Improvement restriction data envelopment analysis for new energy in Japan

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Abstract

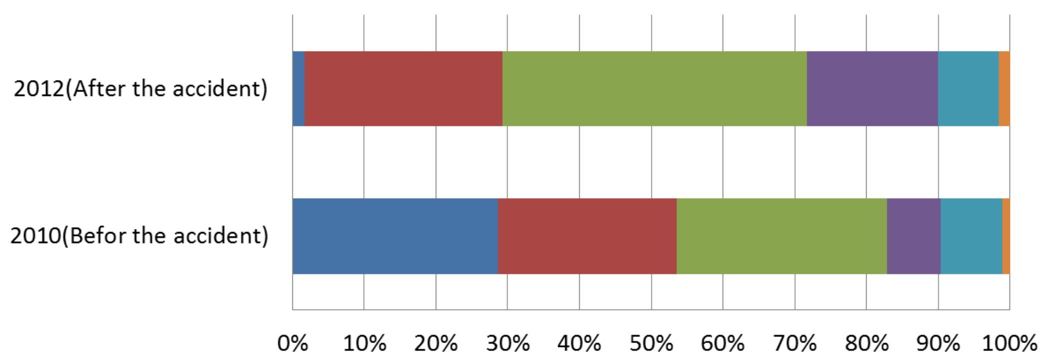
Japan is faced with "the Fukushima' problem," in which a single nuclear accident has led to drastic electrical power shortages. Owing to the strong backlash of public opinion, almost all of Japan's 54 nuclear plants suspended operations. An intensive search has started for alternative forms of energy, ranging from fossil fuels to new energy, such as solar, wind, geothermal, small-scale hydroelectric and biomass energy. There is no clear-cut direction for energy policy, as each option involves costs and CO_2 consequences and Japan has even withdrawn from the Kyoto protocol. A policy that balances energy and the environment is difficult to achieve in the short term; therefore, there is an urgent need for a comprehensive efficiency analysis of new energy in Japan.

A popular tool for judging the efficiency of a Decision Making Unit (DMU) is Data Envelopment Analysis (DEA). The development of multiple efficiency improvement solutions based on DEA has progressed in recent years. An example is the Distance Friction Minimisation (DFM) method, based on a generalised distance function, which serves to improve a DMU's performance by tracing the most appropriate movement towards the efficiency frontier. To produce a more realistic improvement plan for low efficiency DMUs, we proposed a Target-Oriented (TO) DFM model that allows reference points that remain below the efficiency frontier. TO-DFM model specifies a Target-Efficiency Score (TES) for inefficient DMUs. This model is able to compute an improvement projection that an input reduction value and an output increase value in order to achieve a TES, even though in reality these values may have an infeasible case, for example Net-Working Rate may be required more than 100% in improvement projection, but it exceed a physical limit.

This paper aims to present a newly developed adjusted DEA model, emerging from a blend of the TO-DFM and the Improvement Restriction (IR) approach, for generating an appropriate efficiency-improving projection model. The IR approach specifies a restriction input/output items based on absence or presence of the DMU's improvement limit. This approach can compute an input reduction value and an output increase value in order to achieve a TES that maintains an improvement restriction. The above-mentioned Improvement Restriction TO-DFM model will be applied to an efficiency analysis and will produce a realistic efficiency-improvement projection for new energies in Japan.

1. Introduction

Japan is faced with "the Fukushima' problem," in which a single nuclear accident has led to drastic electrical power shortages. Owing to the strong backlash of public opinion, almost all of Japan's 54 nuclear plants suspended operations. Japan have permission to increase thermal power generation based on coal, oil and LNG (liquefied natural gas) in order to compensate for the shortfall following the accident as Figure 1. An intensive search for alternative forms of energy—ranging from fossil fuels to new energy, such as solar, wind, geothermal, small-scale hydroelectric and biomass energy—has started. There is no clear-cut direction for energy policy, as each option involves costs and CO2 consequences and Japan has even withdrawn from the Kyoto protocol. A policy that balances energy and the environment is difficult to achieve in the short term; therefore, there is an urgent need for a comprehensive efficiency and performance analysis of new energy in Japan.



	2010(Befor the accident)	2012(After the accident)
Nuclear	28.6	1.7
Coal	25.0	27.6
LNG	29.3	42.5
Oil	7.5	18.3
Hydraulic	8.5	8.4
New Energy	1.1	1.6

Figure 1 A comparison of electronic power supply between before and after the accident in JAPAN

A standard tool by which to judge efficiency is Data Envelopment Analysis (DEA), proposed by Charnes, Cooper and Rhodes (1978) (CCR hereafter, see appendix A1). This has become an established assessment method in industrial organization. Seiford (2005) mentions some 2800 published articles on DEA. This large number of studies shows that comparative efficiency analysis has become an important research issue.

DEA was developed to analyse the relative efficiency of a decision-making unit (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 not on the frontier is inefficient. 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.

In the last 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 the DEA models. The first contribution was 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 the preferred set of output levels, given the input levels. Next, 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. 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 provides 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. 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 Optimisation (MORO), which optimises the ratios between the observed and the target inputs (or outputs) of a DMU. The second model is called Multiple Objective Target Optimisation (MOTO), which directly optimises the target values. Washio et al. (2012) suggested four types of improvements for making inefficient DMUs efficient in the CCR, by introducing a decision-maker's policy model with the minimal change of input and output values. Finally, Yang et al. (2013) utilise DEA and Nash bargaining game (NBG) theory to improve inefficient banks, in order to: (i) make an inefficient bank Pareto-optimal for multiple perspectives, which could avoid being discontent with some particular perspectives; and (ii) change its attributes and provide various improvement schemes for decision makers. Finally, Suzuki et al. (2010) proposed a Distance Friction Minimisation (DFM) model that is based on a generalised 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 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.

To produce a more realistic improvement plan, we need a method that allows reference points that remain below the efficiency frontier. A Target-Oriented (TO) DFM model which proposed Suzuki et al. (2013) specifies 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 a TES. The TO-DFM result is able to present a more realistic efficiency-improvement plan than those of the original DEA model and the original DFM model for DMUs with an efficiency score below 1 in the initial situation. Even though, in reality these values may have an infeasible case, for example Net-Working Rate may be required more than 100% in improvement projection, but it exceed a physical limit.

This paper aims to present a newly developed adjusted DEA model, emerging from a blend of the TO-DFM and the Improvement Restriction (IR) approach, for generating an appropriate efficiency-improving projection model. The IR approach specifies a restriction input/output items based on absence or presence of DMU's improvement limit. This approach can compute an input reduction value and an output increase value in order to achieve a TES that maintains an improvement restriction.

This study evaluates the efficiency of new energy in Japan based on DEA, and the above-mentioned Improvement Restriction TO-DFM model based on the Super-efficiency model (Andersen and Petersen (1993), see Appendix A2) is applied to produce a realistic efficiency-improvement projection. The focus will be on the three input cost criteria (cost of power generation, energy payback time, and CO_2 emissions) and output performance criteria (net-working rate). Based on the results of the performance analysis and the efficiency-improvement projection of new energies in Japan, this study will offer a quantitative contribution to energy-environment policy in Japan.

The paper is organised as follows. Section 2 introduces DFM methodology and Section 3 introduces a TO model in the framework of a DFM model. Section 4 proposes the new model, which is an IR model in the framework of a TO-DFM model. Section 5 then presents an application of the methodology to an efficiency analysis and an efficiency-improvement projection of the new energy in Japan. Finally, Section 6 draws some conclusions.

2. 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, in the sense of maximising the ratio scale. $v_m{}^*$ is the optimal weight for the 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 the 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 2 and 3.

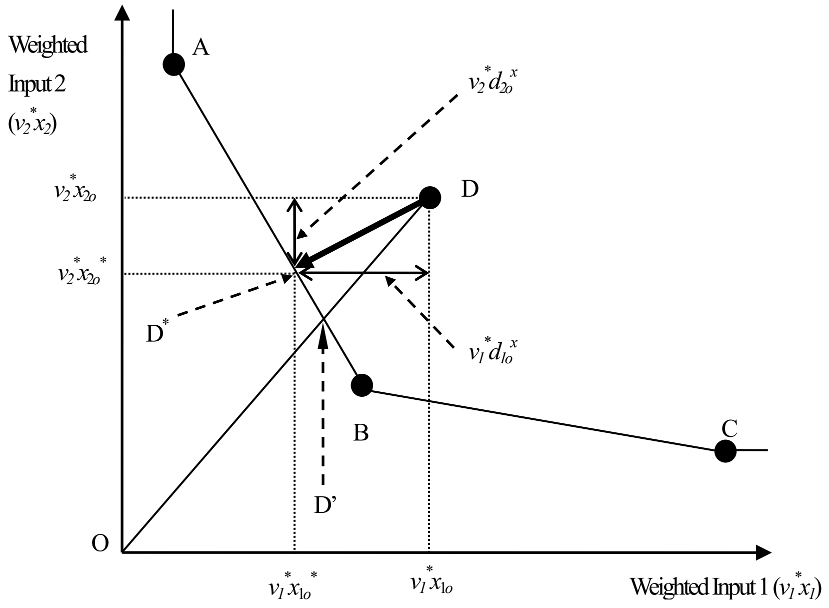


Figure 2 Illustration of the DFM approach (Input- $v_i^*x_i$ space)

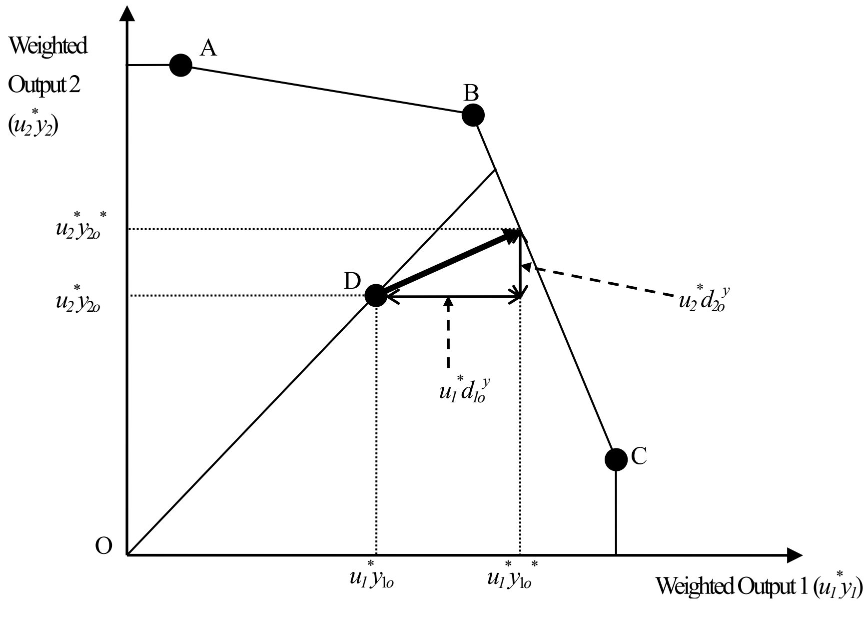


Figure 3 Illustration of the DFM approach (Output - $u_r^*y_r$ space)

In this approach, a generalised 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 minimisation of distance by using a Euclidean distance in weighted space. As mentioned, 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 minimise 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.

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 2 and 3. 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*)].

Hence, we find for the input reduction target and the output augmentation targets:

$$\text{Input reduction target: } \sum_m v_m^* \left(x_{mo} - d_{mo}^x\right) = 1 - \left(1-\theta^*\right) \times \frac{1}{\left(1+\theta^*\right)} = \frac{2\theta^*}{1+\theta^*}. \tag{2.8}$$

Output augmentation target: $\sum_s u_s^*\left(y_{so}+d_{so}^y\right)=\theta^*+\left(1-\theta^*\right)\times\frac{\theta^*}{\left(1+\theta^*\right)}=\frac{2\theta^*}{1+\theta^*}$. (2.9)

An illustration of the above situation is presented in Figure 4.

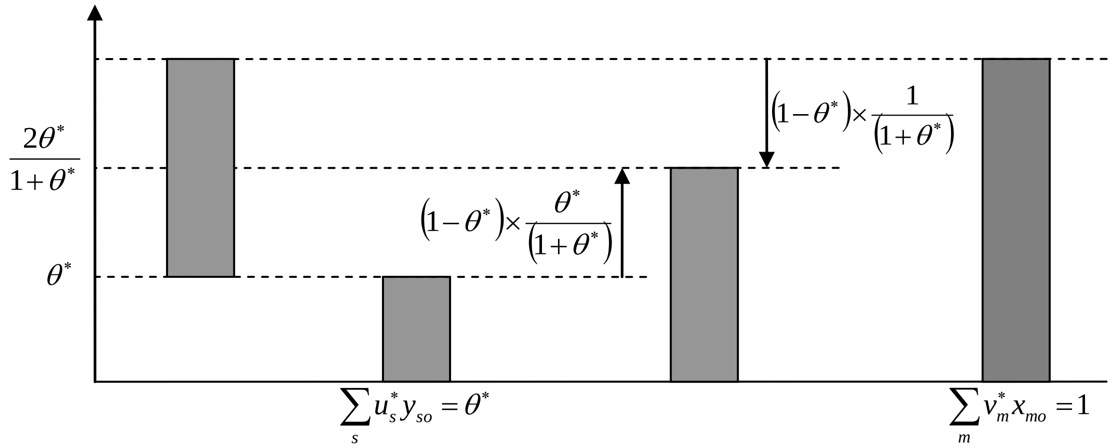


Figure 4 DFM model with an illustration of a balanced contribution of inputs and outputs to close the efficiency gap

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 minimisation solution for an inefficient DMU$_o$ can be expressed by means of formulas (2.10) and (2.11):

$$x_{mo}^* = x_{mo} - d_{mo}^{x*}; \tag{2.10}$$

$$y_{so}^* = y_{so} + d_{so}^{y*}. \tag{2.11}$$

By means of the 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 5).

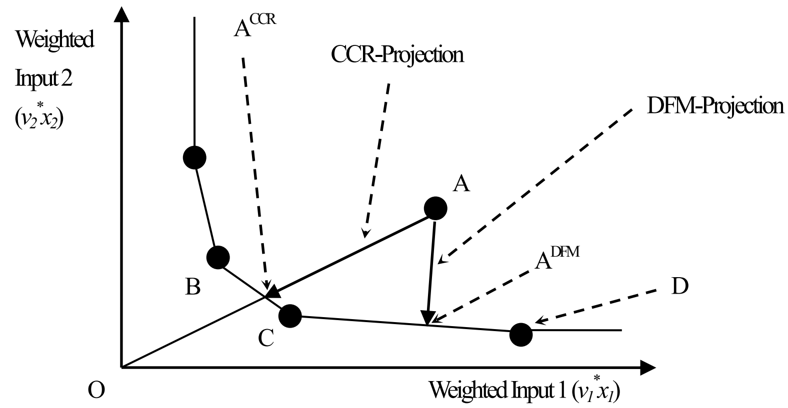


Figure 5 Degree of improvement of the DFM and the CCR projection in weighted input space

3. A Target Oriented-DFM model

The above-mentioned 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 in reality this might be hard to achieve for low-efficiency DMUs. Therefore we consider a method that allows reference points that remain below the efficiency frontier. On the other hand, DMUs that are close to (or exactly on) the efficient frontier might search for a reference point for a further improvement of their efficiency.

Target Oriented (TO) approach in the framework of the DFM model based on the Super-efficiency model (Andersen and Petersen (1993), see Appendix A2), which is based on the CCR-I model. The TO approach comprises the following steps:

Step1. Target Efficiency Score (TES) for DMU_o (hereafter TES_0) is set arbitrarily by the decision or policy maker. Improving projections are categorised in 3 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

Step2. Solve $TES_0 = \dfrac{\theta^* + MP_0\left(1-\theta^*\right)\times\dfrac{\theta^*}{\left(1+\theta^*\right)}}{1 - MP_0\left(1-\theta^*\right)\times\dfrac{1}{\left(1+\theta^*\right)}}$

Then, we get MP_o, which is a Magnification Parameter of TES_0.

Step3. Solve the TO-DFM model using formulas (3.1)–(3.8); then an optimal input reduction value and output increase value to reach a TES_0 can be calculated.

$$\min \ Fr^x = \sqrt{\sum_m \left(v_m^* x_{mo} - v_m^* d_{mo}^x\right)^2} \tag{3.1}$$

$$\min \ Fr^y = \sqrt{\sum_s \left(u_s^* y_{so} - u_s^* d_{so}^y\right)^2} \tag{3.2}$$

$$\text{s.t.} \quad TES_0 = \frac{\sum_s u_s^*\left(y_{so} + d_{so}^y\right)}{\sum_m v_m^*\left(x_{mo} - d_{mo}^x\right)} \tag{3.3}$$

$$\sum_m v_m^*\left(x_{mo} - d_{mo}^x\right) = 1 - MP_0\left(1-\theta^*\right)\times\frac{1}{\left(1+\theta^*\right)} \tag{3.4}$$

$$\sum_s u_s^*\left(y_{so}+d_{so}^y\right)=\theta^*+MP_0\left(1-\theta^*\right)\times\frac{\theta^*}{\left(1+\theta^*\right)} \quad (3.5)$$

$$x_{mo}-d_{mo}^x\geq 0 \quad (3.6)$$

$$d_{mo}^x\geq 0 \quad (3.7)$$

$$d_{so}^y\geq 0\,, \quad (3.8)$$

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

From Figure 6, we notice that a type of TES_0= 1.000 is just equal to the normal DFM model using formulas (2.1)–(2.7). We also notice that the Non-Attainment DFM projection (θ^*<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 plan, 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 will be that the TES_0 parameter will be lower than 1**.**

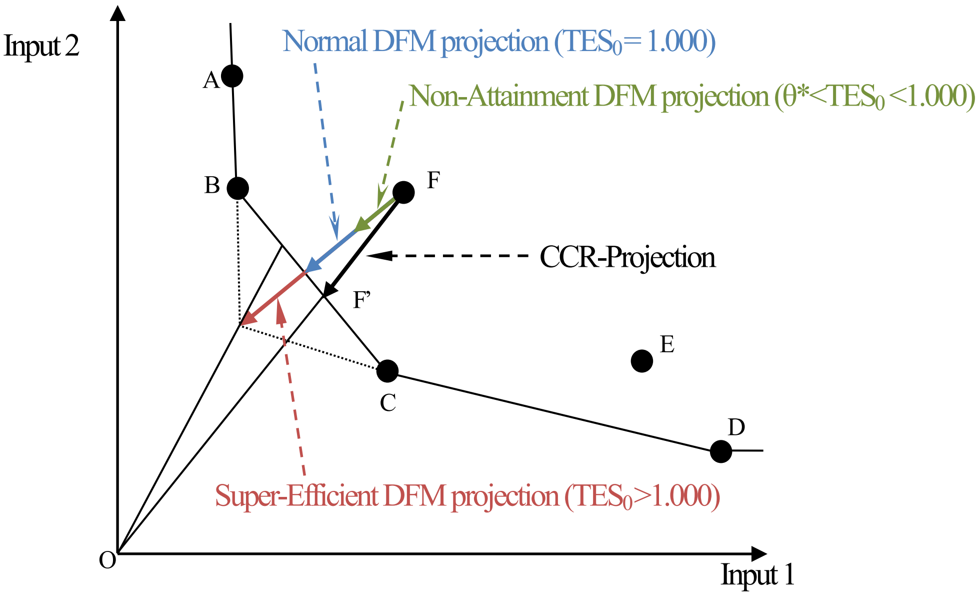


Figure 6 Illustration of the Target Oriented-DFM model for DMU F (Input space)

4. A proposal of Improvement Restriction approach based on TO-DFM model

The above-mentioned TO-DFM model calculates an optimal input reduction value and an output increase value in order to reach a TES, in reality these values may have an infeasible case, for example Net-Working Rate may be required more than 100% in improvement projection, but it exceed a physical limit.

Therefore, in this paper newly proposed Improvement Restriction approach based on TO-EFM model. The IR approach specifies a restriction input/output items based on absence or presence of DMU's improvement limit. This approach can compute an input reduction value and an output increase value in order to achieve a TES that maintains an improvement restriction. The Improvement Restriction approach comprises the following steps:

Step1. Target Efficiency Score (TES) for $DMU_{o\text{-}IR\,(Improvement\ Restriction)}$ (hereafter $TES_{0\text{-}IR}$) is set arbitrarily by the decision or policy maker.

Step2. Input and Output items resolve to unrestricted (UR) and restricted (R) items as following.

Input:

$$\sum_{m\in UR} v_m^*\left(x_{mo} - d_{mo}^x\right) + \sum_{m\in R} v_m^*\left(x_{mo} - d_{mo-deficiency}^x - d_{mo-limit}^x\right)$$

Output:

$$\sum_{s\in UR} u_s^*\left(y_{so} + d_{so}^y\right) + \sum_{s\in R} u_s^*\left(y_{so} + d_{so-deficiency}^y + d_{so-limit}^y\right)$$

where UR is unrestricted items, R is restricted items, $d_{mo-deficiency}^x$ is improvement deficiency value for restrict input item m for any arbitrary inefficient $DMU_{o\text{-}IR}$, $d_{mo-limit}^x$ is improvement limit value for restrict input item m for any arbitrary inefficient $DMU_{o\text{-}IR}$, $d_{so-deficiency}^y$ is improvement deficiency value for restrict output item s for any arbitrary inefficient $DMU_{o\text{-}IR}$, $d_{so-limit}^y$ is improvement limit value for restrict output item s for any arbitrary inefficient $DMU_{o\text{-}IR}$.

Step3. Solve

$$TES_{0-IR} = \frac{\theta^* + \sum_{s\in R} u_s^* \cdot d_{so-limit}^y + MP_{0-IR}\left[\left\{\left(1 - \sum_{m\in R} v_m^* \cdot d_{mo-limit}^x + \right) - \left(\theta^* + \sum_{s\in R} u_s^* \cdot d_{so-limit}^y\right)\right\} \cdot \frac{\left(\sum_{s\in UR} u_s^* \cdot y_{so}\right)}{\left\{\left(\sum_{m\in UR} v_m^* \cdot x_{mo}\right) + \left(\sum_{s\in UR} u_s^* \cdot y_{so}\right)\right\}}\right]}{1 - \sum_{m\in R} v_m^* \cdot d_{mo-limit}^x - MP_{0-IR}\left[\left\{\left(1 - \sum_{m\in R} v_m^* \cdot d_{mo-limit}^x + \right) - \left(\theta^* + \sum_{s\in R} u_s^* \cdot d_{so-limit}^y\right)\right\} \cdot \frac{\left(\sum_{m\in UR} v_m^* \cdot x_{mo}\right)}{\left\{\left(\sum_{m\in UR} v_m^* \cdot x_{mo}\right) + \left(\sum_{s\in UR} u_s^* \cdot y_{so}\right)\right\}}\right]}$$

Then, we get $MP_{o\text{-}IR}$, which is a Magnification Parameter of $TES_{0\text{-}IR}$.

Step4. Solve the IR-TO-DFM model using formulas (4.1)–(4.10); then an optimal input reduction value and output increase value maintaining an improvement restriction to reach a $TES_{0\text{-}IR}$ can be calculated.

$$\min \quad Fr^{x}=\sqrt{\sum_{m\in UR}\left(v_m^{*}\cdot x_{mo}-v_m^{*}\cdot d_{mo}^{x}\right)^{2}+\sum_{m\in R}\left(v_m^{*}\cdot x_{mo}-v_m^{*}\cdot d_{mo-limit}^{x}\right)^{2}} \tag{4.1}$$

$$\min \quad Fr^{y}=\sqrt{\sum_{s\in UR}\left(u_s^{*}\cdot y_{so}-u_s^{*}\cdot d_{so}^{y}\right)^{2}+\sum_{s\in R}\left(u_s^{*}\cdot y_{so}-u_s^{*}\cdot d_{so-limit}^{y}\right)^{2}} \tag{4.2}$$

$$\text{s.t.} \quad TES_0=\frac{\sum_{s\in UR}u_s^{*}\left(y_{so}+d_{so}^{y}\right)+\sum_{s\in R}u_s^{*}\left(y_{so}+d_{so-limit}^{y}\right)}{\sum_{m\in UR}v_m^{*}\left(x_{mo}-d_{mo}^{x}\right)+\sum_{m\in R}v_m^{*}\left(x_{mo}-d_{mo-limit}^{x}\right)} \tag{4.3}$$

$$\begin{aligned}&\sum_{m\in UR}v_m^{*}\left(x_{mo}-d_{mo}^{x}\right)+\sum_{m\in R}v_m^{*}\left(x_{mo}-d_{mo-limit}^{x}\right)\\&=1-\sum_{m\in R}v_m^{*}\cdot d_{mo-limit}^{x}-MP_{0-IR}\left[\left\{\left(1-\sum_{m\in R}v_m^{*}\cdot d_{mo-limit}^{x}+\right)-\left(\theta^{*}+\sum_{s\in R}u_s^{*}\cdot d_{so-limit}^{y}\right)\right\}\cdot\frac{\left(\sum_{m\in UR}v_m^{*}\cdot x_{mo}\right)}{\left\{\left(\sum_{m\in UR}v_m^{*}\cdot x_{mo}\right)+\left(\sum_{s\in UR}u_s^{*}\cdot y_{so}\right)\right\}}\right]\end{aligned} \tag{4.4}$$

$$\begin{aligned}&\sum_{s\in UR}u_s^{*}\left(y_{so}+d_{so}^{y}\right)+\sum_{s\in R}u_s^{*}\left(y_{so}+d_{so-limit}^{y}\right)\\&=\theta^{*}+\sum_{s\in R}u_s^{*}\cdot d_{so-limit}^{y}+MP_{0-IR}\left[\left\{\left(1-\sum_{m\in R}v_m^{*}\cdot d_{mo-limit}^{x}+\right)-\left(\theta^{*}+\sum_{s\in R}u_s^{*}\cdot d_{so-limit}^{y}\right)\right\}\cdot\frac{\left(\sum_{s\in UR}u_s^{*}\cdot y_{so}\right)}{\left\{\left(\sum_{m\in UR}v_m^{*}\cdot x_{mo}\right)+\left(\sum_{s\in UR}u_s^{*}\cdot y_{so}\right)\right\}}\right]\end{aligned} \tag{4.5}$$

$$x_{mo}-d_{mo}^{x}\geq 0 \tag{4.6}$$

$$d_{mo}^{x}\geq 0 \tag{4.7}$$

$$d_{so}^{y}\geq 0 \tag{4.8}$$

$$d_{mo\in R}^{x}=d_{mo-limit}^{x} \tag{4.9}$$

$$d_{so\in R}^{y}=d_{so-limit}^{y} \tag{4.10}$$

5. An application of Improvement Restriction TO-DFM model for efficiency evaluation and improvement of new energy in Japan

5.1 Database and analytical framework

We use the following inputs and outputs data for a set of 8 type new energy in Japan.

Figure 7 presents the inputs and outputs considered in this analysis of new energy efficiency.

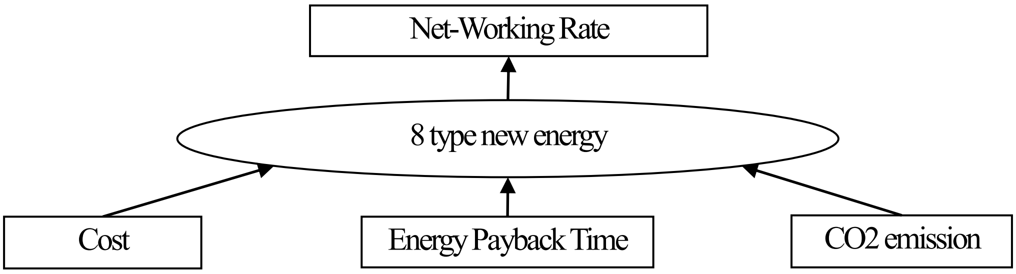


Figure 7 Inputs and Outputs of new energy efficiency

We consider 3 Inputs (I):

(I1) Cost (including construction, fuel and operating cost) (Yen/kWh)

(I2) Energy Payback Time (Year)

(I3) CO_2 emission (Kg-CO_2/kWh)

and 1 Output is incorporated:

(O2) Net-Working Rate (%)

Datasets (I1) were obtained from the "Report of commission for cost verification, energy and environment conference, Japan Cabinet Secretariat" and "Japan Geothermal Developers' Council". Datasets (I2) were obtained from the Report of "Mizuho Information & Research Institute" and "The National Institute of Advanced Industrial Science and Technology (AIST) in JAPAN". Datasets (I3) were obtained from the Report of "Central research institute of electric power industry (CRIEPI) in JAPAN" and "AIST in JAPAN". Datasets (O1) were obtained from the "Report of commission for cost verification, energy and environment conference, Japan Cabinet Secretariat" and "BTS JAPAN website (http://bts.jpn.com/)"

The DMUs and these datasets used in analysis are listed in Table 1.

Table 1 A listing of DMUs and datasets

No.	DMU	(Input) Cost	(Input) Energy payback time	(Input) CO2 emission	(Output) Net-working rate
1	Household Solar (HS)	18.70	2.20	38.00	12.00
2	Mega Solar (MS)	22.10	2.58	55.20	12.00
3	Geothermal (GT)	14.80	0.97	15.00	80.00
4	Woody Biomass (WB)	24.80	3.60	44.00	80.00
5	Biogas (BG)	26.29	3.40	54.97	90.00
6	Small Hydroelectric (SH)	20.55	0.60	5.50	60.00
7	Wind on the Land (WL)	13.05	0.68	29.00	20.00
8	Wind on the Ocean (WO)	15.95	0.68	29.00	30.00

In our application, we first applied the Super-Efficiency CCR-I model (see Appendix A1 and A2), while then the results were used to determine the CCR-I, DFM, TO-DFM, and IR-TO-DFM projections.

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

An efficiency evaluation result for 8 type new energy based on the Super-Efficiency CCR-I model is presented in Figure 8. From Figure 8, it can be seen that Small Hydroelectric (2.045) and geothermal (1.742) are super-efficient DMUs. On the other hands, we noticed that mega solar (0.100), household solar (0.119), wind on the land (0.342), and wind on the ocean (0.490) are low efficiency than biogas (0.633) and woody biomass (0.597). In generally, Solar and wind energies are expected for leading new energy in Japan, nevertheless Net-Working Rate of these energies are lower level as Table 1, then efficiency scores of solar and wind are evaluated a low efficiency. From these facts, it is considered that output fluctuation and its stabilization of new energy are important factor for new energy policy in Japan. Given the above findings, it is necessary to make an effort in efficiency improvement of the new energy.

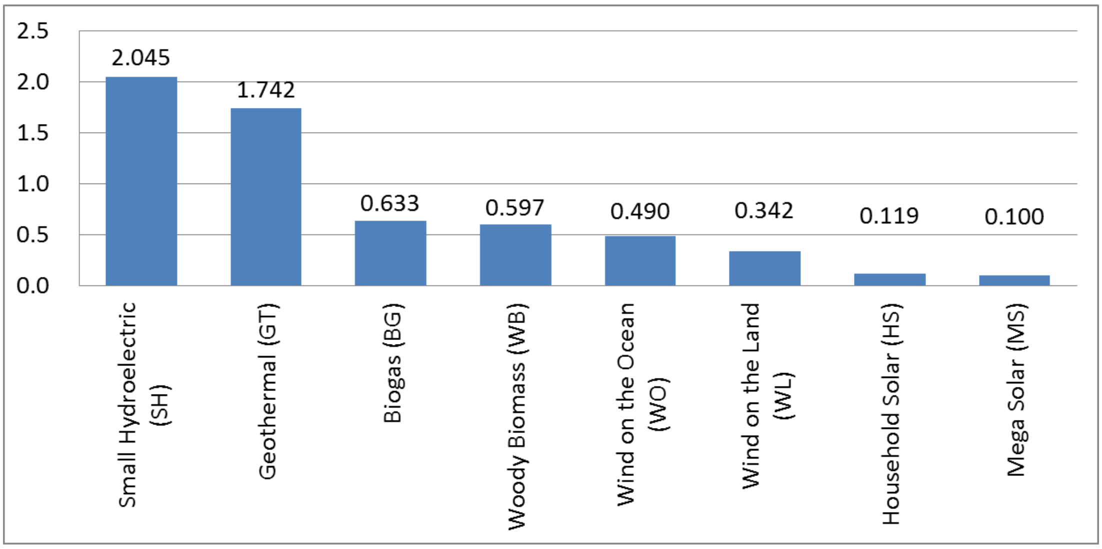


Figure 8 Efficiency scores based on the Super-Efficiency CCR-I model

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

The results of efficiency improvement projection based on the CCR, DFM and TO-DFM models for inefficient DMUs are presented in Table 2.

It appears that, as expected, the empirical ratios of change in the DFM projection are smaller than in the CCR projection. In Table 2, this particularly applies to Wind on the ocean, which is apparently a non-slack type (i.e., s-** and s+** are zero) energy. Apart from the practicality of such a solution, the models clearly show that a different – and perhaps more efficient – solution than the standard CCR projection is available for reaching the efficiency frontier. For instance, the CCR projection shows that Wind on the ocean should reduce its Cost by 51.0%, its energy payback time by 51.0%, and its energy CO2 emission by 85.4%, in order to become efficient. On the other hand, the DFM results show that a reduction in energy payback time of 45.1%, together with an increase in the net-working rate of 34.2% is required to become efficient.

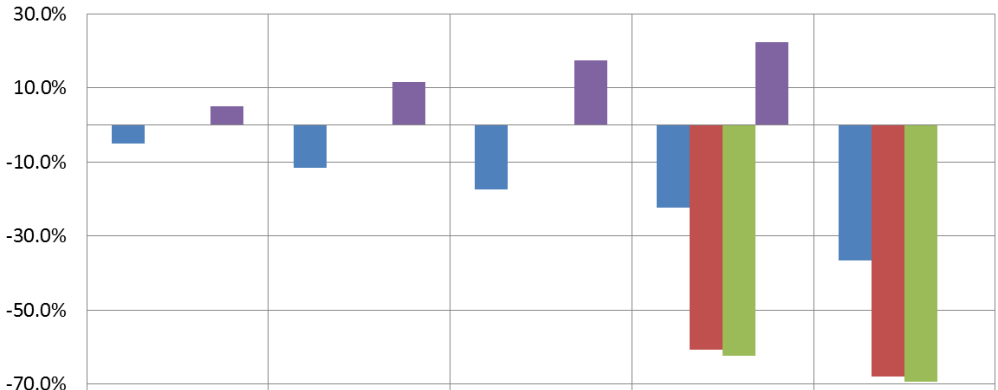
In the case of the TO-DFM model, Target Efficiency Score (TES) for each inefficient DMU are set an efficiency score of proximate upper-level DMU. For example, Woody Biomass score was 0.597. To achieve Bio Gus score (0.633) using the TO-DFM model, a reduction in cost of 3.0 % and an increase in Net working rate of 3.0% are required. It thus appears that the TO-DFM result is able to present a realistic efficiency-improvement plan, compared with the CCR and DFM approach for the DMUs with an efficiency score below 1 in the initial situation.

Table 2 Efficiency-improvement projection results of the CCR, DFM and TO-DFM models

		CCR model		DFM model		TO-DFM model	
DMU	Score	Score(θ**)		Score(θ**)		Score(θ**)	
I/O	Data	Difference	%	Difference	%	Difference	%
Household Solar (HS)	0.181	1.000		1.000		0.381	(WL level)
(I)cost	18.7	-16.5	-88.1%	-14.7	-78.8%	-9.1	-48.4%
(I)energy payback time	2.2	-2.1	-93.4%	-1.9	-88.2%	0.0	0.0%
(I)CO2 emission	0.0	-35.8	-94.1%	-34.0	-89.4%	0.0	0.0%
(O)net-working rate	12.0	0.0	0.0%	9.5	78.8%	5.8	48.4%
Mega Solar (MS)	0.127	1.000		1.000		0.181	(HS level)
(I)cost	22.1	-19.9	-90.0%	-18.1	-81.7%	-1.8	-8.3%
(I)energy payback time	2.6	-2.4	-94.4%	-2.3	-89.8%	0.0	0.0%
(I)CO2 emission	0.0	-53.0	-95.9%	-51.1	-92.6%	0.0	0.0%
(O)net-working rate	12.0	0.0	0.0%	9.8	81.7%	1.0	8.3%
Woody Biomass(WB)	0.597	1.000		1.000		0.633	(BG level)
(I)cost	24.8	-10.0	-40.3%	-6.3	-25.3%	-0.7	-3.0%
(I)energy payback time	3.6	-2.6	-73.1%	-2.4	-66.3%	0.0	0.0%
(I)CO2 emission	0.0	-29.0	-65.9%	-25.2	-57.3%	0.0	0.0%
(O)net-working rate	80.0	0.0	0.0%	20.2	25.3%	2.4	3.0%
BioGas(BG)	0.633	1.000		1.000		0.800	(arbitrarily level)
(I)cost	26.3	-9.6	-36.7%	-5.9	-22.4%	-3.1	-11.6%
(I)energy payback time	3.4	-2.3	-67.9%	-2.1	-60.7%	0.0	0.0%
(I)CO2 emission	0.0	-38.1	-69.3%	-34.3	-62.4%	0.0	0.0%
(O)net-working rate	90.0	0.0	0.0%	20.2	22.4%	10.5	11.6%
Wind on the Land (WL)	0.381	1.000		1.000		0.490	(WO level)
(I)cost	13.1	-8.5923237	-65.84%	0.000	0.0%	0.000	0.0%
(I)energy payback time	0.7	-0.4477226	-65.84%	-0.420	-61.8%	-0.153	-22.5%
(I)CO2 emission	0.0	-25.71102	-88.66%	0.000	0.0%	0.000	0.0%
(O)net-working rate	20.0	0	0.00%	9.815	49.1%	3.569	17.8%
Wind on the Ocean (WO)	0.490	1.000		1.000		0.597	(WB level)
(I)cost	16.0	-8.1	-51.0%	0.0	0.0%	0.0	0.0%
(I)energy payback time	0.7	-0.3	-51.0%	-0.3	-45.1%	-0.1	-12.9%
(I)CO2 emission	0.0	-24.8	-85.4%	0.0	0.0%	0.0	0.0%
(O)net-working rate	30.0	0.0	0.0%	10.3	34.2%	2.9	9.8%

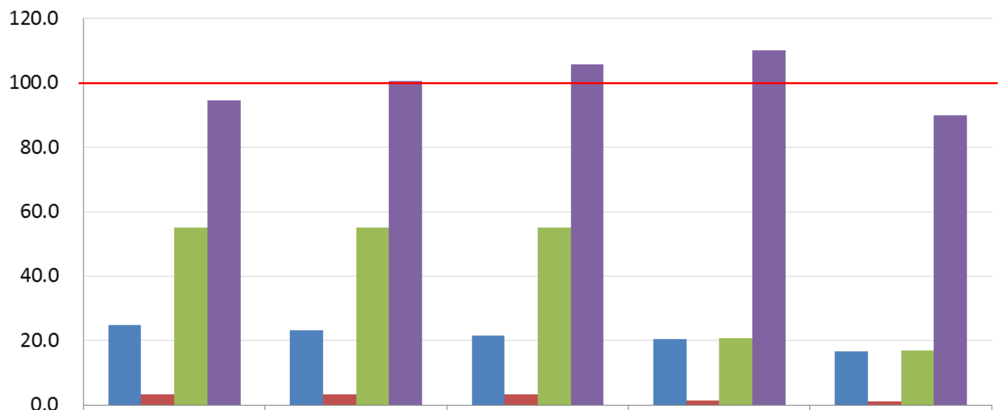
5.4 Efficiency improvement projection of the Target Oriented-DFM model

In this subsection, we will use the Bio-Gas as example and present an efficiency improvement projection result based on the TO-DFM model. Efficiency score of Bio-Gas is 0.633 (see figure 8). We consider steps to improve efficiency towards 0.7, 0.8, 0.9 and 1.0. The resulting input reduction percentage and the output increase percentage based on the TO-DFM model are presented in Figure 9.



	TES=0.700	TES=0.800	TES=0.900	TES=1.000 (Normal DFM)	CCR-I (Score=1.000)
(I)Cost	-5.0%	-11.6%	-17.4%	-22.4%	-36.7%
(I)Energy payback time	0.0%	0.0%	0.0%	-60.7%	-67.9%
(I)CO2 emission	0.0%	0.0%	0.0%	-62.4%	-69.3%
(O)Net-working rate	5.0%	11.6%	17.4%	22.4%	0.0%

Figure 9 Efficiency improvement projection results (%) based on TO-DFM (Bio-Gas)



	TES=0.700	TES=0.800	TES=0.900	TES=1.000 (Normal DFM)	CCR-I (Score=1.000)
(I)Cost	25.0	23.2	21.7	20.4	16.7
(I)Energy payback time	3.4	3.4	3.4	1.3	1.1
(I)CO2 emission	55.0	55.0	55.0	20.7	16.9
(O)Net-working rate	94.5	100.5	105.6	110.2	90.0

Figure 10 Efficiency improvement projection results (actual number) based on TO-DFM (Bio-Gas)

These results show that if it implements an efficiency improvement plan with a TES amounting to 0.7, a reduction in cost of 5.0% and an increase in Net-working rate of 5.0% are required. Furthermore, for a plan to achieve a TES of 1.000, a reduction in cost of 22.4%, in Energy payback time of 60.7%, in CO 2 emission of 62.4% and an increase in Net-working rate of 22.4% would be required.

Projection results on actual number based on the TO-DFM model are presented in Figure 10.

From figure 10, it appear that value of Net -working rate exceed 100(%) in the case of TES=0.8 to 1.0. It is clearly an infeasible solution.

5.5 Efficiency improvement projection of the Improvement Restriction TO-DFM model

In this subsection, we will use the Bio-Gas as example and present an efficiency improvement projection result based on the Improvement Restriction TO-DFM model. As we confirmed that the infeasible case in subsection 5.4, that Net -working rate exceed 100(%) in the case of TES=0.8 to 1.0, then we set out Net -working rate as restricted output item. This study assumed that improvement limitation of Net -working rate set out 95(%).

Efficiency score of Bio-Gas is 0.633 (see figure 8). We consider steps to improve efficiency towards 0.7, 0.8, 0.9 and 1.0. The projection result of input reduction percentage and the output increase percentage, also each actual number, based on the IR-TO-DFM model are presented in Figure 11 and 12.

	TES=0.700	TES=0.800	TES=0.900	TES=1.000	CCR-I (Score=1.000)
(I)Cost	-5.0%	-16.4%	-17.4%	-33.1%	-36.7%
(I)Energy payback time	0.0%	0.0%	0.0%	-66.1%	-67.9%
(I)CO2 emission	0.0%	0.0%	0.0%	-67.6%	-69.3%
(O)Net-working rate	5.0%	5.6%	5.6%	5.6%	0.0%

Figure 11 Efficiency improvement projection results (%) based on the IR-TO-DFM (Bio-Gas)

	TES=0.700	TES=0.800	TES=0.900	TES=1.000	CCR-I (Score=1.000)
(I)Cost	25.0	22.0	19.5	17.6	16.7
(I)Energy payback time	3.4	3.4	3.4	1.2	1.1
(I)CO2 emission	55.0	55.0	55.0	17.8	16.9
(O)Net-working rate	94.5	95.0	95.0	95.0	90.0

Figure 12 Efficiency improvement projection results (actual number) based on IR-TO-DFM (Bio-Gas)

From Figure 11 and 12, it can be confirmed that an efficiency improvement plan with a TES amounting from 0.8 to 1.0, an increase percentage in Net-working rate of 5.6%, and its actual number of 95(%) are fixed. From this fact, it appears that IR-TO-DFM model can produce more realistic efficiency improvement projection than DFM and TO-DFM model.

6. Conclusion

In this paper, we have presented a new methodology, the IR-TO-DFM model. Its feasibility was tested for the new energy in Japan, and the new model was adopted in realistic circumstances.

The results appear to offer a meaningful contribution to decision making and planning for an efficiency improvement in the Energy-Environment sector in Japan. 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 environmental-energy decision making and planning.

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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,…, M) for DMU$_j$(j = 1,…,J); y_{sj} is the output *s* (s = 1,…,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 maximising the numerator.

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

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

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

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).

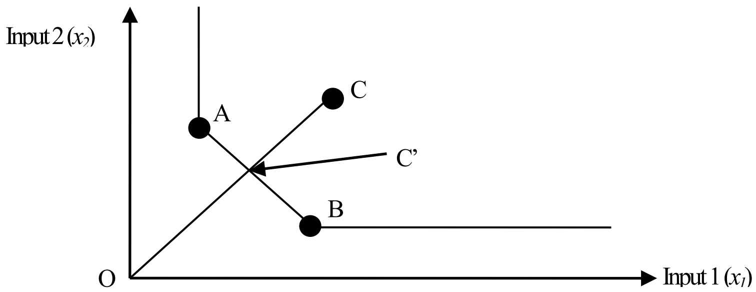

Figure A1 Illustration of original DEA projection in input space

A2. Super-efficiency model

In a standard DEA model, all efficient DMUs get the score 1, so that there is no way to differentiate between them. This has led to focused research to discriminate between efficient DMUs, in order to arrive at a ranking, or even a numerical rating of these efficient DMUs, without affecting the results for the 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.

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

$$
\begin{aligned}
&\min_{\theta,\lambda,S^-,S^+} \quad \theta - es^- - es^+ \\
\text{s.t.} \quad & \theta x_o = \sum_{j=1,\neq o}^{J} \lambda_j x_j + s^- \\
& y_o = \sum_{j=1,\neq o}^{J} \lambda_j y_j - s^+ \\
& \lambda_j, s^-, s^+ \geq 0
\end{aligned}
\tag{A.4}
$$

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