District heating plants
Ramanathan (2000)	A	India	CCR multiplier form				No	Energy efficiency study
Ramanathan (2001)	A	-	CCR multiplier form				No	Compare energy supply technologies
Ramanathan (2002)	A	64 countries	SD	SD	C	R	No	Environmental performance
Ramanathan (2005a)	A	17 countries	SD	SD	C,V	R	Yes	Environmental performance
Ramanathan (2005b)	T+A	India	SD	SD	C	SB	No	Projection of energy consumption
Resende (2002)	A	Brazil	SD	SD	C,V	R	No	Electricity distribution utilities
Sanhueza et al. (2004)	A	Chile	SD	SD	C	R	No	Electricity distribution utilities
Sarkis and Weinrach (2001)	A	US	CCR multiplier form and its extensions				No	Evaluate waste treatment technologies
Sueyoshi (1999)	T+A	Japan	SD	SD	V	Cost	No	Electricity generation plants
Sueyoshi (2000)	T+A	Japan	Stochastic extension of CCR multiplier form				No	Petroleum industry

Table A.1 Studies of DEA in E&E with their specific features [continued]

Study	Type	Country/Region	Reference Technology			Efficiency measure	MPI	Application scheme
			Inputs	Outputs	RTS			
Sueyoshi and Goto (2001)	T+A	Japan	SD	SD		R,SB	Yes	Electricity generation plants
Thakur et al. (2006)	A	India	SD	SD	C,V	R	No	State-owned electric utilities
Thompson et al. (1992)	T+A	US	CCR multiplier form + AR				No	Coal mines
Thompson et al. (1995)	T+A	US	CCR multiplier form + AR				No	Petroleum industry
Thompson et al. (1996)	A	US	CCR multiplier form + AR				No	Petroleum industry
Triantis and Otis (2004)	T	-	Dominance-based DEA extensions				No	Environmental performance
Tyteca (1997)	T+A	US	SD	WD	C	R	No	Environmental performance
Tyteca (1998)	T+A	US	CCR multiplier form with bad outputs				No	Environmental performance
Weyman-Jones (1991)	A	UK	SD	SD	C	R	No	Electricity distribution utilities
Yaisawarng and Klein (1994)	T+A	US	SD+N	WD	C,V,NI	R	No	Electricity generation plants
Yunos and Hawdon (1997)	A	27 countries	SD	SD	C,V	R	Yes	Electricity generation plants
Zaim (2004)	T+A	US	SD	WD	C	R	No	Environmental performance
Zaim and Taskin (2000a)	T+A	24 OECD countries	SD	SD,WD	C	H	No	Impacts of environmental regulations
Zaim and Taskin (2000b)	T+A	24 OECD countries	SD	SD,WD	C	H	No	Impacts of environmental regulations
Zhang and Bartels (1998)	T+A	3 countries	SD	SD	C	R	No	Electricity distribution utilities
Zhou et al. (2006b)	T+A	30 OECD countries	SD	SD,WD	C	R,SB	No	Environmental performance
Zhou et al. (in press-a)	T+A	8 world regions	SD	WD	C,V,NI	R	No	Environmental performance
Zhou et al. (2007c)	T+A	26 OECD countries	SD	WD	C	NR	Yes	Environmental performance
Zofio and Prieto (2001)	T+A	14 OECD countries	SD	SD,WD	C	H,SB	No	Environmental performance

Note: T: Theory; A: Application; SD: Strong disposable; WD: Weak disposable; NC: Non-controllable; B: Bounded; AR: Assurance region; RTS: Returns to scale; C: Constant returns to scale; V: Variant returns to scale; NI: Non-increasing returns to scale; R: Radial; NR: Non-radial; SB: Slacks-based; H: Hyperbolic; DDF: Directional distance function; MPI: Malmquist productivity index.

APPENDIX B CLASSIFICATION TABLE OF STUDIES SURVEYED ON DA IN E&E MODELING

Table B.1 Studies of DA in E&E modeling with their specific features

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Afgan and Carvalho (2002)	1	-	S/P	I	Elec	Others	-
Afgan et al. (2000)	1	-	S/P	I	EG	Others	-
Ahmed and Husseiny (1978)	1	US	S/P	VII	Elec	MAUT	-
Akash et al. (1999)	2	Jordan	S/P	III	Elec	AHP	-
Aki et al. (2003)	2	-	O/T	IV	EG	MODM	-
Allett (1986)	4	UK	O/T	VI	-	MAUT	-
Amagai and Leung (1989a)	6	Japan	S/P	II	Elec	MODM	-
Amagai and Leung (1989b)	1	Japan	S/P	II	Elec	MODM	-
Anandalingam (1987)	4	US	S/P	V	-	MAUT	-
Ang et al. (1999)	1	US	S/P	II	Elec	ID	-
Antunes et al. (2004)	1	Portugal	S/P	II	Elec	MODM	-
Aras et al. (2004)	1	Turkey	O/T	IV	RE	AHP	-
Atanackovic et al. (1998)	2	-	O/T	IV	Elec	Others	-
Atherton and French (1998)	4	-	O/T	VI	-	ID	-
Balestieri and Barros (1997)	1	-	O/T	IV	Elec	MODM	
Balson et al. (1992)	4	US	O/T	VI	-	DT	-
Barda et al. (1990)	4	Algeria	S/P	IV	Elec	ELECTRE	-
Beccali et al. (1998)	2	Italy	S/P	III	RE	ELECTRE	-
Beccali et al. (2003)	1	Italy	S/P	III	RE	ELECTRE	-
Bell (1984)	4	US	O/T	IV	Elec	DT	-
Bell et al (2000)	6	-	S/P	V	-	Meta	-
Bell et al. (2001)	4	-	S/P	V	-	Meta	-
Bell et al. (2003)	5	US	S/P	V	-	Meta	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Bergendahl et al. (1985)	6	-	S/P	I	EG	Others	-
Borges and Antunes (2003)	4	-	S/P	I	EG	MODM	-
Borison (1995)	4	US	O/T	III	Elec	ID	DT
Bose and Anandalingams (1996)	1	India	S/P	I	EG	MODM	AHP
Boyen and Wehenkel (1999)	5	-	O/T	VII	Elec	DT	-
Brar et al. (2002)	2	-	O/T	IV	Elec	MODM	-
Broussard and Wolff (1985)	6	US	S/P	III	O/G	DT	ID
Burnett et al. (1993)	4	US	O/T	III	O/G	Others	-
Capros et al. (1988)	4	Greece	S/P	IV	RE	ELECTRE	DT
Cavallaro and Ciraolo (2005)	1	Italy	S/P	III	RE	Others	-
Chambal et al. (2003)	3	US	O/T	VI	-	MAUT	-
Chattopadhyay and Ramanathan (1998)	2	-	O/T	IV	Elec	AHP	MODM
Chedid (2002)	2	Lebanon	S/P	I	RE	AHP	-
Chedid et al. (1999)	1	Lebanon	S/P	I	Mix	MODM	-
Cheng et al. (2003)	5	Canada	O/T	VI	-	Meta	-
Chung and Poon (1996)	1	China (Hong Kong)	O/T	VI	-	Others	-
Chung et al. (2003)	2	China	S/P	II	Elec	MODM	-
Climaco et al. (1995)	1	-	S/P	II	Elec	MODM	-
Crawford et al. (1978)	4	US	O/T	IV	Elec	MAUT	DT
Dey (2002)	3	India	S/P	III	O/G	AHP	-
Diakoilaki et al. (1999)	1	EU & US	S/P	I	EG	Others	-
Dunning et al. (2001)	4	US	O/T	IV	N	ID	DT
Dyer et al. (1998)	4	US	S/P	III	N	MAUT	DT

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Dyer and Lorber (1982)	4	-	O/T	III	N	MAUT	-
Elkarmi and Mustafa (1993)	1	Jordan	S/P	I	RE	AHP	-
Espie et al. (2003)	2	UK	S/P	II	Elec	MAUT	-
Evans (1984)	1	UK	S/P	III	Elec	DT	-
Faucheux and Froger (1995)	3	-	S/P	V	-	Others	-
Ferreira et al. (2004)	1	Brazil	S/P	I	O/G	MAUT	-
Georgoploulou et al. (1997)	3	Greece	S/P	I	Elec	ELECTRE	-
Georgoploulou et al. (1998)	3	Greece	S/P	IV	RE	PROMETHEE	
Georgoploulou et al. (2003)	3	Greece	S/P	V	-	ELECTRE	-
Gholamnezhad and Satty (1982)	5	US	S/P	I	EG	AHP	-
Golab et al. (1981)	4	US	S/P	III	RE	MAUT	-
Goumas and Lygerou (2000)	4	Greece	S/P	III	RE	PROMETHEE	-
Goumas et al. (1999)	1	Greece	S/P	III	RE	PROMETHEE	-
Grauer (1985)	6	-	S/P	I	EG	MODM	-
Gregory and Lichtenstein (1987)	4	US	O/T	VI	-	MAUT	-
Gungor and Arikan (2000)	5	Turkey	S/P	I	Mix	Others	-
Hamalainen (1990)	4	Finland	S/P	I	N	AHP	-
Hamalainen and Karjalainen (1989)	6	Finland	S/P	I	EG	AHP	-
Hamalainen and Karjalainen (1992)	4	Finland	S/P	I	EG	MAUT	AHP
Hamalainen et al. (2000)	4	Finland	S/P	IV	N	MAUT	-
Hamalainen and Seppalainen (1986)	5	Finland	S/P	I	Elec	AHP	-
Haralambopoulos and Polatidis (2003)	1	Greece	S/P	III	RE	PROMETHEE	-
Hobbs (1980)	4	US	S/P	IV	Elec	Meta	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Hobbs (1997)	3	-	S/P	V	-	DT	-
Hobbs et al. (1997)	3	US	S/P	V	-	DT	-
Hobbs and Horn (1997)	1	Canada	S/P	I	O/G	Meta	-
Hobbs and Maheshwari (1990)	1	US	S/P	II	Elec	DT	-
Hobbs and Meier (1994)	2	US	S/P	II	Elec	Meta	-
Hogan et al. (1985)	6	-	S/P	IV	Elec	DT	-
Hokkanen et al. (2000)	3	Finland	O/T	VI	-	Others	-
Hokkanen and Salminen (1997a)	4	Finland	O/T	VI	-	ELECTRE	-
Hokkanen and Salminen (1997b)	4	Finland	O/T	VI	-	ELECTRE	-
Hosseini (1986)	4	US	O/T	IV	O/G	DT	-
Huang et al. (1996)	1	-	S/P	V	-	AHP	-
Huang et al. (1997)	1	US	S/P	V	-	AHP	-
Iniyan and Sumathy (2000)	1	India	S/P	I	RE	MODM	-
Jackson et al. (1999)	4	US	O/T	VI	-	DT	ID
Janssen et al. (1985)	6	Netherlands	O/T	VI	-	Others	-
Jenkins (2001)	6	Canada	O/T	VI	-	Others	-
Jones and Hope (1989)	6	UK	S/P	I	EG	MAUT	-
Jones et al. (1990)	4	UK	S/P	I	EG	MAUT	-
Jorge et al. (2000)	2	-	O/T	IV	Elec	MODM	-
Judd and Weissenberger (1982)	4	-	O/T	IV	N	DT	-
Kablan (2004)	1	Jordan	S/P	I	EG	AHP	-
Kafka and Polke (1988)	5	German	O/T	IV	N	DSS	-
Kagazyo et al. (1997)	1	Japan	S/P	III	EG	AHP	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Kalika and Frant (1999)	1	-	S/P	II	Elec	Others	-
Kalika and Frant (2000)	6	Israel	S/P	II	Elec	MODM	Others
Kalika and Frant (2001)	6	Israel	S/P	II	Elec	MODM	-
Kalu (1998)	4	Nigeria	S/P	I	O/G	MODM	-
Karagiannidis and Moussiopoulos (1997)	6	Greece	O/T	VI	-	ELECTRE	-
Karni et al. (1992)	4	Israel	S/P	I	Elec	AHP	-
Kavrakoglu and Kiziltan (1983)	4	Turkey	S/P	II	Elec	MODM	-
Keefer (1991)	4	US	O/T	IV	O/G	DT	-
Keefer (1995)	4	US	O/T	IV	O/G	DT	-
Keefer et al. (1991)	4	US	O/T	IV	O/G	DT	-
Keeney (1979)	4	US	O/T	IV	Elec	MAUT	-
Keeney (1987)	4	US	O/T	IV	N	MAUT	-
Keeney et al. (1986)	4	US	O/T	III	Elec	MAUT	DT
Keeney and McDaniels (1992)	4	Canada	S/P	IV	Elec	MAUT	-
Keeney and McDaniels (1993)	4	Canada	S/P	IV	O/G	MAUT	-
Keeney and McDaniels (2001)	4	North America	S/P	V	-	MAUT	-
Keeney et al. (1995)	4	Canada	O/T	IV	Elec	MAUT	ID
Keeney and Nair (1977a)	1	US	O/T	IV	N	MAUT	-
Keeney and Nair (1977b)	6	US	S/P	IV	N	MAUT	-
Keeney and Ozernoy (1982)	4	US	S/P	V	-	MAUT	-
Keeney et al. (1987)	1	German	S/P	I	EG	MAUT	-
Keeney and Sicherman (1983)	4	US	S/P	IV	C & N	MAUT	-
Keeney and Smith (1982)	4	US	S/P	I	N	MAUT	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Keeney and von Winterfeldt (1994)	4	US	S/P	V	-	MAUT	DT
Keeney et al. (1990)	4	German	S/P	I	EG	MAUT	-
Kelly and Thorne (2001)	1	Slovakia	O/T	IV	N	MAUT	-
Kim et al. (1999)	1	Korea	S/P	I	N	MODM	AHP
Kirkwood (1982)	4	US	S/P	IV	N	MAUT	-
Kirkwood and Sarin (1985)	4	-	O/T	VI	-	MAUT	-
Koroneos et al. (2004)	1	Greece	S/P	I	RE	MODM	-
Koundinya et al. (1995)	1	India	S/P	II	Elec	MODM	AHP
Kreczko et al. (1987)	1	UK	O/T	III	N	DT	-
Kumar and Sheble (1997)	2	-	O/T	IV	Elec	ID	DT
Kunsch and Teghem Jr. (1987)	4	-	S/P	I	N	MODM	-
Lahdelma et al. (2002)	4	Finland	O/T	VI	-	Others	-
Lahdelma et al. (2001)	6	Finland	O/T	VI	-	Others	-
Lathrop and Watson (1982)	4	US	O/T	VI	-	MAUT	-
Levin et al. (1985)	4	-	S/P	II	Elec	Others	-
Linares (2002)	2	Spain	S/P	II	Elec	MODM	AHP
Linares and Romero (2000)	4	Spain	S/P	II	Elec	MODM	AHP
Lincoln and Rubin (1979)	4	US	O/T	VI	-	MAUT	-
Logan (1990)	1	-	O/T	III	Elec	DT	ID
Lootsma et al. (1990)	4	Netherlands	S/P	I	Elec	Others	-
Lootsma et al. (1986)	4	Netherlands	S/P	I	EG	AHP	-
Lotov et al. (1998)	6	US	O/T	VI	-	MODM	-
Loulou and Kanudia (1999)	4	Canada	S/P	V	-	Others	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Madden et al. (1983)	4	US	O/T	VI	-	DT	-
Mamlook et al. (2001a)	1	Jordan	S/P	I	Elec	Others	-
Mamlook et al. (2001b)	2	Jordan	S/P	I	RE	Others	-
Manne and Richels (1978)	1	US	S/P	III	N	DT	-
Martins et al. (1996)	4	-	S/P	II	Elec	MODM	-
Marttunen and Hamalainen (1995)	4	Finland	O/T	VI	-	AHP	MAUT
Matos (1999)	5	-	S/P	II	Elec	Others	-
Mavrotas et al. (1999)	4	Greece	S/P	II	Elec	MODM	-
McDaniels (1996)	3	Canada	O/T	VI	-	MAUT	-
Merkhofer and Keeney (1987)	4	US	O/T	VI	-	MAUT	-
Miettinen and Hamalainen (1997)	4	Finland	S/P	VII	-	Meta	-
Miettinen and Hamalainen (1999)	3	-	O/T	VI	-	MAUT	-
Mirasgedis and Diakoulaki (1997)	4	6 EU countries	O/T	VI	-	Others	-
Mladineo et al. (1987)	4	Yugoslavia	S/P	IV	RE	PROMETHEE	-
Mohsen and Akash (1997)	2	Jordan	S/P	I	RE	AHP	-
Mukherjee and Ma (1985)	6	-	S/P	III	Elec	MAUT	-
Niemeyer (1985)	6	-	S/P	IV	Elec	DT	-
Nigim et al. (2004)	1	Canada	S/P	I	RE	AHP	-
North and Stengel (!982)	4	US	S/P	III	N	DT	ID
Oatley et al. (1997)	2	UK	O/T	IV	Elec	ID	
Oliveria and Antunes (2004)	4	Portugal	S/P	V	-	MODM	-
Pan and Rahman (1998)	2	US	S/P	II	Elec	MAUT	AHP
Pan et al. (2000)	2	US	S/P	II	Elec	MAUT	AHP

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Peck (1985)	6	-	S/P	III	Elec	DT	-
Peerenboom et al. (1989)	4	US	O/T	III	EG	MAUT	-
Pineda-Henson et al. (2002)	3	-	O/T	VI	-	AHP	-
Poh and Ang (1999)	5	Singapore	S/P	V	-	AHP	-
Pohekar and Ramachandran (2004)	1	India	S/P	I	Mix	Others	-
Procaccia et al. (1997)	5	France	O/T	IV	Elec	DT	-
Psarras et al. (1990)	4	Greece	S/P	I	EG	MODM	-
Ramanathan (1998)	4	-	S/P	V	-	AHP	-
Ramanathan (1999)	3	-	S/P	V	-	AHP	-
Ramanathan (2001)	3	-	O/T	VI	-	AHP	-
Ramanathan and Ganesh (1993)	1	India	S/P	I	Mix	MODM	-
Ramanathan and Ganesh (1994)	1	India	S/P	I	Mix	MODM	-
Ramanathan and Ganesh (1995a)	1	India	S/P	I	Mix	MODM	AHP
Ramanathan and Ganesh (1995b)	5	India	S/P	I	Mix	MODM	AHP
Renn (2003)	1	Germany	S/P	I	EG	MAUT	-
Ridgley (1996)	1	11 countries/regions	S/P	V	-	MODM	-
Rios Insua et al. (2000)	4	-	O/T	VI	-	MAUT	-
Rios Insua and Salewicz (1995)	4	Zambia	O/T	IV	RE	MAUT	-
Rogers and Bruen (1998)	4	-	O/T	VI	-	ELECTRE	-
Roy and Bouyssou (1986)	4	US	S/P	IV	N	ELECTRE	-
Rubin (1985)	6	-	S/P	IV	N	DT	-
Saaty (1979)	5	US	S/P	VII	O/G	AHP	-
Saaty and Bennett (1977)	6	-	S/P	III	Elec	AHP	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Saaty and Gholammehad (1981)	1	-	S/P	VII	O/G	AHP	-
Saaty and Gholammehad (1982)	2	US	O/T	VI	-	AHP	-
Saaty et al. (1977)	1	-	S/P	I	EG	AHP	-
Salminen et al. (1998)	4	Finland	O/T	VI	-	Meta	-
Sanghvi and Limaye (1979)	1	US	S/P	II	Elec	DT	-
Sarin et al. (1979)	4	-	O/T	III	RE	MAUT	-
Saxena et al. (1989)	6	India	S/P	I	EG	AHP	-
Schimmelpfennig (1995)	1	-	S/P	I	RE	DT	-
Schulz and Stehfest (1984)	4	Germany	S/P	I	EG	MODM	-
Seppala et al. (2002)	3	-	O/T	VII	-	Meta	-
Sheble (1999)	2	US	O/T	IV	Elec	DT	-
Siddiqi (2000)	2	US	S/P	IV	Elec	DT	-
Siskos and Hubert (1983)	4	France	S/P	I	Mix	ELECTRE	-
Siskos et al. (1986)	4	France	O/T	VI	-	ELECTRE	-
Skikos and Machias (1992)	2	Greece	O/T	VII	RE	Others	-
Smith and Mccardle (1999)	4	US	S/P	III	O/G	DT	-
Solnes (2003)	3	Iceland	S/P	III	O/G	AHP	-
Son and Min (1998)	1	-	S/P	IV	Elec	AHP	-
Stewart Jr. and Horowitz (1991)	5	US	O/T	III	O/G	AHP	-
Suganthi and William (2000)	1	India	S/P	I	RE	MODM	-
Taha and Wolf (1996)	4	US	O/T	IV	Elec	DT	-
Therdyothin et al. (1992)	1	Thailand	S/P	II	Elec	AHP	-
Toland et al. (1998)	4	US	O/T	VI	-	Meta	-

Table B.1 Studies of DA in E&E modeling with their specific features [Continued]

Study	Source of publication	Country/region	A.L.	A.A.	E.T.	Methods	
						Major	Minor
Topcu and Ulengin (2005)	1	Turkey	S/P	I	Mix	PROMETHEE	-
Tzeng et al. (2004)	1	China (Taiwan)	S/P	V	-	AHP	Others
Tzeng and Shiau (1987)	1	China (Taiwan)	S/P	I	EG	ELECTRE	Others
Tzeng et al. (1992)	1	China (Taiwan)	S/P	I	EG	PROMETHEE	AHP
Tzeng and Tsaur (1993)	1	China (Taiwan)	S/P	V	-	PROMETHEE	AHP
Tzeng et al. (2002)	3	China (Taiwan)	S/P	V	-	AHP	Others
Vaillancourt and Waaub (2005)	4	15 countries/regions	S/P	V	-	PROMETHEE	-
Varis et al. (1989)	5	Finland	O/T	VI	-	ID	-
Varis and Kuikka (1989)	6	Finland	O/T	VI	-	ID	-
Von Winterfeldt (1982)	4	UK	O/T	IV	O/G	DT	-
Von Winterfeldt and Schweitzer (1998)	4	US	S/P	III	N	MODM	-
Voropai and Ivanova (2002)	2	Russia	S/P	II	Elec	MAUT	-
Vuk et al. (1991)	4	Slovenia	O/T	VI	-	PROMETHEE	-
Wang and Feng (2002)	1	China	S/P	I	EG	AHP	-
Wang and McTernan (2002)	3	US	O/T	VI	-	DT	-
Wehenkel and Pavella (1986)	5	-	O/T	IV	Elec	DT	-
Winebrake and Creswick (2003)	5	US	S/P	III	RE	AHP	-
Wu and Wei (1997)	1	China	S/P	V	-	AHP	-
Zhu and Irving (1996)	2	China	O/T	IV	Elec	MODM	AHP
Ziont and Deshpande (1978)	6	US	S/P	I	EG	MODM	-
Ziont and Deshpande (1981)	6	US	S/P	I	EG	MODM	-

Note: A.L.: Application level; A.A.: Application area; E.T.: Energy type. For the definitions of the symbols used in the columns of source of publication, A.L., A.A., E.T. and Methods, please refer back to Sections 2.2.1 and 2.2.2.

APPENDIX C PROOFS OF SOME RESULTS

C.1

Proof. Assume that $(\mathbf{x},\mathbf{y},\mathbf{u}) \in T_{VRS}$. Then there exists $\alpha, z_1, \cdots, z_K$ such that $(\mathbf{x},\mathbf{y},\mathbf{u})$ satisfies the equations in (3.5). If we let $\alpha^* = \alpha / \theta$, then we have

$$\alpha^*(\theta y_m) = (\alpha/\theta)(\theta y_m) = \alpha y_m \le \sum_{k=1}^{K} z_k y_{mk}$$

$$\alpha^*(\theta u_j) = (\alpha/\theta)(\theta u_j) = \alpha u_j = \sum_{k=1}^{K} z_k u_{jk}$$

It implies that $(\mathbf{x},\theta\mathbf{y},\theta\mathbf{u})$ also satisfies the equations in (3.5), i.e., $(\mathbf{x},\theta\mathbf{y},\theta\mathbf{u}) \in T_{VRS}$.

Since $\sum_{k=1}^{K} z_k = 1$, $\alpha u_j = \sum_{k=1}^{K} z_k u_{jk} \le \max\{u_{jk}, k = 1,\cdots,K\}$. If $u_j \to 0$, $\alpha \to \infty$.

Since $\alpha y_m \le \sum_{k=1}^{K} z_k y_{mk} \le \max\{y_{mk}, k = 1,\cdots,K\}$, we have $y_m \to 0$.

C.2

Proof. Without loss of generality, we assume that the first entity has a value dominating other entities for the first sub-indicator, i.e., $I_{11} = \max\{I_{i1}, i = 1,2,\cdots,m\}$. Obviously, $w_{11}^g = 1/I_{11}$, $w_{12}^g = \cdots = w_{1n}^g = 0$ is a feasible solution to (8.1) for the first entity. Since $w_{11}^g I_{11} + w_{12}^g I_{12} + \cdots w_{1n}^g I_{1n} = 1$, the set of weights is an optimal solution to (8.1) for the first entity. Therefore, the first entity will obtain an aggregated performance score of 1.

C.3

Definition C.3.1: Entity i is a strongly nondominated entity (compared to the convex combinations of other entities) if there is no $\lambda_1, \cdots, \lambda_{i-1}, \lambda_{i+1}, \cdots, \lambda_m$ such that $\lambda_1 I_{1j} + \cdots + \lambda_{i-1} I_{i-1,j} + \lambda_{i+1} I_{i+1,j} + \cdots + \lambda_m I_{mj} \geq I_{ij}$ for $j = 1, \cdots, n$ and for at least one index of j such that the inequality holds, where $\lambda_k \geq 0, k = 1, \cdots, i-1, i+1, \cdots, m$ and $\lambda_1 + \cdots + \lambda_{i-1} + \lambda_{i+1} + \cdots + \lambda_m = 1$.

Definition C.3.2: Entity i is a weakly nondominated entity (compared to the convex combinations of other entities) if there is no $\lambda_1, \cdots, \lambda_{i-1}, \lambda_{i+1}, \cdots, \lambda_m$ such that $\lambda_1 I_{1j} + \cdots + \lambda_{i-1} I_{i-1,j} + \lambda_{i+1} I_{i+1,j} + \cdots + \lambda_m I_{mj} > I_{ij}$ for $j = 1, \cdots, n$, where $\lambda_k \geq 0$, $k = 1, \cdots, i-1, i+1, \cdots, m$ and $\lambda_1 + \cdots + \lambda_{i-1} + \lambda_{i+1} + \cdots + \lambda_m = 1$.

Proof. Without loss of generality, we assume that the first entity is a strongly or weakly nondominated entity (compared to the convex combinations of other entities). The dual problem of (8.1) for the first entity can be written as follows:

$$\begin{aligned} &\min \sum_{k=1}^{m} y_k \\ &\text{s.t. } I_{1j} y_1 + I_{2j} y_2 + \cdots + I_{mj} y_m \geq I_{1j}, \ j = 1,2,\cdots,n \\ &\quad\ y_k \geq 0, \ k = 1,2,\cdots,m \end{aligned} \tag{C.1}$$

Assume that the optimal solution to model (C.1) is $y_1^*, y_2^*, \cdots, y_m^*$. Obviously, at least one index of k such that $y_k^* > 0$. Now consider the following two cases:

Case I. $y_2^* = y_3^* = \cdots = y_m^* = 0$

According to the definition of (C.1), $y_1^* = 1$ and the optimal objective value of (C.1) is 1. Therefore, the optimal objective value of (8.1) for the first entity is 1.

Case II. At least one of $y_k^*, k = 2, \cdots, m$ is larger than 0.

In the case, provided that the optimal objective value of (8.1), i.e., gI_1, is less than 1. As a result, y_1^* must be less than 1. Since model (C.1) is the dual problem of (8.1), we have

$$y_1^* + y_2^* + \cdots + y_m^* = gI_1 < 1 \tag{C.2}$$

$$I_{2j} y_2^* + \cdots + I_{mj} y_m^* \geq I_{1j}(1 - y_1^*), \ \ j = 1,2,\cdots,n \tag{C.3}$$

From (C.3), we have

$$\left(\frac{y_2^*}{1 - y_1^*}\right) I_{2j} + \cdots + \left(\frac{y_m^*}{1 - y_1^*}\right) I_{mj} \geq I_{1j}, \ \ j = 1,2,\cdots,n \tag{C.4}$$

From (C.2), we have

$$1 - y_1^* > gI_1 - y_1^* = y_2^* + \cdots + y_m^* \tag{C.5}$$

Combing the (C.4) and (C.5), we have

$$\left(\frac{y_2^*}{y_2^* + \cdots + y_m^*}\right) I_{2j} + \cdots + \left(\frac{y_m^*}{y_2^* + \cdots + y_m^*}\right) I_{mj} > I_{1j}, \ \ j = 1,2,\cdots,n \tag{C.6}$$

Since the left hand side of (C.6) is a convex combination of entities 2 to *n*, the first entity is a weakly (and strongly) donominated entity (compared to the convex combination of other entities). This contradicts the condition given in the problem. As a result, our assumption that the optimal objective value of (8.1) for the first entity is less than 1 does not hold.

Summarizing Case I and II, we find that the optimal objective value of (8.1) for the first entity is 1. Proof is completed.

APPENDIX D MATLAB FUNCTION OF THE ENVIRONMENTAL PERFORMANCE INDEXES UNDER DIFFERENT ENVIRONMENTAL DEA TECHNOLOGIES

```
% This function is used to calculate EPIs under the CRS, NIRS and VRS
environmental DEA technologies, namely PEI1, PEI2, PEI3 and MEI. For
the technical details, see Chapter 3.
% The number of DMUs, inputs, desirable outputs and undesirable
outputs, i.e., K, N, M and J are function parameters.

function [PEI1 PEI2 PEI3 MEI]=epi(data,K,N,M,J)
% "data" (a K*(N+M+J) matrix) is arranged by the following rules:
     % Rows-DMUs; columns-inputs, desirable and undesirable outputs.

X=data(:,1:N);
% X: Input matrix, X(i,j) denotes the j-th input for DMUi
Y=data(:,N+1:N+M);
% Y: Desirable output matrix, Y(i,j) denotes the j-th desirable
output for DMUi
U=data(:,N+M+1:N+M+J);
% U: Undesirable output matrix, U(i,j) denotes the j-th undesirable
output for DMUi

% calculating pure EPI under CRS environmental DEA technology
for i=1:K
    [x1(:,i),fval1(i)]=linprog([zeros(K,1);1],[X' zeros(N,1);-Y'
zeros(M,1)],[X(i,:)';-Y(i,:)'],[U' -U(i,:)],zeros(J,1),zeros(K+1,1));
end
PEI1=fval1';

% calculating pure EPI under NIRS environmental DEA technology
for i=1:K
    [x2(:,i),fval2(i)]=linprog([zeros(K,1);1],[X' zeros(N,1);-Y'
zeros(M,1);ones(1,K) 0],[X(i,:)';-Y(i,:)';1],[U' -
U(i,:)],zeros(J,1),zeros(K+1,1));
end
PEI2=fval2';

% calculating pure EPI under VRS environmental DEA technology
for i=1:K
    [x3(:,i),fval3(i)]=linprog([zeros(K+1,1);1],[X' -X(i,:)'
zeros(N,1);-Y' zeros(M,2)],[zeros(N,1);-Y(i,:)'],[U' zeros(J,1) -
U(i,:)';ones(1,K) -1
0],zeros(J+1,1),zeros(K+2,1),[inf(K,1);1;inf(1)]);
end
PEI3=fval3';

% calculating mixed EPI under VRS environmental DEA technology
for i=1:K
    [x4(:,i),fval4(i)]=linprog([zeros(K+1,1);1],[X' -X(i,:)'
zeros(N,1);-Y' zeros(M,2)],[zeros(N,1);-Y(i,:)'],[U' zeros(J,1) -
U(i,:)';ones(1,K) -1 0],zeros(J+1,1),zeros(K+2,1));
end
MEI=fval4';
```

APPENDIX E MATLAB FUNCTION OF THE SLACKS-BASED EFFICIENCY MEASURES FOR MODELING ENVIRONMENTAL PERFORMANCE

```
% This function can be used to calculate two slacks-based EPIs under
the CRS environmental DEA technologies, namely SBEI1 and SBEI2. For
more technical details, see Chapter 5.
% The number of DMUs, inputs, desirable outputs, undesirable outputs
are the parameters K, N, M, J, respectively.

function [lamda SBEI1 SBEI2 theta1 theta2]=sbei(data,K,N,M,J)

% “data” is arranged by the following rules:
    % Rows-DMUs; columns-inputs, desirable and undesirable outputs.
    % Dimension-K*(N+M+J)

X=data(:,1:N);
% X: input matrix, X(i,j) denotes the j-th input for DMUi
Y=data(:,N+1:N+M);
% Y: desirable output matrix, Y(i,j) denotes the j-th desirable
output for DMUi
U=data(:,N+M+1:N+M+J);
% U: undesirable output matrix, U(i,j) denotes the j-th undesirable
output for DMUi


options=optimset('largescale','off','simplex','on');
% use simplex to solve small or median scale problem

% Calculation of SBEI1

% Step 1: calculate the radial undesirable outputs orientation
efficiency score
for i=1:K
    [x1(:,i),fval1(i)]=linprog([zeros(K,1);1],[X' zeros(N,1);-Y'
zeros(M,1)],[X(i,:)';-Y(i,:)'],[U' -U(i,:)'], zeros(J,1),
zeros(K+1,1),[],[],options);
end
% The number of decision variables, i.e., x1, is K+1 for every LP
lamda=fval1';

% Step 2: Caluclate the economic inefficiency score after adjusting
undesirable outputs
for i=1:K
    [x2(:,i),fval2(i)]=linprog([zeros(1,K) -1/N./X(i,:) zeros(1,M)
1]',[],[],[X' eye(N) zeros(N,M) -X(i,:)';Y' zeros(M,N) -eye(M) -
Y(i,:)';U' zeros(J,N+M) -lamda(i).*U(i,:)';zeros(1,K+N) 1/M./Y(i,:)
1],[zeros(N+M+J,1);1],zeros(K+N+M+1,1),[],[],options);
end
% The number of decision variables, i.e., x2, is K+N+M+1 for every LP

% Step 3: Calculate SBEI1
SBEI1=lamda.*fval2';
```

```
% Calculation of SBEI2
% Step 1: Calculate slacks-based efficiency scores when undesirable
outputs
          % are not considered
for i=1:K
    [x3(:,i),fval3(i)]=linprog([zeros(1,K) -1/N./X(i,:) zeros(1,M)
1]',[],[],[X' eye(N) zeros(N,M) -X(i,:)';Y' zeros(M,N) -eye(M) -
Y(i,:)';zeros(J,K+N) 1/M./Y(i,:) 1],[zeros(N+M,1);1],
zeros(K+N+M+1,1),[],[],options);
end
% The number of decision variables, i.e., x3, is K+N+M+1
theta1=fval3';

% Step2: Calculate slacks-based efficiency scores when undesirable
outputs
         % are considered
for i=1:K
    [x4(:,i),fval4(i)]=linprog([zeros(1,K) -1/N./X(i,:) zeros(1,M)
1]',[],[],[X' eye(N) zeros(N,M) -X(i,:)';Y' zeros(M,N) -eye(M) -
Y(i,:)';U' zeros(J,N+M) -U(i,:)';zeros(J,K+N) 1/M./Y(i,:) 1],
[zeros(N+M+J,1);1],zeros(K+N+M+1,1),[],[],options);
end
% The number of decision variables, i.e., x4, is K+N+M+1
theta2=fval4';

% Step 3: Calculate SBEI2
SBEI2=theta1./theta2;
```

APPENDIX F MATLAB FUNCTION OF THE LINEAR PROGRAMMING APPROACH TO CONSTRUCTING COMPOSITE INDICATORS

```
% This function is based on the models in Chapter 8, which can be
used to derive the CIs under different scenarios

function [CI,gI,gw,bI,bw]=mpci(data,lamda,L,U)
% data: sub-indicator matrix  lamda: adjusting parameter, 0<=lamda<=1
% L: column vector for lower limits U: column vector for upper limits

[M,N]=size(data);

% Use simplex to solve small or median scale problem
options=optimset('largescale','off','simplex','on');

% Calculation of gI
for i=1:M
    % Generate the left and right hand sides for the constraints due
to weight restrictions
    ALU=[L*data(i,:)-diag(data(i,:));-U*data(i,:)+diag(data(i,:))];
    bLU=zeros(2*N,1);
    % Solving optimization problem
    [gw(:,i),gI(i,1)]=linprog(-data(i,:),[data;ALU],[ones(M,1);bLU],
[],[],zeros(N,1),[]);
end
gI=-gI;

% Calculation of bI
for i=1:M
    % Generate the left and right hand sides for the constraints due
to weight restrictions
    ALU=[L*data(i,:)-diag(data(i,:));-U*data(i,:)+diag(data(i,:))];
    bLU=zeros(2*N,1);
    % Solving optimal problem
    [bw(:,i),bI(i,1)]=linprog(data(i,:),[-data;ALU],[-ones(M,1);bLU],
[],[],zeros(N,1),[]);
end

% Calculation of CI
for i=1:M
    CI(i,1)=lamda*(gI(i,1)-min(gI))/(max(gI)-min(gI))+(1-
lamda)*(bI(i,1)-min(bI))/(max(bI)-min(bI));
end
```