An evaluation of energy-environment-economic efficiency for EU, APEC and ASEAN countries: design of a Target-Oriented DFM model with fixed factors in Data Envelopment Analysis

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Abstract

This paper aims to offer an advanced assessment methodology for sustainable national energy-environment-economic efficiency strategies, based on an extended Data Envelopment Analysis (DEA) in which distinct countries are regarded as Decision Making Units (DMUs). The aim is to show how much various countries can improve their combined efficiency profile. Standard DEA models use a uniform input reduction or a uniform output increase in their improvement projections. The development of novel efficiency-improvement solutions based on DEA has greatly progressed in recent years. A recent example is the Distance Friction Minimisation (DFM) method, which aims to generate an original contribution to efficiency-enhancement strategies by deploying a weighted projection function, while it may address both input reduction and output increase as a strategy of a DMU. To design a feasible improvement strategy for low-efficiency DMUs, we develop a Target-Oriented (TO) DFM model that allows for less ambitious reference points that remain below the efficiency frontier. The TO-DFM model calculates then a Target-Efficiency Score (TES) for inefficient DMUs. This model is able to compute an input reduction value and an output increase value in order to achieve this TES. However, in many real-world cases the input factor may not be immediately flexible or adjustable, due to indivisibility (or lumpiness) of the input factor. Usually, a DEA model does not include such a non-controllable or a fixed factor. In this study, we aim to integrate the TO-DFM model with a fixed factor (FF) model in order to cope with realistic circumstances in our search for an efficiency improvement projection in combined energy-environment-economic strategies of individual nations.

The present paper aims to offer an original contribution to efficiency enhancement in national sustainability strategies by means of the above described DEA approach. After the description of the methodology, a complementary Super-efficiency (SE) approach to DEA is used in our comparative study on the efficiency assessment of energy-environment-economic targets for the EU, APEC and ASEAN (A&A) countries, using appropriate data sets ranging from the years 2003 to 2012. In the present study, we consider two inputs (primary energy consumption and population) and two outputs (CO_2 and GDP), including a fixed input factor, namely the 'population' production factor that cannot be flexibly adjusted. On the basis of our DEA analysis results, it appears that EU countries exhibit generally a higher efficiency than A&A countries. In particular, it turns out that Cyprus, Luxembourg and Ireland may be seen as super-efficient countries in the EU, and Brunei as a high performance country in A&A. The above-mentioned TO-DFM-FF projection model is used to address realistic circumstances and requirements in an operational sustainability strategy for efficiency improvement in inefficient countries in the A&A region.

Keywords: Data Envelopment Analysis (DEA), Fixed Factor, Energy-Environment-Economic efficiency, EU, APEC, ASEAN countries, Target-oriented DEA, Super-efficiency
JEL code: C00, Q48

1. Introduction

Economic growth has to be accompanied simultaneously by resource and environment conservation in a sustainable world. In 2014, the 'International Energy Efficiency Scorecard', published by ACEEE (American Council for an Energy-Efficient Economy)(2014), pointed out: 'Countries can preserve their resources, address global warming, stabilize their economies, and reduce the costs of their economic outputs by using energy more efficiently—an eminently achievable goal.' This report analysed the world's 16 largest economies (countries/regions). The report looked at 31 criteria, divided roughly in half between policies and quantifiable performance in order to evaluate how efficiently these economies use energy. The scores for the policy criteria were based on the presence in a country/region of a best-practice policy. However, this evaluation relied heavily on rather subjective policy criteria. Therefore, the actual conditions of energy efficiency for each country/region were not evaluated in an appropriate or testable manner.

A standard tool by which to judge efficiency among different actors is Data Envelopment Analysis (DEA), proposed by Charnes, Cooper and Rhodes (1978) (hereafter CCR: see Appendix A1). This has become over the past decades an established quantitative assessment method in the evaluation literature. Seiford (2005) mentions even more than 2800 published articles on DEA in various fields and this number is nowadays already much higher. Meanwhile, there are in a sustainability context also several studies that have applied DEA models to measure aggregate energy-environment-economic efficiency among countries or regions, regarded as Decision Making Units (DMUs). For example, Zhou et al. (2008) presented a literature survey on the application of DEA to energy and environmental (E&E) studies, followed by a classification of 100 publications in this field. This study argues that all this research which provides lists of DMUs is confined to just one country or major region, such as the OECD, APEC, and the EU, or developing countries, but without a rigorous cross-regional comparison, for example, the EU vs. APEC and ASEAN (hereafter A&A). A&A countries are places where remarkable economic development is taking place, but comparing them from the viewpoint of energy-environment-economic efficiency with the performance of EU countries brings to light often contrasting findings. Martínez (2011) measures energy-efficiency development in non-energy-intensive sectors (NEISs) in both Germany and Colombia, based on a DEA model. And Wu et al. (2013) apply a DEA model - and related Malmquist indices - for an efficiency evaluation of regions in China. The above list of studies shows that comparative efficiency analysis in the energy-environment sector using DEA models has increasingly become an important research topic in recent years (see also Suzuki et al. 2011).

It should be noted that DEA was originally developed to analyse the relative efficiency of a DMU by constructing a piecewise linear production frontier and projecting the performance of each DMU onto that frontier. A DMU that is located on the frontier is efficient, whereas a DMU that is off on the frontier is inefficient. The wealth of DEA studies has demonstrated that an inefficient DMU can become efficient by reducing its inputs, or by increasing its outputs. In the standard DEA approach, this is achieved by a uniform reduction in all inputs (or a uniform increase in all outputs). However, in principle, there are an infinite number of possible improvements that could be implemented in order to reach the efficient frontier, and, hence, there are many solutions should a DMU plan to enhance its efficiency. We refer to the standard textbook of Cooper et al. (2006) for a full exposition.

It is noteworthy that in the past few decades, the existence of many possible efficiency improvement solutions has prompted a rich literature on the methodological integration of Multiple Objective Linear Programming (MOLP) and DEA models. We will offer a concise overview here (see also Suzuki et al. (2010)). One of the first contributions was offered by Golany (1988) who proposed an interactive MOLP procedure, which aimed at generating a set of efficient points for a DMU. This model allows a decision maker to select a preferred set of output levels, given the input levels. Likewise, Thanassoulis and Dyson (1992) developed adjusted models, which can be used to estimate alternative input and output levels, in order to render relatively inefficient DMUs more efficient. These models are able to incorporate preferences for a potential improvement of individual input and output levels. The resulting target levels reflect the user's relative preference over alternative paths to efficiency. Later on, Joro et al. (1998) demonstrated the analytical similarity between a DEA model and a Reference Point Model in a MOLP formulation from a mathematical viewpoint. In addition, the Reference Point Model offers suggestions which make it possible to search freely on the efficient frontier for good solutions, or for the most-preferred solution (MPS), based on the decision maker's preference structure. Furthermore, Halme et al. (1999) developed a Value Efficiency Analysis (VEA), which included the decision maker's preference information in a DEA model. The foundation of VEA originates from the Reference Point Model in a MOLP context. Here, the decision maker identifies the MPS, such that each DMU could be evaluated by means of the assumed value function based on the MPS approach. A further development of this approach was made by Korhonen and Siljamäki (2002), who dealt with several practical aspects related to the use of a VEA. In addition, Korhonen et al. (2003) developed a multiple objective approach, which allows for changes within the time frame concerned. Lins et al. (2004) proposed two multi-objective approaches that determine the basis for the incorporation of a posteriori preference information. The first of these models is called Multiple Objective Ratio Optimization (MORO), which optimizes the ratios between the observed and the target inputs (or outputs) of a DMU. The second model is called Multiple Objective Target Optimization (MOTO), which directly optimizes the target values. Washio et al. (2012) suggested four types of improvements for making inefficient DMUs efficient in the CCR framework, by introducing a decision-maker's policy model with a minimal change of input and output values. More recently, Yang and Morita (2013) utilised DEA and Nash bargaining game (NBG) theory to help improve inefficient banks in the financial sector, in order to: (i) make an inefficient bank Pareto-optimal from multiple perspectives, which could avoid being dissatisfied with some particular management or market perspectives; and (ii) change its attributes and provide various improvement schemes for decision makers. Furthermore, Suzuki et al. (2010) proposed a Distance Friction Minimization (DFM) model that is based on a generalized distance function and serves to improve the performance of a DMU by identifying the most appropriate movement towards the efficiency frontier surface. The DFM model is able to calculate either an optimal input reduction value or an optimal output increase value in order to reach an efficiency score of 1.000, even though in reality this might be hard to achieve for low-efficiency DMUs. Recently, Suzuki et al. (2015) presented a newly developed adjusted DEA model, emerging from a blend of the DFM and the target-oriented (TO) approach based on a Super-Efficiency model, for generating an appropriate efficiency-improving projection model. The TO approach specifies a target-efficiency score (TES) for inefficient DMUs. This approach can compute an input reduction value and an output increase value in order to achieve a higher TES. However, in many cases, the input factor may not be flexible or adjustable due to the indivisible nature or inertia in the input factor. Usually, the DEA model does not allow for a non-controllable or a fixed input factor.

In this study, we will present empirical results from a comparative assessment on energy-efficiency in various countries, by integrating the TO-DFM model with a fixed factor (FF) model (see Suzuki et al. 2011) in order to cope with realistic circumstances in our search for a feasible efficiency improvement projection. After the description of the methodology, a Super-efficiency model (Andersen and Petersen (1993): see Appendix A2) for DEA is used in a comparative study on the efficiency assessment of energy-environment-economic goals for EU and A&A countries, using appropriate data sets ranging from 2003 to 2012. In this study, we consider two inputs (primary energy consumption and population) and two outputs (CO_2 and GDP), including a fixed input factor related to population. In this comparative analysis, we will conceive of 'population' as a production factor that cannot be flexibly adjusted in a short period of time. The above-mentioned TO-DFM-FF projection model is used to consider realistic circumstances and requirements in an operational strategy for a feasible efficiency improvement in inefficient countries in A&A.

The paper is organized as follows. Section 2 describes our DFM methodology, while Section 3 introduces the combined TO-DFM model. Section 4 proposes the newly developed model, which is a Fixed Factor (FF) model in the framework of a TO-DFM model. Section 5 then presents an application of the methodology to an efficiency analysis of "Energy-Environment-Economics" performance of the EU and A&A countries. Finally, Section 6 offers some conclusions.

2. Outline of the Distance Friction Minimisation (DFM) approach

An efficiency-improvement solution in the original DEA model (abbreviated hereafter as the CCR-input model: see Appendix A1) requires that the input values are reduced radially by a uniform ratio θ^* (θ^* =OD'/OD in Figure A1).

The (v^*, u^*) values obtained as an optimal solution for formula (A.1) result in a set of optimal weights for DMU_o. Hence, (v^*, u^*) is the set of most favourable weights for DMU_o, measured on a ratio scale. v_m^* is the optimal weight for input item *m*, and its magnitude expresses how much in relative terms the item is contributing to efficiency. Similarly, u_s^* does the same for output item *s*. These values show not only which items contribute to the performance of DMU_o, but also the extent to which they do so. In other words, it is possible to express the distance frictions (or alternatively, the potential increases) in improvement projections.

We use the optimal weights u_s^* and v_m^* from (A.1), and then describe the efficiency improvement projection model. A visual presentation of this approach (DFM projection) is given in Figures 1 and 2 (see also Suzuki et al. (2010)).

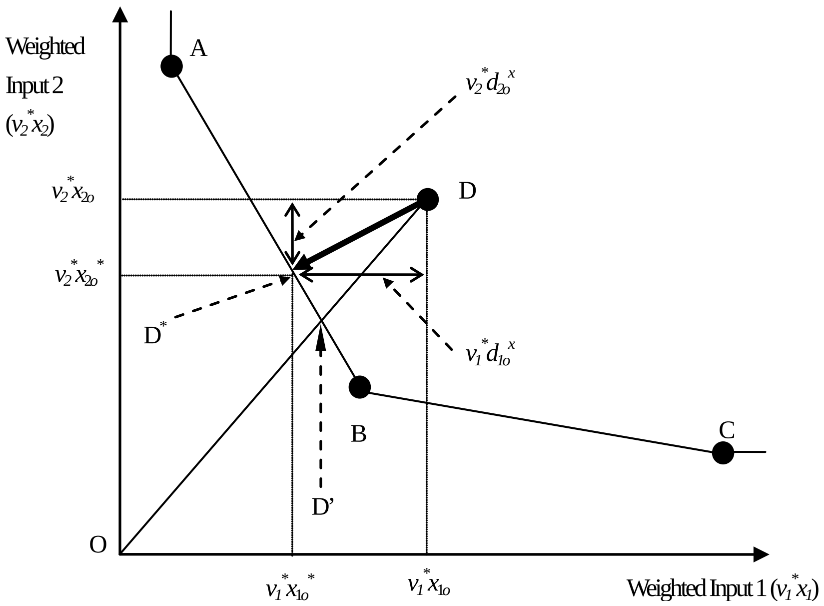


Figure 1 Illustration of the DFM approach (Input-$v_i^* x_i$ space)

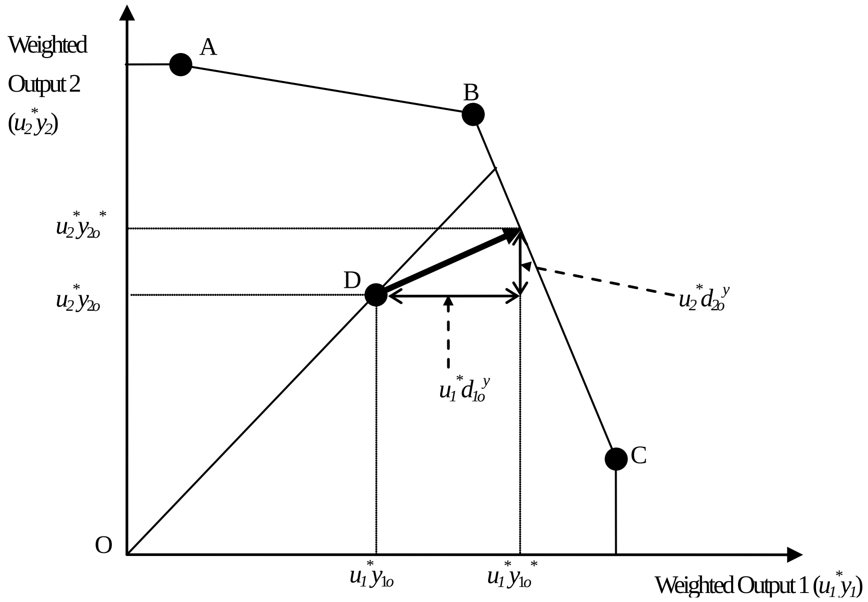


Figure 2 Illustration of the DFM approach (Output - $u_r^* y_r$ space)

In this approach, a generalized distance indicator is employed to assist a DMU to improve its efficiency by a movement towards the efficiency frontier surface. Of course, the direction of efficiency improvement depends on the input/output data characteristics of the DMU. It is now appropriate to define the projection functions for the minimization of distance by using a Euclidean distance in weighted space. As mentioned earlier, a suitable form of multidimensional projection functions that serves to improve efficiency is given by a Multiple Objective Quadratic Programming (MOQP) model, which aims to minimize the aggregated input reductions, as well as the aggregated output increases. Thus, the DFM approach can generate a new contribution to efficiency enhancement problems in decision analysis by employing a weighted Euclidean projection function, and, at the same time, it might address both input reduction and output increase. Here, we only briefly describe the various steps (for more details, see Suzuki et al., 2010, Suzuki and Nijkamp 2011, and Kourtit et al. 2013).

First, the distance function Fr^x and Fr^y is specified by means of (2.1) and (2.2), which are defined by the Euclidean distance shown in Figures 1 and 2. Next, the following MOQP is solved by using d_{mo}^x (a reduction of distance for x_{io}) and d_{so}^y (an increase of distance for y_{so}) as variables:

$$\min Fr^x = \sqrt{\sum_m \left(v_m^* x_{mo} - v_m^* d_{mo}^x\right)^2} \tag{2.1}$$

$$\min Fr^y = \sqrt{\sum_s \left(u_s^* y_{so} - u_s^* d_{so}^y\right)^2} \tag{2.2}$$

$$\text{s.t.} \quad \sum_m v_m^* \left(x_{mo} - d_{mo}^x \right) = \frac{2\theta^*}{1+\theta^*} \tag{2.3}$$

$$\sum_s u_s^* \left(y_{so} + d_{so}^y \right) = \frac{2\theta^*}{1+\theta^*} \tag{2.4}$$

$$x_{mo} - d_{mo}^x \geq 0 \tag{2.5}$$

$$d_{mo}^x \geq 0 \tag{2.6}$$

$$d_{so}^y \geq 0\,, \tag{2.7}$$

where x_{mo} is the amount of input item m for any arbitrary inefficient DMU$_o$; and y_{so} is the amount of output item s for any arbitrary inefficient DMU$_o$. The constraint functions (2.3) and (2.4) refer to the target values of input reduction and output augmentation. The fairness in the distribution of contributions from the input and output side to achieve efficiency is established as follows. The total efficiency gap to be covered by inputs and outputs is (1-θ*). The input and the output side contribute according to their initial levels 1 and θ*, implying shares θ*/(1+θ*) and 1/(1+θ*) in the improvement contribution. Clearly, the contributions from both sides equal (1-θ*)[θ*/(1+θ*)] and (1-θ*)[1/(1+θ*)].

It is now possible to determine each optimal distance d_{mo}^{x*} and d_{so}^{y*} by using the MOQP model (2.1)-(2.7). The distance minimization solution for an inefficient DMU$_o$ can be expressed by means of formulas (2.8) and (2.9):

$$x_{mo}^* = x_{mo} - d_{mo}^{x*}\,; \tag{2.8}$$

$$y_{so}^* = y_{so} + d_{so}^{y*}\,. \tag{2.9}$$

By means of the above described DFM model, it is possible to present a new efficiency-improvement solution based on the standard CCR projection. This means an increase in new options for efficiency-improvement solutions in DEA. The main advantage of the DFM model is that it yields an outcome on the efficient frontier that is as close as possible to the DMU's input and output profile (see Figure 3). This approach has functioned as an ingredient for many recent DEA studies of the authors.

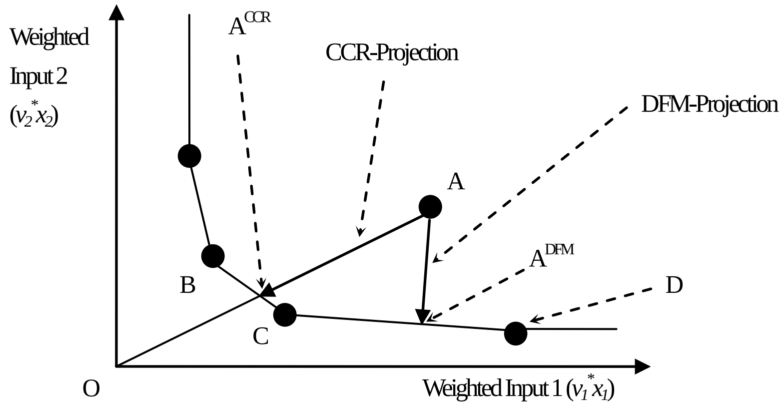


Figure 3 Degree of improvement of the DFM and the CCR projection in weighted input space

At this stage it may be appropriate to judge the advantages of the DFM approach in comparison with some other approaches. In particular, the additive model (Charnes, 1985) and the Slack-Based Measure (hereafter SBM; Tone, 2001) model are representative for the class of non-radial models, which focus only on the presence or absence of slacks in input/output space (see also Figure 4). These models generally assume equality for each weight related to input and output items, so that a characteristic feature for each input-output item for each DMU is that it does not take into account an efficiency-improvement projection. If these models wish to take into account unequal weights, we need some a priori information from decision or policy makers. Our DFM model is based on a radial type of model which is a completely different type of model, as this model employs optimal weights that are automatically and objectively computed by the CCR model. This is a methodological advantage of this approach.

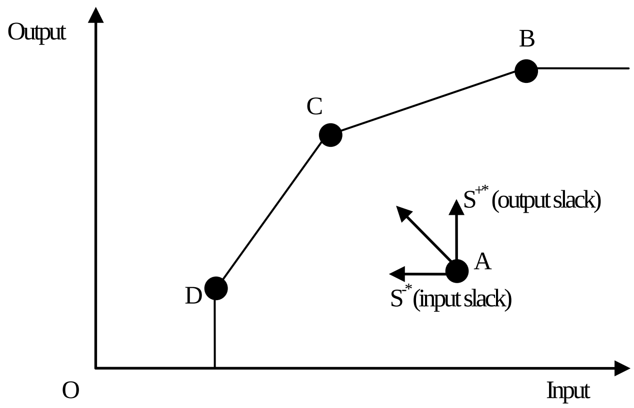


Figure 4 Illustration of the non-radial model in input/output space

The DFM model is based on both an input reduction and an output increase which is clearly a non-oriented characteristic. A non-oriented model takes into account simultaneous adjustments of outputs and inputs. A representative improving projection model in a non-oriented space is proposed by Silva et al. (2003) and Frei et al. (1999). These models can project the closest target onto an efficient frontier based on non-oriented models. Closest-targets models can find a shortest-distance projection which is an integrated simultaneous input and output improvement, as in Figure 5.

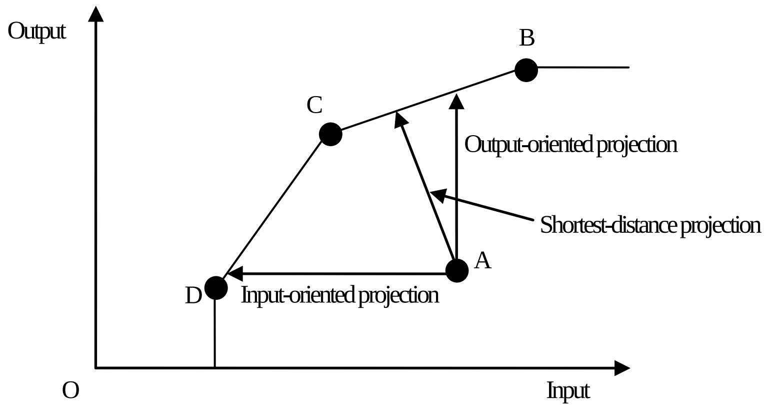


Figure 5 Illustration of the closest-target model in input/output space

In contrast, the DFM model can independently produce an input improvement projection and an output improvement projection as in Figures 1 and 2. The DFM model can also produce a projection such that the balance in the distribution of shares from the input and output sides ensures a situation that achieves efficiency. Thus, this projection of our DFM model can overcome the above-mentioned challenge that one input or one output item will never bear (almost) the entire burden of improvement. More specifically, the input side and the output side contribute according to their initial levels 1 and θ^*, implying respective shares $\theta^*/(1+\theta^*)$ and $1/(1+\theta^*)$ in the improvement contribution. Clearly, the contributions from both sides equal $(1-\theta^*)[\theta^*/(1+\theta^*)]$ and $(1-\theta^*)[1/(1+\theta^*)]$. This approach clearly enhances the feasibility of this DEA model.

The DFM model is able to calculate either an optimal input reduction value or an optimal output increase value in order to reach an efficiency score of 1.000, even though in reality this might be hard to achieve for low-efficiency DMUs. The DFM approach has been used as an operational stepping stone for a series of DEA variants, inter alia a Target-Oriented model (see section 3).

3. A Target-Oriented-DFM model

As mentioned above, the DFM model is able to calculate an optimal input reduction value and an output increase value in order to reach an efficiency score of 1.000, even though sometimes this may be a difficult task for less efficient DMUs. Therefore, we propose here a method that allows reference points that remain below the efficiency frontier. On the other hand, DMUs which are close to (or exactly on) the efficient frontier might search for an appropriate reference point for a further improvement of their efficiency.

Next, it is a new challenge to develop a Target-Oriented (TO) model nested within a DFM framework, based on the Super-efficiency model (Andersen and Petersen (1993): see Appendix A2), which originates from the original CCR-I model. The Super-Efficiency model based on a radial projection (CCR model) seeks to arrive at a ranking of all efficient DMUs. The efficiency scores from a Super-efficiency model are thus obtained by eliminating the data on the DMU_o to be evaluated from the solution set. For the input model, this can then result in values which may be regarded, according to the DMU_o, as a state of super-efficiency. These values are then used to rank the DMUs, and, consequently, efficient DMUs may then obtain an efficiency score above 1.000. An efficiency score and optimum weight for inefficient DMUs is in complete accordance with the standard CCR model.

The TO approach adopted here comprises the following steps:

Step 1. The Target Efficiency Score (TES) for DMU_o (hereafter TES_0) is set arbitrarily by the decision - or policy - maker. Improving projections are categorized in three types, depending on the score of the TES as follows:

- $\theta^* < TES_0 < 1.000$; *Non-Attainment* DFM projection (it does not reach the efficiency frontier) . This makes sense for DMUs that are far below the efficiency frontier;
- $TES_0 = 1.000$; *Normal* DFM projection (it just reaches the efficiency frontier);
- $TES_0 > 1.000$; *Super-Efficient* DFM projection (it is beyond the efficiency frontier). This makes sense for DMUs that are already on the efficiency frontier.

Step 2. Solve $$TES_0 = \frac{\theta^* + MP_0\left(1-\theta^*\right)\times\dfrac{\theta^*}{\left(1+\theta^*\right)}}{1 - MP_0\left(1-\theta^*\right)\times\dfrac{1}{\left(1+\theta^*\right)}}. \qquad (3.1)$$

Then, we get MP_o, which is a Magnification Parameter of TES_o. MP_o assumes an intermediate role by adjusting the input reduction target and the output increase target in formulas (3.5) and (3.6) in order to ensure an alignment of the TES_0 and DFM projection score for DMU_o.

Step 3. Solve the TO-DFM model using formulas (3.2)–(3.9); then, an optimal input reduction value and output increase value to reach a TES_0 can be calculated as follows:

$$\min \quad Fr^x = \sqrt{\sum_m \left(v_m^* x_{mo} - v_m^* d_{mo}^x\right)^2} \; ; \tag{3.2}$$

$$\min \quad Fr^y = \sqrt{\sum_s \left(u_s^* y_{so} - u_s^* d_{so}^y\right)^2} \; ; \tag{3.3}$$

$$\text{s.t.} \quad TES_0 = \frac{\sum_s u_s^* \left(y_{so} + d_{so}^y\right)}{\sum_m v_m^* \left(x_{mo} - d_{mo}^x\right)} ; \tag{3.4}$$

$$\sum_m v_m^* \left(x_{mo} - d_{mo}^x\right) = 1 - MP_0 \left(1 - \theta^*\right) \times \frac{1}{\left(1 + \theta^*\right)} ; \tag{3.5}$$

$$\sum_s u_s^* \left(y_{so} + d_{so}^y\right) = \theta^* + MP_0 \left(1 - \theta^*\right) \times \frac{\theta^*}{\left(1 + \theta^*\right)} ; \tag{3.6}$$

$$x_{mo} - d_{mo}^x \geq 0 ; \tag{3.7}$$

$$d_{mo}^x \geq 0 ; \tag{3.8}$$

$$d_{so}^y \geq 0 . \tag{3.9}$$

An illustration of the TO-DFM model is given in Figure 6.

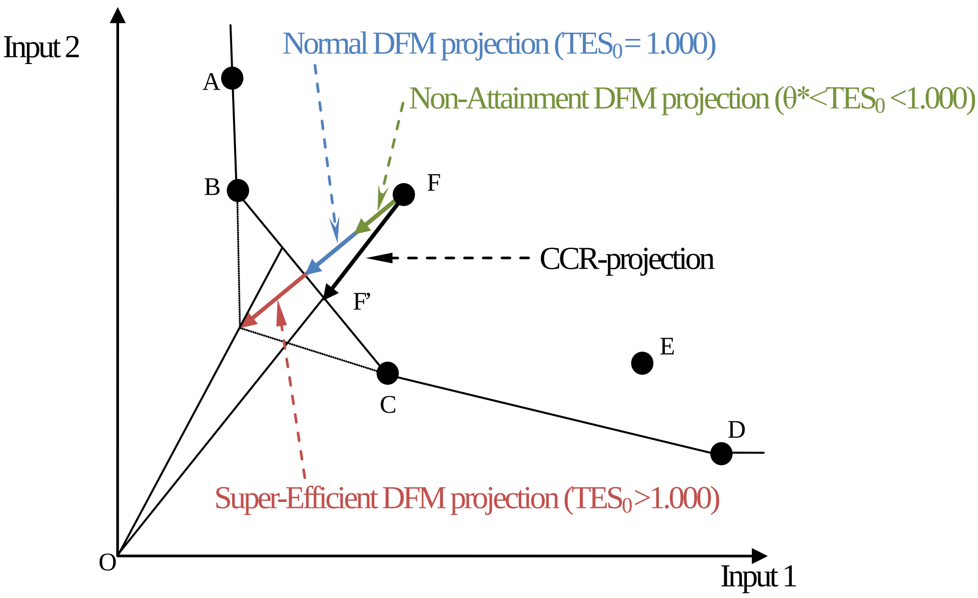


Figure 6 Illustration of the Target-Oriented-DFM model in input space

From Figure 6, we notice that a value of $TES_0 = 1.000$ is just equal to the normal DFM model using formulas (3.1)–(3.7). We also observe that the Non-Attainment DFM projection ($\theta^* < TES_0 < 1$) does not reach the efficiency frontier; thus, this is one of the improvement goal projections to reach a TES_0 lower than 1.000. Additionally, a Super-Efficient DFM projection ($TES_0 > 1.000$) offers an above 1.000 improvement level, which is relevant in particular for DMUs that are already close to the efficiency frontier.

Figure 6 shows that the direction of the target setting is determined by the DFM model, whereas the degree to which the efficiency score is improved depends on the TES parameter set by the decision maker. The usual situation where DMUs try to improve their position incrementally is that the TES_0 parameter will be lower than 1. We will next extend the above DEA variant by introducing inertia or lumpiness in one of the input factor (see Section 4).

4. Design of a Target-Oriented DFM model with fixed factors

We now design a new version of the TO-DFM model that takes into account the presence of fixed factors (see Suzuki et al. 2011). A fixed factor is an input factor that cannot be flexibly adjusted in the short run. The efficiency improvement projection, which incorporates a fixed factor (FF) in a TO-DFM model, is presented as follows:

The TO-DFM-FF approach adopted here comprises the following steps:

Step 1. The Target Efficiency Score (TES) for DMU_o with a fixed factor (hereafter TES_0^{FF}) is set arbitrarily by the decision - or policy - maker. Improving projections are categorized in three types, depending on the score of the TES, the same way as with the TO-DFM model.

Step 2. Solve
$$TES_o^{FF} = \frac{\theta^* + \dfrac{MP_o^{FF}\left(1-\theta^*\right)\left(\theta^* - \sum_{s \in ND} u_s^* y_{so}\right)}{\left(1 - \sum_{m \in ND} v_m^* x_{mo}\right) + \left(\theta^* - \sum_{s \in ND} u_s^* y_{so}\right)}}{1 - \dfrac{MP_o^{FF}\left(1-\theta^*\right)\left(1 - \sum_{m \in ND} v_m^* x_{mo}\right)}{\left(1 - \sum_{m \in ND} v_m^* x_{mo}\right) + \left(\theta^* - \sum_{s \in ND} u_s^* y_{so}\right)}}. \tag{4.1}$$

We then get MP_o^{FF}, which is a Magnification Parameter of TES_o^{FF}. MP_o^{FF} assumes an intermediate role by adjusting the input reduction target and the output increase target in formulas (4.5) and (4.6) in order to ensure an alignment of the TES_0^{FF} and a DFM projection score for DMU_o.

$$\min\ Fr^{x} = \sqrt{\sum_{m\in D}\left(v_m^* x_{mo} - v_m^* d_{mo}^{x}\right)^2}\ ; \tag{4.2}$$

$$\min\ Fr^{y} = \sqrt{\sum_{s\in D}\left(u_s^* y_{so} - u_s^* d_{so}^{y}\right)^2}\ ; \tag{4.3}$$

$$\text{s.t.}\ \ TES_o^{FF} = \frac{\sum_{s\in D} u_s^*\left(y_{so} + d_{so}^{y}\right) + \sum_{s\in ND} u_s^* y_{so}}{\sum_{m\in D} v_m^*\left(x_{mo} - d_{mo}^{x}\right) + \sum_{m\in ND} v_m^* x_{mo}}\ ; \tag{4.4}$$

$$\sum_{m\in D} v_m^*\left(x_{mo} - d_{mo}^{x}\right) + \sum_{m\in ND} v_m^* x_{mo} = 1 - \frac{MP_o^{FF}\left(1-\theta^*\right)\left(1 - \sum_{m\in ND} v_m^* x_{mo}\right)}{\left(1 - \sum_{m\in ND} v_m^* x_{mo}\right) + \left(\theta^* - \sum_{s\in ND} u_s^* y_{so}\right)}\ ; \tag{4.5}$$

$$\sum_{s\in D} u_s^*\left(y_{so} + d_{so}^{y}\right) + \sum_{s\in ND} u_s^* y_{so} = \theta^* + \frac{MP_o^{FF}\left(1-\theta^*\right)\left(\theta^* - \sum_{s\in ND} u_s^* y_{so}\right)}{\left(1 - \sum_{m\in ND} v_m^* x_{mo}\right) + \left(\theta^* - \sum_{s\in ND} u_s^* y_{so}\right)}\ ; \tag{4.6}$$

$$x_{mo} - d_{mo}^{x} > 0\ ; \tag{4.7}$$

$$d_{mo}^{x} \geq 0\ ; \tag{4.8}$$

$$d_{so}^{y} \geq 0\ , \tag{4.9}$$

where the symbols $m \in D$ and $s \in D$ refer to the set of ‘discretionary’ inputs and outputs; the symbols $m \in ND$ and $s \in ND$ refer to the set of ‘non-discretionary’ inputs and outputs.

The meaning of functions (4.2) and (4.3) is to consider only the distance friction of discretionary inputs and outputs. The constraint functions (4.5) and (4.6) are incorporated in the non-discretionary factors for the efficiency gap. The target values for input reduction and output augmentation with a balanced allocation depend on all total input-output scores and fixed factor situations, as presented in Figure 7 in the case of TES_0^{FF} =1.000 (i.e. MP_o^{FF}=1.000). The calculated result of (4.5) will then coincide with the calculated result of (4.6).

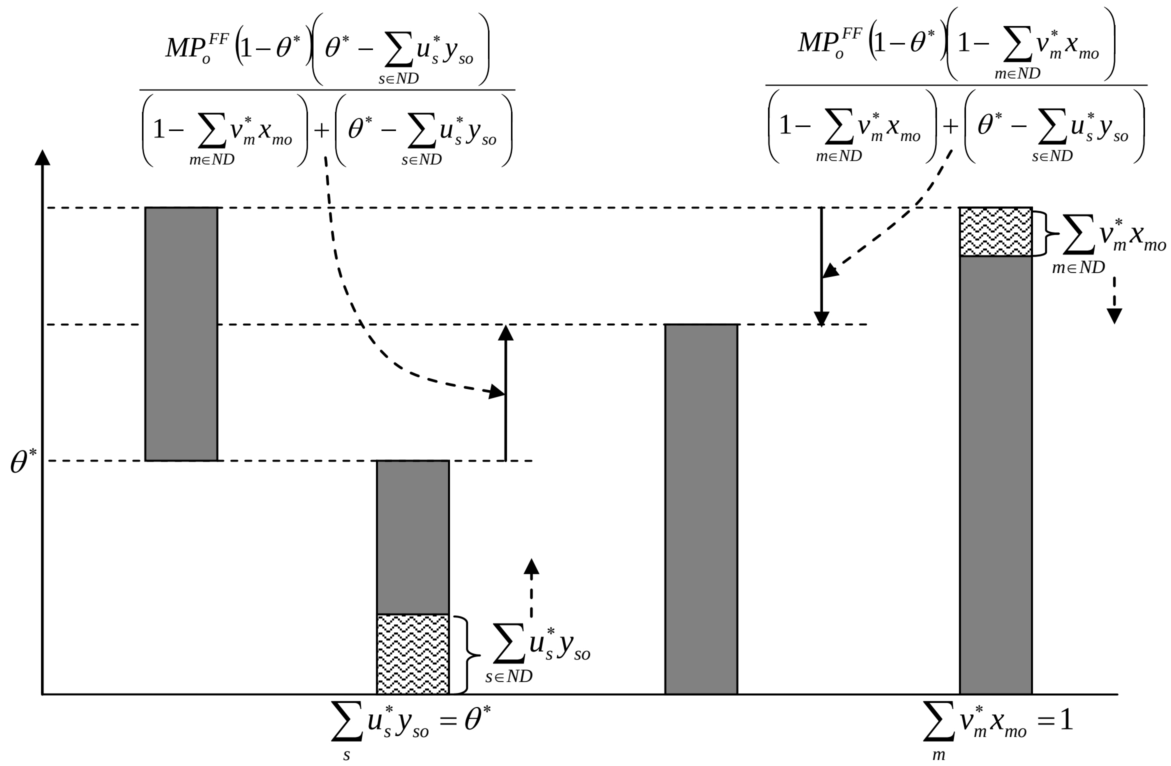


Figure 7 Distribution of the total efficiency gap (in the case of TES_0^{FF} =1.000 (MP_o^{FF}=1.000))

Finally, the optimal solution for an inefficient DMU_o can now be expressed by means of (4.10) - (4.13):

$$x_{mo}^{**} = x_{mo} - d_{mo}^{x*} - s^{-**},\ m \in D; \tag{4.10}$$

$$y_{so}^{**} = y_{so} + d_{so}^{y*} + s^{+**},\ s \in D; \tag{4.11}$$

$$x_{mo}^{**} = x_{mo},\ m \in ND; \tag{4.12}$$

$$y_{so}^{**} = y_{so},\ s \in ND. \tag{4.13}$$

The slacks $s^{-**}, m \in ND$ and $s^{+**}, s \in ND$ are not incorporated in (4.12) and (4.13), because these factors are 'fixed' or 'non-discretionary' inputs and outputs, in a way similar to the Banker and Morey (1986) model. This approach will hereafter be described as the TO-DFM-FF approach.

5. An evaluation of energy-environment-economic efficiency for EU and A&A countries

5.1 Database and analytical framework

There is a vast difference in energy use, environmental quality, economic growth and demographic composition in many countries. It may be interesting to obtain new insights from a comparative study on energy-efficiency in such countries, which may provide lessons for national sustainability policies. From that perspective, we have to look at input-output ratios as measures of efficiency or productivity, using the DEA framework sketched out above.

We use for our analysis the following relevant input and output data from 2003 to 2012 for a set of 27 EU countries (Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, the Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and the UK), and 20 ASEAN and APEC (A&A) countries (Australia, Brunei, Cambodia, Canada, Chile, China, Indonesia, Japan, Korea, Malaysia, Mexico, Myanmar, New Zealand, Peru, the Philippines, Russia, Singapore, Thailand, the USA, and Vietnam) to evaluate and compare their energy-environment-economic efficiency. The DMUs used in our analysis are listed in Table 1.

Table 1 A list of DMUs

No.	EU	No.	EU
1	Austria	15	Italy
2	Belgium	16	Latvia
3	Bulgaria	17	Lithuania
4	Croatia	18	Luxembourg
5	Cyprus	19	Netherlands
6	Czech	20	Poland
7	Denmark	21	Portugal
8	Estonia	22	Romania
9	Finland	23	Slovak
10	France	24	Slovenia
11	Germany	25	Spain
12	Greece	26	Sweden
13	Hungary	27	UK
14	Ireland		

No.	A&A	No.	A&A
28	Australia	38	Mexico
29	Brunei	39	Myanmar
30	Cambodia	40	New Zealand
31	Canada	41	Peru
32	Chile	42	Philippines
33	China	43	Russia
34	Indonesia	44	Singapore
35	Japan	45	Thailand
36	Korea	46	USA
37	Malaysia	47	Vietnam

As shown in Table 1, we set out the DMUs as 27 EU countries and 20 A&A countries. We note that Lao People's Democratic Republic, Papua New Guinea, China Hong Kong and Taiwan are omitted in the list for reason of data restrictions. Malta is omitted in the list for a reason of too much small data. In our subsequent DEA context, we will focus on both input and output variables.

For our comparative sustainability analysis of various countries, we consider two Inputs (I):

(I1) Population (thousands) (Reference: UN Statistics Division);

(I2) Energy Consumption (Peta Joule) (Reference: International Energy Agency), while also two Outputs (O) are incorporated:

(O 1) GDP (at constant 2005 prices - hundred million US Dollars) (Reference: UN Statistics Division);

(O 2) CO_2 Emission (million tons) (Reference: International Energy Agency)-

CO_2 Emission is denoted in our study as a multiplicative inverse of the 'bad' output to make it a 'good' output (for details, see also Scheel (2001) and Seiford (2002)).

In our application, we first employed the Super-Efficiency CCR model (see Appendices A1 and A2), while next the results were used to determine the CCR, DFM and TO-DFM-FF projections. Additionally, we applied the TO-DFM-FF model using Japan 2012 as a reference country for our benchmark experiment.

5.2 Efficiency evaluation based on Super-Efficiency CCR-I model

The efficiency evaluation result for the 47 countries from 2003 to 2012 based on the Super-Efficiency CCR model is presented in Figure 8.

From Figure 8, it can be seen that Luxembourg, Cyprus, Ireland, and Brunei may be regarded as super-efficient DMUs. It also can be seen that the efficiency scores of EU countries are higher on average than the A&A countries. We can also compare an average score between the EU and A&A countries, based on a two-sample T-test (statistical significance test for differences in the average efficiency score between the EU and A&A countries), as shown in Figure 9. From Figure 9, we notice that the gap between the average scores for EU and A&A countries has narrowed from 2003 to 2005, but after 2006, the gap has widened year by year. In particular, the gap in 2011 and 2012 shows a statistical significance (in Figure 9, * means: 5 significant at a 5% level). Given the above findings, it seems necessary to make a serious effort for the efficiency improvement of the energy-environment-economic efficiency for APEC and ASEAN countries (see Section 5.3).

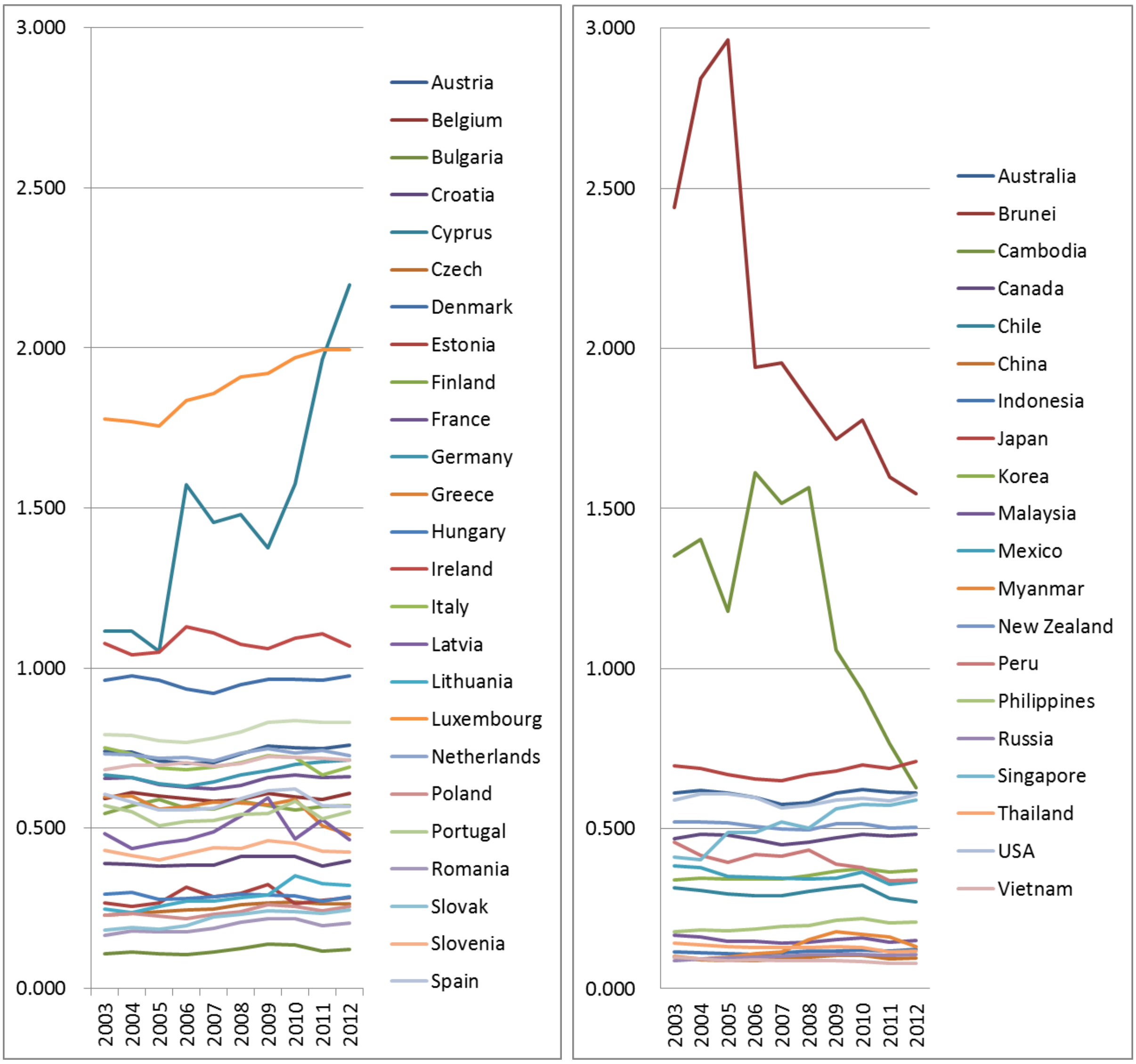
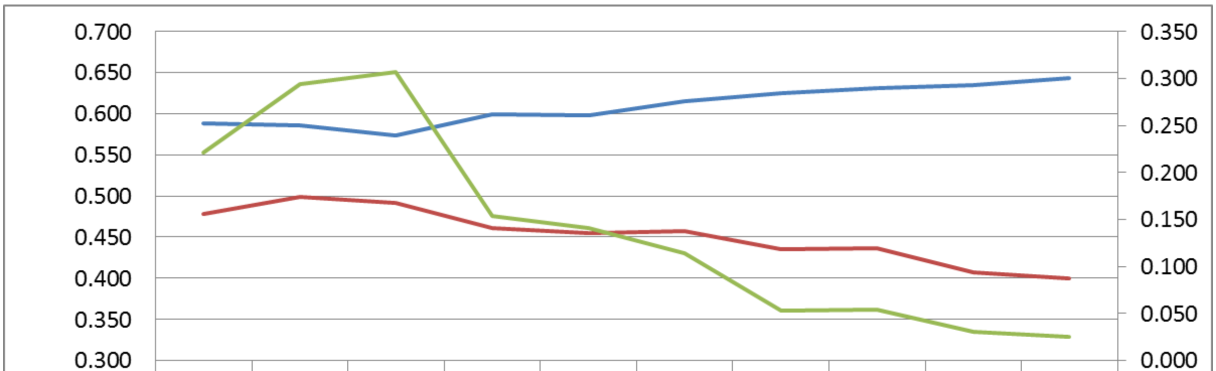


Figure 8 Efficiency scores based on the Super-Efficiency CCR-I model



	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
EU	0.589	0.585	0.573	0.600	0.599	0.615	0.625	0.631	0.634	0.644
A&A	0.478	0.499	0.492	0.461	0.455	0.457	0.436	0.437	0.407	0.400
T-test	0.221	0.294	0.307	0.154	0.140	0.114	0.053	0.054	0.031*	0.025*

Figure 9 Average scores of EU and A&A countries, and T-test values

5.3 Efficiency improvement projection based on the CCR, DFM and TO-DFM-FF models

The results of an efficiency improvement projection based on the application of CCR and DFM models for inefficient A&A countries in 2012 are presented in Table 2 (θ** in Table 2 expresses the efficiency score after the improvement projection).

In regard to Table 2, we note that the results of an efficiency improvement projection for CO_2 may be difficult to understand as a consequence of the use of 'inverse' numbers (translating the 'bad' output into a 'good' output). And therefore, we have recalculated the results into normal numbers, as presented in Table 3.

Table 2 Efficiency-improvement projection results of CCR, DFM, and TO-DFM-FF models (A&A countries)

		CCR model		DFM model		TO-DFM-FF model	
DMU	Score	Score(θ**)		Score(θ**)		Score(θ**)	
I/O	Data	Difference	%	Difference	%	Difference	%
Australia	0.612	1.000		1.000		0.644	(EU Ave level)
(FI)Population	23050.0	-8948.3	-38.8%	-2262.6	-9.8%	0.000	0.0%
(I)Energy Consumption	5371.0	-2085.1	-38.8%	-1850.7	-34.5%	-174.151	-3.2%
(O)GDP	9253.4	0.0	0.0%	2228.7	24.1%	300.035	3.2%
(O)CO_2 (inverse)	0.00259	1.5	56847.0%	1.0	38824.6%	0.000	0.0%
Cambodia	0.626	1.000		1.000		0.644	(EU Ave level)
(FI)Population	14865.0	-13532.7	-91.0%	-13226.7	-89.0%	0.000	0.0%
(I)Energy Consumption	230.0	-85.9	-37.4%	-52.8	-23.0%	-3.135	-1.4%
(O)GDP	99.9	189.4	189.6%	255.8	256.1%	0.000	0.0%
(O)CO_2 (inverse)	0.23981	0.0	0.0%	0.1	23.0%	0.003	1.4%
Canada	0.483	1.000		1.000		0.644	(EU Ave level)
(FI)Population	34838.0	-17994.4	-51.7%	-3249.9	-9.3%	0.000	0.0%
(I)Energy Consumption	10514.0	-5430.7	-51.7%	-5164.6	-49.1%	-1880.593	-17.9%
(O)GDP	12941.9	0.0	0.0%	4506.1	34.8%	2314.865	17.9%
(O)CO_2 (inverse)	0.00187	2.8	148344.7%	1.5	81630.8%	0.000	0.0%
Chile	0.271	1.000		1.000		0.644	(EU Ave level)
(FI)Population	17465.0	-13985.3	-80.1%	-11989.0	-68.6%	0.000	0.0%
(I)Energy Consumption	1558.0	-1136.0	-72.9%	-893.8	-57.4%	-635.113	-40.8%
(O)GDP	1649.3	0.0	0.0%	946.2	57.4%	672.327	40.8%
(O)CO_2 (inverse)	0.01286	0.0	66.4%	0.0	161.8%	0.000	0.0%
China	0.097	1.000		1.000		0.644	(EU Ave level)
(FI)Population	1377065.0	-1280474.3	-93.0%	-1200913.3	-87.2%	0.000	0.0%
(I)Energy Consumption	121178.0	-109463.0	-90.3%	-99813.4	-82.4%	-89532.486	-73.9%
(O)GDP	45781.7	0.0	0.0%	37710.0	82.4%	33825.839	73.9%
(O)CO_2 (inverse)	0.00012	0.6	487129.7%	1.1	888457.3%	0.000	0.0%
Indonesia	0.122	1.000		1.000		0.644	(EU Ave level)
(FI)Population	246864.0	-237842.2	-96.4%	-230787.6	-93.5%	0.000	0.0%
(I)Energy Consumption	8942.0	-7847.8	-87.8%	-6992.2	-78.2%	-6085.349	-68.1%
(O)GDP	4276.1	0.0	0.0%	3343.7	78.2%	2910.062	68.1%
(O)CO_2 (inverse)	0.00230	0.1	2315.1%	0.1	4203.6%	0.000	0.0%
Japan	0.711	1.000		1.000		0.750	(arbitrary level)
(FI)Population	127250.0	-36757.0	-28.9%	-27895.2	-21.9%	0.000	0.0%
(I)Energy Consumption	18936.0	-5469.8	-28.9%	-2110.3	-11.1%	-692.874	-3.7%
(O)GDP	46953.6	0.0	0.0%	7926.2	16.9%	1718.044	3.7%
(O)CO_2 (inverse)	0.00082	2.7	336289.2%	4.8	589089.6%	0.000	0.0%
Korea	0.370	1.000		1.000		0.644	(EU Ave level)
(FI)Population	49003.0	-30888.2	-63.0%	-18198.5	-37.1%	0.000	0.0%
(I)Energy Consumption	11030.0	-6952.6	-63.0%	-5813.3	-52.7%	-4101.349	-37.2%
(O)GDP	11652.6	0.0	0.0%	5362.6	46.0%	4332.847	37.2%
(O)CO_2 (inverse)	0.00169	1.8	104690.8%	1.5	88440.6%	0.000	0.0%
Malaysia	0.149	1.000		1.000		0.644	(EU Ave level)
(FI)Population	29240.0	-25053.5	-85.7%	-21954.7	-75.1%	0.000	0.0%
(I)Energy Consumption	3401.0	-2893.2	-85.1%	-2517.4	-74.0%	-2120.415	-62.3%
(O)GDP	1984.3	0.0	0.0%	1468.8	74.0%	1237.145	62.3%
(O)CO_2 (inverse)	0.00510	0.0	404.1%	0.0	777.3%	0.000	0.0%

Table 2(continued) Efficiency-improvement projection results of the CCR, DFM, and TO-DFM-FF models (A&A countries)

		CCR model		DFM model		TO-DFM-FF model	
DMU	Score	Score(θ**)		Score(θ**)		**Score(θ**)**	
I/O	Data	Difference	%	Difference	%	Difference	%
Mexico	0.334	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	120847.0	-99132.7	-82.0%	-88288.8	-73.1%	0.000	0.0%
(I)Energy Consumption	7888.0	-5254.4	-66.6%	-3939.2	-49.9%	-2500.020	-31.7%
(O)GDP	10292.1	0.0	0.0%	5139.7	49.9%	3261.960	31.7%
(O)CO_2 (inverse)	0.00229	0.1	5717.0%	0.2	8621.9%	0.000	0.0%
Myanmar	0.131	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	52797.0	-52058.0	-98.6%	-51497.7	-97.5%	0.000	0.0%
(I)Energy Consumption	639.0	-555.5	-86.9%	-491.3	-76.9%	-423.383	-66.3%
(O)GDP	230.2	0.0	0.0%	191.9	83.4%	174.281	75.7%
(O)CO_2 (inverse)	0.08584	0.0	0.0%	0.1	62.1%	0.038	44.7%
New Zealand	0.505	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	4460.0	-2207.3	-49.5%	-1389.9	-31.2%	0.000	0.0%
(I)Energy Consumption	794.0	-393.0	-49.5%	-274.1	-34.5%	-131.828	-16.6%
(O)GDP	1276.2	0.0	0.0%	419.6	32.9%	211.882	16.6%
(O)CO_2 (inverse)	0.03111	0.1	306.3%	0.1	378.3%	0.000	0.0%
Peru	0.339	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	29988.0	-27442.0	-91.5%	-26217.4	-87.4%	0.000	0.0%
(I)Energy Consumption	909.0	-600.7	-66.1%	-448.5	-49.3%	-281.624	-31.0%
(O)GDP	1197.6	0.0	0.0%	603.6	50.4%	379.006	31.6%
(O)CO_2 (inverse)	0.02182	0.0	0.0%	0.0	7.0%	0.000	0.0%
Philippines	0.209	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	96707.0	-93643.4	-96.8%	-91637.0	-94.8%	0.000	0.0%
(I)Energy Consumption	1782.0	-1410.4	-79.2%	-1167.1	-65.5%	-910.014	-51.1%
(O)GDP	1452.1	0.0	0.0%	951.0	65.5%	741.519	51.1%
(O)CO_2 (inverse)	0.01258	0.0	49.6%	0.0	147.6%	0.000	0.0%
Russia	0.108	1.000		1.000		**infeasible case**	
(FI)Population	143170.0	-127776.1	-89.3%	-111111.0	-77.6%		
(I)Energy Consumption	31677.0	-28271.0	-89.3%	-26247.8	-82.9%		
(O)GDP	9806.1	0.0	0.0%	7902.1	80.6%		
(O)CO_2 (inverse)	0.00060	1.4	240447.8%	1.6	257732.1%		
Singapore	0.590	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	5303.0	-2173.5	-41.0%	-1036.1	-19.5%	0.000	0.0%
(I)Energy Consumption	1049.0	-430.0	-41.0%	-326.4	-31.1%	-59.993	-5.7%
(O)GDP	1873.9	0.0	0.0%	483.0	25.8%	107.167	5.7%
(O)CO_2 (inverse)	0.02010	0.2	1045.0%	0.2	929.0%	0.000	0.0%
Thailand	0.118	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	66785.0	-61645.2	-92.3%	-57587.5	-86.2%	0.000	0.0%
(I)Energy Consumption	5299.0	-4675.6	-88.2%	-4183.5	-78.9%	-3661.454	-69.1%
(O)GDP	2436.1	0.0	0.0%	1923.3	78.9%	1683.290	69.1%
(O)CO_2 (inverse)	0.00390	0.0	710.9%	0.1	1351.1%	0.000	0.0%
USA	0.605	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	317505.0	-125551.5	-39.5%	0.0	0.0%	0.000	0.0%
(I)Energy Consumption	89623.0	-35439.8	-39.5%	-35337.8	-39.4%	-3484.242	-3.9%
(O)GDP	141377.6	0.0	0.0%	34841.3	24.6%	5496.286	3.9%
(O)CO_2 (inverse)	0.00020	28.4	14407875.2%	15.8	8040357.1%	0.000	0.0%
Vietnam	0.078	1.000		1.000		**0.644**	**(EU Ave level)**
(FI)Population	90796.0	-89043.9	-98.1%	-87546.3	-96.4%	0.000	0.0%
(I)Energy Consumption	2715.0	-2502.5	-92.2%	-2320.9	-85.5%	-2126.349	-78.3%
(O)GDP	830.4	0.0	0.0%	709.9	85.5%	650.381	78.3%
(O)CO_2 (inverse)	0.00700	0.0	53.9%	0.0	185.4%	0.000	0.0%

Table 3 Efficiency-improvement projection results for CO_2 in 'normal' numbers

		Data		CCR		DFM		TO-DFM-FF	
DMU	Score	(O)CO2 (inverse)	(O)CO2	Difference	%	Difference	%	Difference	%
Australia	0.612	0.002589	386.27	-385.592	-99.824%	-385.278	-99.743%	0.000	0.000%
Cambodia	0.626	0.239808	4.17	0.000	0.000%	-0.779	-18.680%	-0.056	-1.345%
Canada	0.483	0.001874	533.74	-533.380	-99.933%	-533.087	-99.878%	0.000	0.000%
Chile	0.271	0.012858	77.77	-31.020	-39.886%	-48.063	-61.801%	0.000	0.000%
China	0.097	0.000122	8205.86	-8204.176	-99.979%	-8204.936	-99.989%	0.000	0.000%
Indonesia	0.122	0.002296	435.48	-417.449	-95.859%	-425.361	-97.676%	0.000	0.000%
Japan	0.711	0.000817	1223.30	-1222.936	-99.970%	-1223.092	-99.983%	0.000	0.000%
Korea	0.370	0.001687	592.92	-592.354	-99.905%	-592.250	-99.887%	0.000	0.000%
Malaysia	0.149	0.005105	195.89	-157.032	-80.164%	-173.561	-88.601%	0.000	0.000%
Mexico	0.334	0.002295	435.79	-428.298	-98.281%	-430.794	-98.853%	0.000	0.000%
Myanmar	0.131	0.085837	11.65	0.000	0.000%	-4.464	-38.321%	-3.599	-30.894%
New Zealand	0.505	0.031114	32.14	-24.230	-75.388%	-25.421	-79.094%	0.000	0.000%
Peru	0.339	0.021825	45.82	0.000	0.000%	-3.014	-6.578%	0.000	0.000%
Philippines	0.209	0.012585	79.46	-26.359	-33.173%	-47.374	-59.620%	0.000	0.000%
Russia	0.108	0.000603	1659.03	-1658.340	-99.958%	-1658.387	-99.961%		
Singapore	0.590	0.020101	49.75	-45.405	-91.266%	-44.915	-90.282%	0.000	0.000%
Thailand	0.118	0.003896	256.65	-224.999	-87.668%	-238.963	-93.109%	0.000	0.000%
USA	0.605	0.000197	5074.14	-5074.105	-99.999%	-5074.077	-99.999%	0.000	0.000%
Vietnam	0.078	0.007000	142.85	-50.001	-35.002%	-92.792	-64.957%	0.000	0.000%

From Table 2, it appears that the DFM model clearly shows that a different – and likely more efficient – solution than the standard CCR projection is available for reaching the efficiency frontier. In this particular case, we could not identify a non-slack type (i.e., s^{-**} and s^{+**} are zero) country; this is particularly confirmed for the USA. For instance, the CCR projection in Table 2 and 3 shows that the USA should reduce its Population and Energy Consumption by 39.5%, together with an increase in the CO_2 (inverse) of 14407875.2% (-99.999% in 'normal numbers'), in order to become efficient. On the other hand, the DFM results show that a reduction in Energy Consumption by 39.4%, together with an increase in the GDP of 24.6% and in the CO_2 (inverse) of 8040357.1% (-99.999% in 'normal numbers'), is required to become efficient.

The results of the efficiency improvement projection based on the TO-DFM-FF model for inefficient A&A countries are presented in Table 2 and 3. The parameter θ** in the results of TO-DFM-FF in Table 2 expresses a target efficiency score (TES) based on the EU average score level (0.644), while Japan is set at 0.750 as an arbitrary level, because the current score is already exceeded (0.711). The anomalous result of Russia was at the end regarded as an infeasible case that is not in agreement with the constraint function (4.7). More specifically, the regarded, reduction value for energy consumption (35973.710 Peta Joule) exceeded the current level (316677.000 Peta Joule).

The TO-DFM-FF model is able to present a more realistic efficiency-improvement energy plan, which we compared with the results of the DFM model in Table 2 and 3. For instance, the DFM results in Table 2 and 3 show that Korea should reduce its Population by 37.1% and its Energy Consumption by 52.7%, and increase its GDP by 46.0% and its CO_2 level (inverse) by 88440.6% (-99.887% in 'normal numbers') in order to become efficient. On the other hand, the TO-DFM-FF results in Table 2 show that a reduction in Energy Consumption of 37.2 %, and an increase in GDP of 37.2 % are required to reach the EU average level (0.644). Note also that Population is interpreted in our application as a fixed factor in the TO-DFM-FF and model.

We also note that the efficiency improvement levels of CO_2 in our CCR and DFM models seems to offer unrealistic outcomes, like 14407875.2%, (-99.999% in 'normal numbers'), 8040357.1% (-99.999% in 'normal numbers'), and 88440.6% (-99.887% in 'normal numbers') caused by the existence of 'slack', as a results of vast differences absolute numbers of relevant variables in the countries under consideration (e.g., Russia or the USA vs. Luxembourg or Cyprus). On the other hand, our TO-DFM-FF results seem to offer more realistic outcomes than in the previous models. The TO-DFM-FF model provides policy-makers with practical and transparent solutions that are available in the DFM projection to reach the target efficiency level. These results provide a meaningful contribution to decision support and planning for the efficiency improvement of the countries' energy-environment-economic resources.

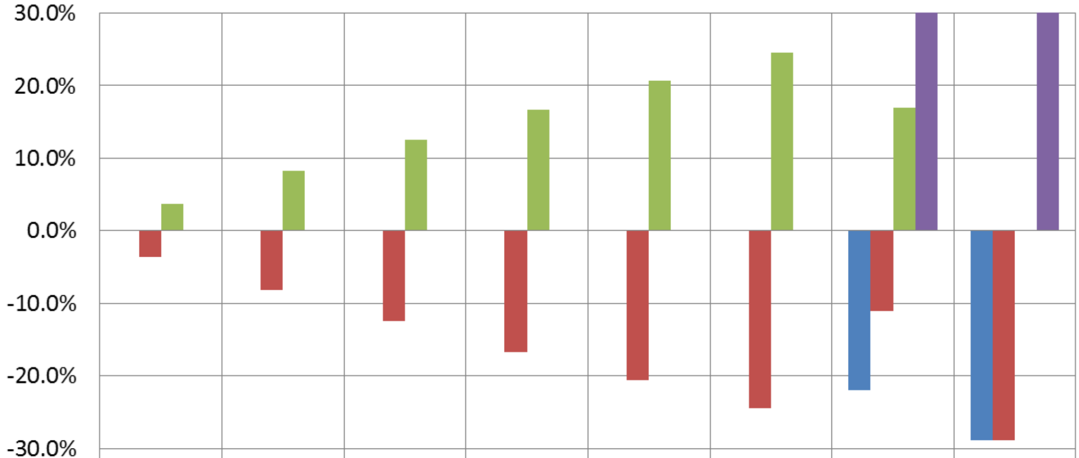
5.4 Efficiency-improvement projection of the TO-DFM-FF model

In this subsection, we will use Japan 2012 as an illustrative case and point of reference, and present an efficiency-improvement projection result based on the TO-DFM-FF model. The 2012 efficiency value is 0.711 (see Table 2). We now consider the steps to improve efficiency towards 0.750, 0.800, 0.850, 0.900, 0.950 and 1.000. The resulting input reduction values and the output increase values based on the TO-DFM-FF model are presented in Figure 10.

These results show that, if Japan implements an efficiency improvement plan with a TES amounting to 0.850, a reduction in Energy Consumption of 12.5% and an increase in GDP of 12.5% are required.

Furthermore, the normal DFM results in Figure 10 show that Japan should reduce its Population by 21.9% and the Energy Consumption by 11.1%, and increase its GDP by 16.9% and the CO_2 (inverse) with 589089.6% (-99.983% in 'normal numbers' in Table 3) in order to become efficient. On the other hand, the TES=1.000 (TO-DFM-FF) results in Figure 10 show that a reduction in Energy Consumption of 24.5%, and an increase in GDP of 24.5% would be required. From the above finding, we note that the TO-DFM-FF model is able to present a more realistic efficiency-improvement plan, compared with the normal DFM. Note also that Population is interpreted in the application as a fixed factor in the TO-DFM-FF model.

Our new proposed TO-DFM-FF model can not only compute a stepwise projection that falls below the 1.000 levels, but it is also able to compute an outcome just to reach the efficiency frontier (TES=1.000). From this fact, it appears that the TO-DFM-FF model can produce a more realistic efficiency improvement projection than the previous CCR, DFM and TO-DFM models.



	TES=0.750	TES=0.800	TES=0.850	TES=0.900	TES=0.950	TES=1.000 (TO-DFM-FF)	S=1.000 (Normal DFM)	CCR-I (S=1.000)
(FI)population	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	-21.9%	-28.9%
(I)energy consumption	-3.7%	-8.2%	-12.5%	-16.7%	-20.7%	-24.5%	-11.1%	-28.9%
(O)GDP	3.7%	8.2%	12.5%	16.7%	20.7%	24.5%	16.9%	0.0%
(O)CO2 (inverse)	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	589089.6%	336289.2%

Figure 10 Efficiency-improvement projection results based on the TO-DFM-FF model (Japan 2012)

6. Conclusion

In this paper, we have presented a new DEA methodology, the TO-DFM-FF model. Its feasibility was tested for improving energy-environment-economic efficiency for the EU, APEC and ASEAN countries; the new model was examined on the basis of real-world information on relevant indicators. This new analytical tool combines both flexibility in energy-environment-economic strategies, while considering also a fixed input constellation such as population. The results show that in many cases there is considerable scope for improvement along various strategic lines in the various countries under consideration.

The results appear to offer a meaningful contribution to sustainable decision making and planning for an efficiency improvement in the energy-environment-economic sector in these countries. These findings are mapped out in a detailed way in the present study. This model has the potential to become a policy instrument that could offer great benefits for combined energy-environmental-economic decision making and planning at national or sectoral policy levels. An important caveat of the present approach is noteworthy, viz. large scale differences in relevant policy variables of the DMUs considered may cause flaws in the outcomes.

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Appendix

A1. Outline of DEA and Efficiency Improvement Projection

The standard Charnes et al. (1978) model (abbreviated hereafter as the CCR-input model) for a given DMU$_j$ $(j=1,\cdots,J)$ to be evaluated in any trial o (where o ranges over 1, 2 …, J) may be represented as the following fractional programming (FP_o) problem:

$$(FP_o) \quad \max_{v,u} \quad \theta = \frac{\sum_s u_s y_{so}}{\sum_m v_m x_{mo}}$$

$$\text{s.t.} \quad \frac{\sum_s u_s y_{sj}}{\sum_m v_m x_{mj}} \le 1 \;\; (j=1,\cdots,J) \qquad \text{(A.1)}$$

$$v_m \ge 0\,,\, u_s \ge 0\,,$$

where θ represents an objective variable function (efficiency score); x_{mj} is the volume of input m ($m = 1,\ldots, M$) for DMU$_j$($j = 1,\ldots,J$); y_{sj} is the output s ($s = 1,\ldots,S$) of DMU j; and v_m and u_s are the weights given to input m and output s, respectively. Model (A.1) is often called an input-oriented CCR model, while its reciprocal (i.e. an interchange of the numerator and denominator in the objective function (A.1) with a specification as a minimisation problem under an appropriate adjustment of the constraints) is usually known as an output-oriented CCR model. Model (A.1) is obviously a fractional programming model, which may be solved stepwise by first assigning an arbitrary value to the denominator in (A.1), and then maximizing the numerator (see also Cooper et al. (2006) and Suzuki et al. (2010)).

The improvement projection $(\hat{x}_o, \hat{y}_o)$ can now be defined in (A.2) and (A.3) as:

$$\hat{x}_o = \theta^* x_o - s^{-*}\,; \qquad \text{(A.2)}$$

$$\hat{y}_o = y_o + s^{+*}\,. \qquad \text{(A.3)}$$

These equations indicate that the efficiency of (x_o, y_o) for DMU$_o$ can be improved if the input values are reduced radially by the ratio θ^* and the input excesses s^{-*} are eliminated (see Figure A1).

The original DEA models presented in the literature have focused on a uniform input reduction or on a uniform output increase in the efficiency-improvement projections, as shown in Figure A1 (θ^* =OC'/OC).

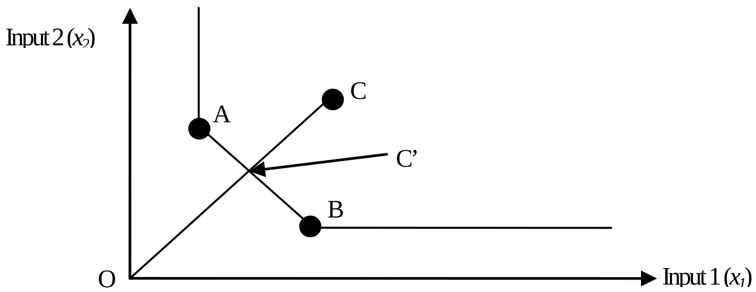

Figure A1 Illustration of original DEA projection in input space

A2. A Super-efficiency DEA Model

In a standard DEA model, all efficient DMUs get by definition a score equal to 1, so that there is no logical way to differentiate between them. This problem has led to focused research to discriminate between efficient DMUs, in order to arrive at an unambiguous ranking, or even a numerical rating of these efficient DMUs, without affecting the results for non-efficiency. In particular, Andersen and Petersen (1993) developed a radial Super-Efficiency model, while, later on, Tone (2002, 2003) designed a *slacks-based* measure (SBM) of super-efficiency in DEA. In general, a Super-Efficiency model aims to identify the relative importance of each individual efficient DMU, by designing and measuring a score for its 'degree of influence' if this efficient DMU is omitted from the efficiency frontier (or production possibility set). If this elimination really matters (i.e. if the distance from this DMU to the remaining efficiency frontier is large) and, thus, the firm concerned has a high degree of influence and outperforms the other DMUs, it gets a high score (and is thus super-efficient). Therefore, for each individual DMU a new distance result is obtained, which leads to a new ranking, or even a rating of all the original efficient DMUs.

Anderson and Petersen (1993) have developed the Super-Efficiency model based on a radial projection (including a CCR model) to arrive at a ranking of all efficient DMUs. The efficiency scores from a super-efficiency model are thus obtained by eliminating the data on the DMU$_o$ to be evaluated from the solution set. For the input model, this can then result in values, which may be regarded, according to the DMU$_o$, as a state of super-efficiency. These values are then used to rank the DMUs, and, consequently, efficient DMUs may then obtain an efficiency score above 1.000 (see also Suzuki et al. (2014)).

The super-efficiency model based on a CCR-I model can now be written as follows:

$$\min_{\theta,\lambda,S^-,S^+} \quad \theta - es^- - es^+$$

s.t. $$\theta x_o = \sum_{j=1,\neq o}^{J} \lambda_j x_j + s^- \tag{A.4}$$

$$y_o = \sum_{j=1,\neq o}^{J} \lambda_j y_j - s^+$$

$$\lambda_j, s^-, s^+ \geq 0,$$

where e is a unit vector (1,...,1), representing a utility factor for all elements.