Preference Elicitation in Generalized Data Envelopment Analysis
-In Search of a New Energy Balance in Japan

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The recent dramatic change in energy supply in Japan has prompted a search for a new energy-environment-economic efficiency policy, in which a compromise has to be found between a sufficient supply of energy resources, the development of low carbon emission technology, and a continuation of economic growth. The prefectures in Japan are regarded as decision-making units (DMUs) which are responsible for the design of a new sustainable energy balance in these regions. The main challenge is now to design an efficient energy-environment-economic (EEE) system.

The present paper aims to develop a balanced decision-support tool for achieving an efficient energy supply in all Japanese prefectures. To that end, a new variant of Data Envelopment Analysis (DEA) is presented, which is characterized by two integrated features: (i) the use of a general Distance Friction Minimization (DFM) model to achieve the most appropriate movement towards the efficiency frontier surface; (ii) the incorporation of preference-based (PB) adjustments in efficiency policy strategies regarding the input reduction or the output increase allocation of DMUs in order to balance rigorous efficiency decisions with political priorities at the regional level. This paper illustrates this new methodology by means of an application to prefectural energy efficiency strategies in Japan.

Keywords: Data Envelopment Analysis (DEA); Distance Friction Minimization (DFM);
Preference Based (PB); Energy-Environment-Economic efficiency

JEL classifications: C00, R58, Q48

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1. In Search of a New Energy Balance in Japan

After the Fukushima nuclear catastrophe in Japan, the country was faced with an unprecedented challenge in its energy policy: namely, to seek a new energy supply balance after the abandonment of nuclear power technology and supply. This sudden transformation in energy supply policy called for an intensive search for energy alternatives that could meet the requirements of both supply efficiency and sustainable energy supply, while avoiding a situation of electrical power shortage. Thus, the new energy policy of Japan has to find the right balance in the triangular relationship Energy - Environment - Economy, governed by the policy objectives of electrical power savings, low carbon emissions, and the continuation of economic growth. To meet these goals, a strategic foresight analysis of energy supply in the country is necessary.

Although the national government in Japan is responsible for the overall strategic design of future energy policy, the actual implementation of energy policy takes place at the decentralized level of 47 prefectures. These prefectures may be seen as decision agents which may have to find a new balance in the supply of energy resources that would be efficient and environmentally-sustainable. These conflicting objectives call for an operational assessment framework for a balanced energy supply at the prefectural level. The main aim of the present chapter is to identify the most efficient and sustainable prefectural strategies in Japan, so that other – lower-performing – prefectures can improve their performance through a comparative benchmarking exercise. The analytical tool used in the present chapter is based on Data Envelopment Analysis (DEA), while the prefectures are regarded here as agents or Decision Making Units (DMUs). We present a new type of DEA in which two new elements are included, viz. an adjusted distance measure for the most appropriate movement towards the efficiency frontier, and a preference elicitation approach for the incorporation of a decision maker's value judgment of input and/or output goals. These integrated elements will be used in a new DEA context, with a view to the identification of the most efficient DMUs (i.e. the Japanese prefectures).

This study is organized as follows. Section 2 provides a brief standard introduction to efficiency improvement projection in DEA, including a short overview of DEA developments. This is followed by an exposition of: (i) a Distance Friction Minimization (DFM) approach (in Section 3); and (ii) a Preference-Based (PB) approach (in Section 4). Next, Section 5 contains an empirical application of the above methodology to energy policy at the prefectural level in Japan, including the presentation of various research findings. Finally, Section 6 makes some concluding remarks.

2. Efficiency Improvement Projection in DEA

A popular tool to judge efficiency in organizations is Data Envelopment Analysis (DEA). Over recent years comparative efficiency analysis has become a well-established field as part of a benchmarking exercise. DEA was originally developed to analyze the relative efficiency of a DMU, by constructing a piecewise linear production frontier, and then projecting the performance of each DMU onto the frontier concerned. A DMU located on the frontier is efficient, whereas a DMU that is not on the frontier is inefficient. An inefficient DMU may then become (more) 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 rise in all outputs). DEA already has a long history. The standard DEA model was developed by Charnes et al. (1978) for assessing the performance of a given DMU_j (j=1,…, J), and can be represented as the following fractional programming problem:

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

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

$$v_m \ge 0 \,,\; u_s \ge 0 \,, \qquad (2.1)$$

where θ represents an objective 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.

The improvement projections $(\hat{x}_o, \hat{y}_o)$ are usually defined in (2.2) and (2.3) as follows:

$$\hat{x}_o = \theta^* x_o - s^{-*} \quad (22)$$

$$\hat{y}_o = y_o + s^{+*}. \quad (23)$$

These projections 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. The original DEA models presented in the literature have focused on a uniform input reduction or a uniform output increase in the efficiency-improvement projections. In principle, an infinite number of improvements are required to reach the efficiency frontier, and hence there is a multiplicity of solutions for any DMU to enhance its efficiency.

The existence of many possible efficiency improvement solutions has led to a rich literature on the methodological integration of the MOLP (Multiple Objective Linear Programming) and the DEA models. The first contribution was made by Golany (1988), who proposed an interactive MOLP procedure, which aimed to generate 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. Thanassoulis and Dyson (1992), Joro et al. (1998), Halme et al. (1999), Korhonen and Siljamäki (2002), Korhonen et al. (2003), Lins et al. (2004), Washio et al. (2012), and Yang and Morita (2013) have also proposed efficiency improvement solutions.

3. The Distance Friction Minimization (DFM) Approach

We now present the principles of a recently developed and more appropriate approach. Detailed descriptions and empirical applications can be found, inter alia, in Suzuki et al. (2010). As mentioned above, the original efficiency improvement solution in the original CCR-input model requires that the input values are reduced radially by a uniform ratio θ*. The (v*, u*) values obtained as an optimal solution for formula (2.1) result in a set of optimal weights for DMU_o. Hence, (v*, u*) is the set of the most favorable weights for DMU_o, in the sense of maximizing 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 to what extent they do so. In other words, it is possible to express the distances (or alternatively, the potential increases) in improvement projections.

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. This approach may address both an input reduction and an output increase as a strategy for a DMU. A major advantage of this model is that there is no need to incorporate the value judgment of a decision maker. Nevertheless, it may also be attractive to develop it further to incorporate policy-maker value judgments on political priorities.

We will use the optimal weights u_s* and v_m* from (2.1), and then describe the efficiency improvement projection model. A visual presentation of this approach (DFM projection) is given in Figures 3 and 4. In this approach a generalized distance function is employed to assist a DMU to improve its efficiency by a movement towards the efficiency frontier surface. The direction of efficiency improvement depends, of course, on the input/output data characteristics of the DMU. It is now appropriate to define projection functions for the minimization of distance in weighted spaces. As mentioned, a suitable form of multidimensional projection functions that serves to improve efficiency is given by an MOQP (Multiple Objective Quadratic Programming) 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 may address both input reduction and output increase. We briefly describe the various steps, based on Suzuki et al. (2010).

First, the distance functions Fr^x and Fr^y is specified by means of (3.1) and (3.2), which are defined by the distances shown in Figures 3 and 4. Next, the following MOQP is solved by using (a reduction of distance for x_{mo}) and (an increase of distance for y_{so}) as variables:

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

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

$$\text{s.t.} \quad \sum_m v_m^* \left(x_{mo} - d_{mo}^x \right) = \frac{2\theta^*}{1+\theta^*} \quad (3.3)$$

$$\sum_s u_s^* \left(y_{so} + d_{so}^y \right) = \frac{2\theta^*}{1+\theta^*} \quad (3.4)$$

$$x_{mo} - d_{mo}^x \geq 0, d_{mo}^x \geq 0, d_{so}^y \geq 0 \quad (3.5)$$

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 (3.3) and (3.4) refer to the target values of input reduction and output augmentation. The proportional distribution of the input and output contributions in achieving 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 derive for the input reduction target and the output augmentation targets the following expressions:

Input reduction target:

$$\sum_m v_m^*\left(x_{mo} - d_{mo}^x\right) = 1 - \left(1-\theta^*\right) \times \frac{1}{\left(1+\theta^*\right)} = \frac{2\theta^*}{1+\theta^*} . \quad (3.6)$$

Output augmentation target:

$$\sum_s u_s^*\left(y_{so} + d_{so}^y\right) = \theta^* + \left(1-\theta^*\right) \times \frac{\theta^*}{\left(1+\theta^*\right)} = \frac{2\theta^*}{1+\theta^*} . \quad (3.7)$$

It is now possible to determine each optimal distance d_{mo}^{x*} and d_{so}^{y*} by using the MOQP model (3.1)-(3.5). The distance minimization solution for an inefficient DMU_o can be expressed by means of formulas (3.8) and (3.9):

$$x_{mo}^* = x_{mo} - d_{mo}^{x*}; \quad (3.8)$$

$$y_{so}^* = y_{so} + d_{so}^{y*}. \quad (3.9)$$

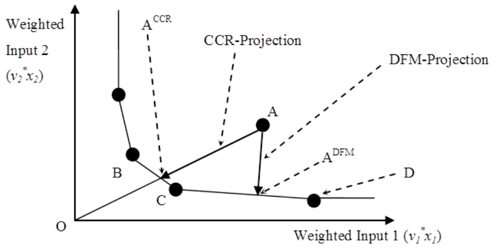


Fig. 1 Degree of improvement of the DFM and the CCR projection in weighted input space

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 1). For more details we refer to Suzuki et al. (2010).

4. A Preference-Based (PB) DFM Model

In this section, we propose a preference-based (hereafter PB) approach to the DFM model. The rationale of this approach is the following. A DMU may have specific priorities on the cost side and on the benefit side of its operation. For example, in various cases the goal of minimizing all cost items may affect the profit condition. Similarly, extreme output maximization may jeopardize cost efficiency. Therefore, in many decision-making situations, a balance between input and output targets has to be found. Our PB approach specifies an Output Augmentation Parameter (OAP) of the total efficiency gap (1-θ*) in the DFM model. The value of the OAP ranges from 0 to 1. For example, if the OAP is specified to be 1.0, then the PB model can compute an efficiency-improving projection so that the total efficiency gap (1-θ*) is fully allocated to output augmentation. If, for instance, the OAP is specified to be 0.7, then the PB model can compute an efficiency-improving projection, so that 70 percent of the total efficiency gap (1-θ*) is allocated to output augmentation, and 30 percent of the total efficiency gap (1-θ*) is allocated to input reduction. And, if the OAP is specified to be 0.0, then the PB model can compute an efficiency-improving projection so that the total efficiency gap (1-θ*) is fully closed by the input reduction.

Instead of the constraint functions (3.3) and (3.4) in the DFM model, the PB model uses the constraint functions (4.1) and (4.2):

$$\text{s.t.} \quad \sum_m v_m^*\left(x_{mo} - d_{mo}^x\right) = \theta^* + OAP\left(1-\theta^*\right) \quad (4.1)$$

$$\sum_s u_s^*\left(y_{so} + d_{so}^y\right) = \theta^* + OAP\left(1-\theta^*\right). \quad (4.2)$$

A visual presentation of constraint functions (4.1) and (4.2) is given in Figure 2.

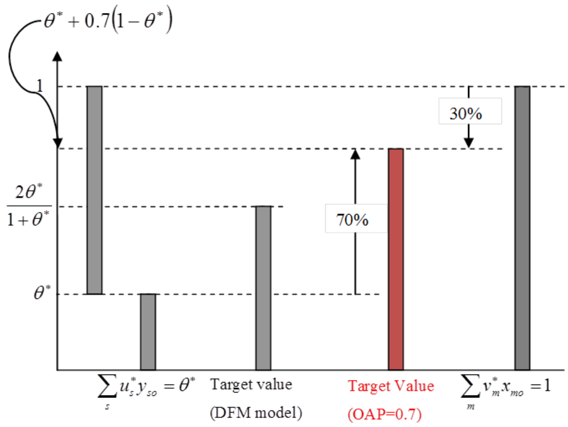


Fig.2 Illustration of the PB-DFM model with a value 0.7 for the OAP parameter

First, the PB model starts with an initial specification of a value for the OAP. This is just a decision maker's value judgment for the allocation percentage of an output augmentation in the total efficiency gap (1-θ*). Next, the target values, which are allocated between input efforts and output efforts based on the OAP, are computed in Figure 2 using constraint functions (4.1) and (4.2). Finally, we are able to compute an input reduction value and an output increase value based on the DFM model. A visual presentation of this new PB-DFM projection is given in Figures 3 and 4. This model will be called a Preference-Based DFM (PB-DFM) model. We now illustrate the feasibility of the PB-DFM model by means of an application to current Japanese energy policy, as sketched in Section 1.

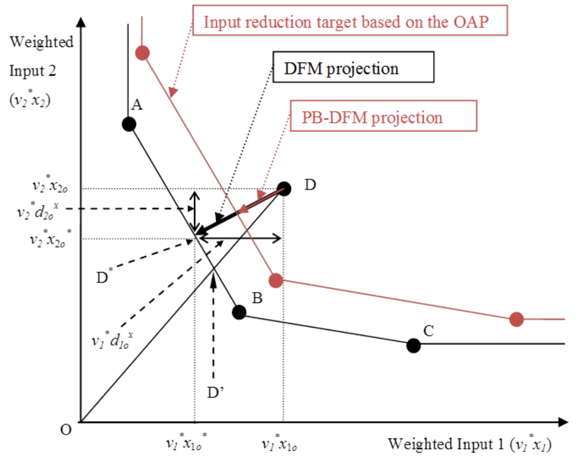


Fig. 3 Illustration of the DFM and PB-DFM approach (Input- $v_i^* x_i$ space)

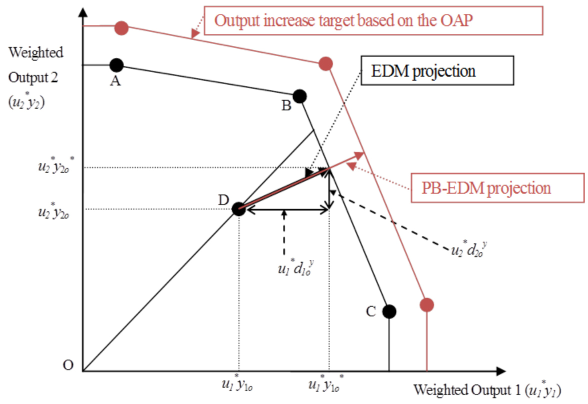


Fig. 4 Illustration of the DFM and PB-DFM approach (Output – $u_r^* y_r$ space)

5. An application of PB-DFM Model for Energy-Environment-Economic (EEE) Efficiency in Japan

5.1 Database and analysis framework

In our empirical work, we use the following input and output data on the EEE key variables for a set of 47 prefectures in Japan.

In our analysis we consider four Inputs (I):

(I1) Electricity consumption in each prefecture (Giga Watt hours / year) (2010); [Data source: Ministry of the Economy, Trade and Industry in Japan(2010).]

(I2) Public capital stock in each prefecture (million yen) (2010); [Data source: Government of Japan (2010).]

(I3) Private-sector capital stock in each prefecture (million yen) (2010); [Data source: Government of Japan (2010).]

(I4) Labor in each prefecture (employed persons) (2010). [Data source: Government of Japan (2010).]

Furthermore, two Outputs (O) are incorporated:

(O1) GDP in each prefecture (million yen /year) (2010); [Data source: Government of Japan (2010).]

(O2) Carbon emission in each prefecture (inverse number) (Giga tons/year) (2010). [Data source: Ministry of the Economy, Trade and Industry in Japan(2010).]

In our application, we first applied the CCR-I model, after which its results were used to determine the CCR-I and DFM projections. Additionally, we applied the PB-DFM model. Finally, these results were compared with each other. We now present the various findings stepwise.

5.2 Efficiency evaluation based on the CCR-I model

The efficiency evaluation results for each of the 47 prefectures based on the CCR-I model are given in Figure 5. The figure shows that 8 prefectures (Okinawa, Kochi, Tokushima, Tottori, Nara, Shiga, Yamanashi, and Tokyo) are efficient DMUs. The remaining 39 prefectures are inefficient. In particular, Niigata (0.696), Miyagi (0.696), Ehime (0.689), Gifu (0.686), and Aichi (0.678) have low efficiency.

Given the above findings, it seems necessary to make an effort to improve the efficiency of the energy-environment-economic (EEE) efficiency for inefficient prefectures.

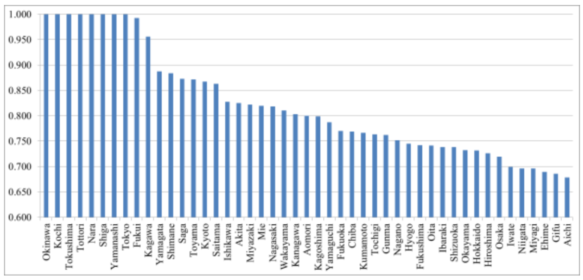


Fig.5 Efficiency score based on the CCR model

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

The efficiency improvement projection results based on the CCR, DFM and PB-DFM models for the 39 inefficient prefectures are presented in Table 1. In the case of the PB-DFM model, we apply an OAP parameter with an initially neutral value of 0.7 as in Figure 3. Next, in Section 5.4, we show that the outcomes change when the decision maker changes his preference parameter OAP.

From Table 1, it appears that the empirical ratios of change in the DFM projection are smaller than those in the CCR projection, as may be expected. In Table 1, this particularly applies to Hokkaido, Miyagi, Akita, Yamagata, Fukushima, Tochigi, Gunma, Toyama, Ishikawa, Nagano, Gifu, Shimane, Ehime, Nagasaki, and Kumamoto which are apparently non-slack type (i.e. s^{-**} and s^{+**} are zero) prefectures. The DFM projection involves both input reduction and output increase, and, clearly, the DFM projection does not involve a uniform ratio, because this

Table 1 Efficiency-improvement projection results of the CCR, DFM and PB-DFM models

		CCR	Normal-DFM	PB-DFM (OPA=0.7)			CCR	Normal-DFM	PB-DFM (OPA=0.7)
DMU	Score	Score(θ**)	Score(θ**)	Score(θ**)	DMU	Score	Score(θ**)	Score(θ**)	Score(θ**)
(Input)/(Output)	Data	%	%	%	(Input)/(Output)	Data	%	%	%
Hokkaido	0.731	1.000	1.000	1.000	Aichi	0.678	1.000	1.000	1.000
(I)PCS	59252111.0	-76.1%	0.0%	0.0%	(I)PCS	34053192.0	-36.9%	-25.1%	-16.5%
(I)PSCS	44889593.7	-26.9%	-16.0%	-8.3%	(I)PSCS	88980912.0	-36.8%	-24.8%	-16.0%
(I)Labour	2374750.0	-26.9%	0.0%	0.0%	(I)Labour	4233682.0	-32.2%	-19.2%	-9.7%
(I)EC	43267.4	-56.5%	0.0%	0.0%	(I)EC	72125.4	-56.6%	-48.6%	-42.7%
(O)GDP	19846756.0	0.0%	15.6%	25.9%	(O)GDP	33871848.0	0.0%	19.2%	33.3%
(O)CE	90.3	0.0%	0.0%	0.0%	(O)CE	56.1	0.0%	0.0%	0.0%
Aomori	0.800	1.000	1.000	1.000	Mie	0.819	1.000	1.000	1.000
(I)PCS	11540768.0	-39.5%	-16.4%	-21.5%	(I)PCS	12381474.0	-43.2%	-39.1%	-36.8%
(I)PSCS	10744292.1	-20.0%	-11.5%	-6.2%	(I)PSCS	24437097.0	-34.6%	-29.0%	-26.0%
(I)Labour	656460.0	-20.0%	0.0%	0.0%	(I)Labour	857656.0	-18.1%	-9.9%	-5.4%
(I)EC	11988.5	-39.7%	-29.0%	-28.7%	(I)EC	22561.2	-47.6%	-44.4%	-42.6%
(O)GDP	4807989.0	0.0%	12.1%	19.1%	(O)GDP	7970244.0	0.0%	10.4%	16.1%
(O)CE	329.9	0.0%	0.0%	0.0%	(O)CE	209.3	0.0%	0.0%	0.0%
Iwate	0.699	1.000	1.000	1.000	Kyoto	0.868	1.000	1.000	1.000
(I)PCS	12132989.0	-43.8%	-8.3%	-17.1%	(I)PCS	13670706.0	-27.4%	-6.6%	-11.6%
(I)PSCS	11424773.8	-30.1%	-18.3%	-9.3%	(I)PSCS	20590606.9	-13.3%	-7.3%	-4.1%
(I)Labour	689089.0	-30.1%	0.0%	0.0%	(I)Labour	1128104.0	-13.3%	0.0%	0.0%
(I)EC	10764.2	-32.4%	-13.7%	-13.0%	(I)EC	19393.0	-37.3%	-29.7%	-29.5%
(O)GDP	4314613.0	0.0%	20.0%	34.1%	(O)GDP	10413400.0	0.0%	7.4%	11.2%
(O)CE	420.6	0.0%	0.0%	0.0%	(O)CE	345.7	0.0%	0.0%	0.0%
Miyagi	0.696	1.000	1.000	1.000	Osaka	0.719	1.000	1.000	1.000
(I)PCS	14343319.0	-49.6%	0.0%	-17.1%	(I)PCS	39713219.0	-39.5%	-30.0%	-23.6%
(I)PSCS	20031378.7	-30.4%	-18.5%	-9.4%	(I)PSCS	87393692.5	-28.5%	-17.0%	-9.3%
(I)Labour	1077902.0	-30.4%	0.0%	0.0%	(I)Labour	4409530.0	-28.1%	-16.3%	-8.4%
(I)EC	20018.9	-54.0%	0.0%	-37.4%	(I)EC	69135.5	-49.0%	-41.2%	-35.9%
(O)GDP	8164598.0	0.0%	18.6%	31.8%	(O)GDP	37376542.0	0.0%	16.4%	27.4%
(O)CE	239.2	0.0%	0.0%	0.0%	(O)CE	93.2	0.0%	0.0%	0.0%
Akita	0.825	1.000	1.000	1.000	Hyogo	0.745	1.000	1.000	1.000
(I)PCS	10761226.0	-39.7%	0.0%	0.0%	(I)PCS	33135092.0	-59.6%	-54.0%	-50.5%
(I)PSCS	9409577.9	-17.5%	-17.3%	-9.5%	(I)PSCS	51620401.8	-33.1%	-23.6%	-17.5%
(I)Labour	527396.0	-17.5%	0.0%	0.0%	(I)Labour	2330113.0	-25.5%	-14.6%	-7.6%
(I)EC	8568.6	-20.6%	0.0%	0.0%	(I)EC	56340.2	-64.8%	-60.0%	-57.0%
(O)GDP	3931020.0	0.0%	12.0%	18.5%	(O)GDP	20416330.0	0.0%	14.7%	24.1%
(O)CE	563.3	0.0%	0.0%	0.0%	(O)CE	77.0	0.0%	0.0%	0.0%
Yamagata	0.887	1.000	1.000	1.000	Wakayama	0.811	1.000	1.000	1.000
(I)PCS	10515916.0	-31.4%	0.0%	0.0%	(I)PCS	7790136.0	-39.0%	-32.7%	-31.2%
(I)PSCS	9952882.1	-11.3%	-7.4%	-4.2%	(I)PSCS	10081469.9	-24.3%	-9.4%	-6.9%
(I)Labour	576009.0	-15.0%	0.0%	0.0%	(I)Labour	444554.0	-18.9%	-10.6%	-5.8%
(I)EC	8101.6	-11.3%	0.0%	0.0%	(I)EC	7914.4	-18.9%	0.0%	0.0%
(O)GDP	4539434.0	0.0%	7.5%	11.2%	(O)GDP	3673439.0	0.0%	12.2%	19.1%
(O)CE	584.1	0.0%	0.0%	0.0%	(O)CE	332.5	0.0%	0.0%	0.0%
Fukushima	0.742	1.000	1.000	1.000	Shimane	0.884	1.000	1.000	1.000
(I)PCS	14886234.0	-48.9%	0.0%	0.0%	(I)PCS	9128071.0	-40.8%	0.0%	0.0%
(I)PSCS	24138593.0	-31.6%	0.0%	0.0%	(I)PSCS	6590792.5	-12.8%	0.0%	0.0%
(I)Labour	925459.0	-25.8%	-15.1%	-7.9%	(I)Labour	355500.0	-14.0%	0.0%	0.0%
(I)EC	17822.9	-25.8%	0.0%	0.0%	(I)EC	5726.6	-11.6%	-6.2%	-3.5%
(O)GDP	7651487.0	0.0%	15.8%	26.0%	(O)GDP	2460017.0	0.0%	0.0%	0.0%
(O)CE	288.1	0.0%	0.0%	0.0%	(O)CE	611.1	0.0%	10.9%	16.3%
Ibaraki	0.738	1.000	1.000	1.000	Okayama	0.732	1.000	1.000	1.000
(I)PCS	16704317.0	-48.2%	-41.4%	-37.0%	(I)PCS	12521509.0	-53.9%	-47.8%	-43.8%
(I)PSCS	34530548.8	-38.2%	-29.5%	-23.9%	(I)PSCS	21336338.4	-33.8%	-24.3%	-18.0%
(I)Labour	1391815.0	-26.2%	-15.0%	-7.8%	(I)Labour	922299.0	-26.8%	-15.5%	-8.0%
(I)EC	31373.4	-57.0%	-51.9%	-48.5%	(I)EC	24547.4	-63.1%	-58.6%	-55.7%
(O)GDP	11950133.0	0.0%	15.3%	25.2%	(O)GDP	7834163.0	0.0%	15.8%	26.1%
(O)CE	127.2	0.0%	0.0%	0.0%	(O)CE	93.0	0.0%	0.0%	0.0%
Tochigi	0.764	1.000	1.000	1.000	Hiroshima	0.726	1.000	1.000	1.000
(I)PCS	10153835.0	-23.6%	0.0%	0.0%	(I)PCS	18511544.0	-56.6%	-50.3%	-46.1%
(I)PSCS	23221258.3	-30.3%	0.0%	0.0%	(I)PSCS	31623962.2	-35.7%	-25.9%	-19.4%
(I)Labour	979347.0	-23.6%	-14.0%	-7.4%	(I)Labour	1383792.0	-27.4%	-15.9%	-8.2%
(I)EC	21042.1	-43.7%	0.0%	0.0%	(I)EC	28102.6	-56.7%	-50.7%	-46.8%
(O)GDP	8312019.0	0.0%	14.4%	23.4%	(O)GDP	11760690.0	0.0%	16.0%	26.7%
(O)CE	310.5	0.0%	0.0%	0.0%	(O)CE	77.0	0.0%	0.0%	0.0%
Gunma	0.762	1.000	1.000	1.000	Yamaguchi	0.787	1.000	1.000	1.000
(I)PCS	10868867.0	-28.3%	0.0%	-12.6%	(I)PCS	10994499.0	-55.0%	-50.8%	-48.3%
(I)PSCS	20700298.3	-23.8%	0.0%	0.0%	(I)PSCS	20536128.8	-43.3%	-37.3%	-33.8%
(I)Labour	984232.0	-23.8%	-13.8%	-7.3%	(I)Labour	676637.0	-21.3%	-11.9%	-6.4%
(I)EC	19829.8	-42.7%	0.0%	-21.3%	(I)EC	26494.5	-69.6%	-67.1%	-65.6%
(O)GDP	8284852.0	0.0%	14.5%	23.4%	(O)GDP	6110901.0	0.0%	12.3%	19.5%
(O)CE	337.4	0.0%	0.0%	0.0%	(O)CE	116.5	0.0%	0.0%	0.0%
Saitama	0.863	1.000	1.000	1.000	Kagawa	0.956	1.000	1.000	1.000
(I)PCS	25509372.0	-36.2%	-32.3%	-30.3%	(I)PCS	6642151.0	-4.4%	-2.3%	-1.3%
(I)PSCS	42159163.4	-13.7%	-7.3%	-4.1%	(I)PSCS	10076370.2	-19.9%	-19.3%	-19.0%
(I)Labour	2772667.0	-29.9%	-25.0%	-22.5%	(I)Labour	476656.0	-10.8%	-10.1%	-9.7%
(I)EC	46801.5	-54.8%	-51.7%	-50.1%	(I)EC	9161.5	-30.5%	-29.3%	-28.8%
(O)GDP	21979233.0	0.0%	7.4%	11.2%	(O)GDP	3846117.0	0.0%	0.0%	0.0%
(O)CE	122.3	0.0%	0.0%	0.0%	(O)CE	625.0	0.0%	3.6%	5.2%
Chiba	0.769	1.000	1.000	1.000	Ehime	0.689	1.000	1.000	1.000
(I)PCS	24613569.0	-44.0%	-37.0%	-32.8%	(I)PCS	11213303.0	-52.5%	0.0%	-38.1%
(I)PSCS	50974915.1	-29.9%	-21.0%	-15.5%	(I)PSCS	15027200.9	-31.1%	0.0%	0.0%
(I)Labour	2348365.0	-23.1%	-13.1%	-6.9%	(I)Labour	703828.0	-31.1%	-18.9%	-9.6%
(I)EC	47067.4	-56.8%	-51.6%	-48.4%	(I)EC	17363.1	-55.1%	0.0%	-31.8%
(O)GDP	21258377.0	0.0%	13.1%	21.1%	(O)GDP	5282850.0	0.0%	20.0%	34.4%
(O)CE	64.7	0.0%	0.0%	0.0%	(O)CE	260.3	0.0%	0.0%	0.0%
Kanagawa	0.803	1.000	1.000	1.000	Fukuoka	0.770	1.000	1.000	1.000
(I)PCS	35387679.0	-39.6%	-33.2%	-29.6%	(I)PCS	24720822.0	-42.6%	-36.3%	-32.5%
(I)PSCS	78450777.4	-28.9%	-21.3%	-16.9%	(I)PSCS	42036117.3	-23.0%	-13.0%	-6.9%
(I)Labour	3529244.0	-19.7%	-10.9%	-5.9%	(I)Labour	2361425.0	-27.2%	-18.1%	-12.5%
(I)EC	62926.5	-50.2%	-45.1%	-42.1%	(I)EC	38337.6	-51.3%	-45.3%	-41.7%
(O)GDP	33417789.0	0.0%	10.9%	17.2%	(O)GDP	19557671.0	0.0%	13.1%	21.0%
(O)CE	74.1	0.0%	0.0%	0.0%	(O)CE	96.3	0.0%	0.0%	0.0%
Niigata	0.696	1.000	1.000	1.000	Saga	0.873	1.000	1.000	1.000
(I)PCS	23150353.0	-65.2%	-60.5%	-57.2%	(I)PCS	7583686.0	-12.8%	-8.1%	-7.3%
(I)PSCS	28199046.1	-34.4%	-24.2%	-17.1%	(I)PSCS	8175861.9	-14.7%	-6.5%	-3.9%
(I)Labour	1182239.0	-30.4%	-17.9%	-9.1%	(I)Labour	412993.0	-12.7%	-7.1%	-4.0%
(I)EC	20985.6	-36.0%	-28.6%	-23.4%	(I)EC	7608.9	-12.7%	0.0%	0.0%
(O)GDP	9366380.0	0.0%	18.6%	31.8%	(O)GDP	2893241.0	0.0%	10.2%	15.3%
(O)CE	226.0	0.0%	0.0%	0.0%	(O)CE	735.7	0.0%	0.0%	0.0%
Toyama	0.871	1.000	1.000	1.000	Nagasaki	0.818	1.000	1.000	1.000
(I)PCS	9510845.0	-20.9%	0.0%	0.0%	(I)PCS	11424311.0	-31.6%	0.0%	0.0%
(I)PSCS	13833473.8	-12.9%	0.0%	0.0%	(I)PSCS	11272370.3	-18.2%	-12.3%	-6.7%
(I)Labour	555660.0	-12.9%	-7.1%	-4.0%	(I)Labour	670352.0	-23.4%	0.0%	0.0%
(I)EC	13759.8	-14.8%	0.0%	0.0%	(I)EC	8924.3	-18.2%	0.0%	0.0%
(O)GDP	4771179.0	0.0%	8.3%	12.5%	(O)GDP	4877933.0	0.0%	12.2%	19.0%
(O)CE	553.1	0.0%	0.0%	0.0%	(O)CE	527.4	0.0%	0.0%	0.0%
Ishikawa	0.827	1.000	1.000	1.000	Kumamoto	0.767	1.000	1.000	1.000
(I)PCS	9387676.0	-20.7%	0.0%	0.0%	(I)PCS	12256488.0	-30.7%	0.0%	-5.0%
(I)PSCS	11277881.2	-17.3%	0.0%	0.0%	(I)PSCS	14091948.1	-23.4%	-13.7%	-7.2%
(I)Labour	609218.0	-17.3%	-17.0%	-9.3%	(I)Labour	855097.0	-23.4%	0.0%	0.0%
(I)EC	9923.9	-24.2%	0.0%	0.0%	(I)EC	14261.9	-37.9%	0.0%	-23.8%
(O)GDP	4590722.0	0.0%	12.0%	18.6%	(O)GDP	6088558.0	0.0%	14.3%	23.1%
(O)CE	687.3	0.0%	0.0%	0.0%	(O)CE	380.1	0.0%	0.0%	0.0%
Fukui	0.993	1.000	1.000	1.000	Oita	0.741	1.000	1.000	1.000
(I)PCS	7581226.0	-1.6%	-1.3%	-1.3%	(I)PCS	9186693.0	-52.8%	-48.0%	-44.9%
(I)PSCS	12891234.4	-33.8%	-33.3%	-33.3%	(I)PSCS	13207465.1	-27.3%	-18.4%	-12.7%
(I)Labour	409695.0	-0.7%	-0.4%	-0.2%	(I)Labour	550330.0	-25.9%	-14.8%	-7.8%
(I)EC	9073.2	-0.7%	0.0%	0.0%	(I)EC	14607.8	-49.0%	-44.6%	-41.8%
(O)GDP	3485807.0	0.0%	0.5%	0.7%	(O)GDP	4582058.0	0.0%	15.6%	25.7%
(O)CE	741.1	0.0%	0.0%	0.0%	(O)CE	149.4	0.0%	0.0%	0.0%
Nagano	0.752	1.000	1.000	1.000	Miyazaki	0.822	1.000	1.000	1.000
(I)PCS	17175783.0	-56.3%	0.0%	0.0%	(I)PCS	8981528.0	-24.7%	-3.1%	-8.0%
(I)PSCS	20837555.5	-24.8%	0.0%	0.0%	(I)PSCS	9198735.5	-17.8%	-10.1%	-5.5%
(I)Labour	1076825.0	-24.8%	-17.1%	-9.0%	(I)Labour	545592.0	-17.8%	0.0%	0.0%
(I)EC	18144.6	-47.5%	0.0%	0.0%	(I)EC	9360.7	-20.3%	-10.1%	-9.8%
(O)GDP	9004613.0	0.0%	15.1%	24.6%	(O)GDP	3921584.0	0.0%	11.5%	17.8%
(O)CE	302.4	0.0%	0.0%	0.0%	(O)CE	517.7	0.0%	0.0%	0.0%
Gifu	0.686	1.000	1.000	1.000	Kagoshima	0.799	1.000	1.000	1.000
(I)PCS	14563077.0	-53.4%	0.0%	-38.4%	(I)PCS	14382328.0	-41.5%	-19.0%	-24.0%
(I)PSCS	20113232.7	-31.4%	0.0%	0.0%	(I)PSCS	13067275.9	-20.1%	-11.5%	-6.2%
(I)Labour	968187.0	-31.4%	-19.1%	-9.7%	(I)Labour	794457.0	-20.1%	0.0%	0.0%
(I)EC	18298.3	-46.7%	0.0%	-17.2%	(I)EC	12740.9	-31.0%	-18.8%	-18.5%
(O)GDP	7353771.0	0.0%	19.9%	34.3%	(O)GDP	5835600.0	0.0%	12.2%	19.2%
(O)CE	286.6	0.0%	0.0%	0.0%	(O)CE	405.5	0.0%	0.0%	0.0%

model looks for the optimal input reduction (i.e. the shortest distance to the frontier, or Distance Friction Minimization).

For instance, the CCR projection shows that Hokkaido should reduce its Public Capital Stock (PCS) by 76.1 percent, Private Sector Capital Stock (PSCS) and Labor by 26.9 percent, Electricity Consumption (EC) by 56.5 percent in order to become efficient.

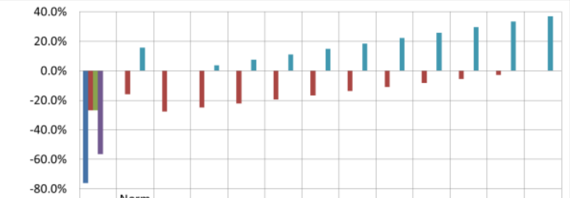
On the other hand, the DFM results show that a reduction in Private Sector Capital Stock (PSCS) of 16.0 percent, and an increase in GDP of 15.6 percent are required for Hokkaido to become efficient. Furthermore, the PB-DFM results show that a reduction in the Private Sector Capital Stock (PSCS) of 8.3 percent, and an increase in the GDP of 25.9 percent are required to become efficient. Apart from the practicality of such a solution, the models show clearly that a different – and perhaps more efficient – solution is available than the standard CCR projection to reach the efficiency frontier.

5.4 Illustration of the results of the PB-DFM model for a given prefecture

In this subsection, we use Hokkaido and Shimane as an example of an inefficient reference prefecture, and present an efficiency improvement projection result based on the PB-DFM model. We assume that the OAP uses steps from 0.0 to 1.0 at intervals of 0.1. Next, the input reduction values and the output increase values based on the PB-DFM model are calculated in Figures 6 and 7.

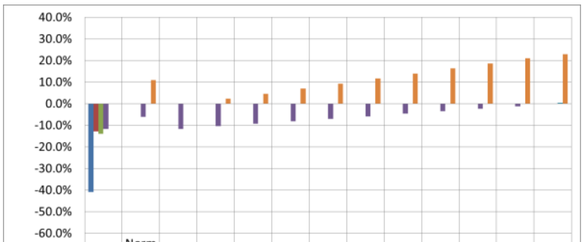
From Figure 6, it can be seen that, if Hokkaido prefecture implements an efficiency improvement plan with an OAP amounting to 0.3 (i.e. 30 percent of the total efficiency gap is allocated for output, and 70 percent of the total efficiency gap is allocated for input), then a reduction in Private Sector Capital Stock (PSCS) of 19.4 percent, and an increase in GDP of 11.1 percent are required to raise efficiency score to 1.000. Furthermore, if such a plan has an OAP of 0.0 (i.e. 100 percent of the total efficiency gap is allocated for input), then a reduction in PSCS of 27.6 percent is required to raise the efficiency score to 1.000.

From Figure 7, it can also be seen that if Shimane prefecture implements an efficiency improvement plan with an OAP amounting to 0.4 (i.e. 40 percent of the total efficiency gap is allocated for output, and 60 percent of the total efficiency gap is allocated for input), then a reduction in Electricity Consumption (EC) of 7.0 percent, and an increase in Carbon Emission (CE) (inverse number) of 9.3 percent are required to raise the efficiency score to reach 1.000. Furthermore, the results of a plan with an OAP of 0.0 (i.e. 100 percent of the total efficiency gap is allocated for input), a reduction in EC of 11.6 percent is required to raise the efficiency score to 1.000.



	CCR	Normal-DFM	OAP =0.0	OAP =0.1	OAP =0.2	OAP =0.3	OAP =0.4	OAP =0.5	OAP =0.6	OAP =0.7	OAP =0.8	OAP =0.9	OAP =1.0
(I)PCS	-76.1	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)PSCS	-26.9	-16.0	-27.6	-24.9	-22.1	-19.4	-16.6	-13.8	-11.1	-8.3%	-5.5%	-2.8%	0.0%
(I)Labour	-26.9	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)EC	-56.5	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(O)GDP	0.0%	15.6%	0.0%	3.7%	7.4%	11.1%	14.8%	18.5%	22.2%	25.9%	29.6%	33.3%	37.0%
(O)CE	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%

Fig.6 Efficiency improvement projection results based on the PB-DFM model for Hokkaido prefecture



	CCR	Normal-DFM	OAP =0.0	OAP =0.1	OAP =0.2	OAP =0.3	OAP =0.4	OAP =0.5	OAP =0.6	OAP =0.7	OAP =0.8	OAP =0.9	OAP =1.0
(I)PCS	-40.8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)PSCS	-12.8	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)Labour	-14.0	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%
(I)EC	-11.6	-6.2%	-11.6	-10.4	-9.3%	-8.1%	-7.0%	-5.8%	-4.6%	-3.5%	-2.3%	-1.2%	0.0%
(O)GDP	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.0%	0.5%
(O)CE	0.0%	10.9%	0.0%	2.3%	4.7%	7.0%	9.3%	11.7%	14.0%	16.3%	18.6%	21.0%	22.9%

Fig. 7 Efficiency improvement projection results based on the PB-DFM model for Shimane prefecture

6. Conclusion

In this chapter we have presented a new methodology, the PB-DFM model. This model is characterized by two integrated features: (i) the use of a general Distance Friction Minimization (DFM) model to achieve the most appropriate movement towards the efficiency frontier surface; and (ii) the incorporation of preference-based (PB) adjustments in efficiency strategies regarding the input reduction allocation – or the output increase allocation – of DMUs in order to balance rigorous efficiency decisions with political priorities.

The results of this methodology may offer a meaningful contribution for the decision making and planning for the improvement of the energy-environment-economic (EEE) efficiency for each prefecture in Japan. This new model may act as a policy navigation instrument (a 'dashboard') that may have great added value for decision making and planning. For example, this approach – based on interactive preference elicitation – may be useful for EEE strategy, a nation-wide agreement on policy where all inefficient prefectures would have to improve their efficiency (to reach the score 1.000), but where the balance of input-output improvement can be freely set, in a decentralized way based on the specific preferences of each prefecture. This framework might form a basis of a new concept like a 'Kyoto Protocol' for each prefecture in Japan.

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