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DEA Non-Radial Approach for Resource Allocation and Energy Usage to Enhance Corporate Sustainability in Japanese Manufacturing Industries

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Abstract: This article discusses how to enhance corporate sustainability by simultaneously measuring operational and environment achievements. In past decades, most companies have made steady efforts to enhance their sustainability levels. However, they still have strategic space for improving sustainability. This research proposes a new use of environmental measurement by data envelopment analysis. We apply the approach to Japanese industrial sectors and obtain five implications. First, they maintain a high level of unified efficiency on resource allocation and energy usage under natural disposability (priority: operation). Second, the efficiency under managerial one (priority: environment) is generally lower than that of natural disposability. Third, among the industries with high operational achievement, only the pharmaceutical product industry presents high attainment on environmental protection. Fourth, the pulp and paper industry as well as the textile product industry have a potential for efficiency improvement by investing in green technology. Finally, desirable congestion indicates a potential of performance improvement by investing in green technology. Those results imply that the current business situation is different from the previous image on Japanese industries, often referred to as "Japan Inc.", where all firms used to operate like a single entity under the governmental regulation.

Keywords: sustainability; green technology; Japanese industries; Data Envelopment Analysis (DEA)

1. Introduction

Japan's Prime Minister, Shinzo Abe, has recently proposed a new economic policy, referred to as "Abenomics," which suggests various directions for Japanese productivity improvements. A report prepared by McKinsey and Company [1] has discussed a guidance regarding the Japanese industrial direction.

Acknowledging the importance of such a new policy direction, we have two major concerns. One of them is that Japan has been gradually losing productivity growth in manufacturing industries. The Japanese firms are now facing fierce competition with overseas firms. The Japanese manufacturing sectors need to improve their productivity. See a report by Nissay Asset Management [2]. The other concern is that Japan has historically faced various environmental problems along with its industrialization.

Besides the two concerns, the participation in international agreements on pollution prevention (e.g, the Kyoto protocol in 1997 and the Paris agreement in 2016) provide the Japanese government with an official excuse on strict regulation, in particular on greenhouse gas (GHG) emission. A policy drawback of the Abenomics is that it does not explicitly discuss the policy necessity in addressing environmental pollution associated with economic activity and growth of industries. Saito [3] has discussed the business direction of Japanese manufacturing sectors.

In discussing the current policy issues from Japanese sustainability, this study conducts an empirical investigation concerning the manufacturing industries. We use data envelopment analysis (DEA) that can provide us with a total performance measure on operational and environmental attainments. The method was first proposed by Charnes et al. [4]. For additional references, see Glover and Sueyoshi [5] and Sueyoshi and Goto [6]. The latter provides a detailed historical review on the method.

This research uses DEA for our empirical purpose since it can avoid a specifying error to decide a functional form between production factors (i.e., inputs and outputs). The method provides a multi-dimensional productivity measurement. In DEA, the term of "efficiency" is specified by a percentage expression and it is used to measure a total productivity level that is different from a single performance measure such as "labor productivity".

The purpose of this research is to measure the performance of Japanese manufacturing industries by Data Envelopment Analysis (DEA). To investigate our research concern, discussed above, we first restructure the method in the manner that it can measure their achievements on operational and environmental attainments. Then, we apply it to the Japanese industries and then discuss business implications obtained from the proposed application.

The remainder of this study is organized as follows: Section 2 summarizes a literature study related to this research. Section 3 discusses underling concepts used for the DEA assessment on industrial sectors. Section 4 describes DEA's analytical structure. Section 5 reorganizes the method so that we can use the new approach for our empirical study. Section 6 applies the new formulations for measuring the performance of Japanese manufacturing industries. Section 7 concludes this study along with addressing future research tasks. The end of this article lists all abbreviations and variables used in the article.

2. Literature Summary

Previous studies on DEA applied to Japanese pollution prevention are classified into the following three groups:

The first group discussed DEA environmental assessment applied to Japanese industries. The group started with Sueyoshi and Goto [7]. Their study applied DEA to assess the performance of Japanese manufacturing industries. The research indicated that large firms had financial and managerial capabilities to improve their environmental attainments because of their capital accumulations. However, the study could not find the similar business linkage in small and medium companies. Sueyoshi and Goto [8] applied DEA for comparison between Japanese Chemical and Pharmaceutical industries. The research investigated their scale measures (i.e., returns to scale (RTS) and damages to scale (DTS)). Finally, Sueyoshi and Goto [9] conducted comparisons between Japanese manufacturing and service industries. They concluded that the former outperformed the latter in their efficiencies.

The second group contained various studies on statistics and econometrics applied to Japanese industries. The group used DEA and traditional measures (e.g., total-factor productivity). The group was interested in performance assessment on many types of industrial sectors that utilized input resources to yield outputs, but often excluded pollution in their assessments. The group included Honma [10] which discussed total-factor energy efficiency measurement regarding the Japanese regional economics. Sueyoshi et al. [11] discussed a corporate governance issue from operational performance in the manufacturing industries. Oggioni et al. [12] measured the environmental efficiency of the world's cement industries, including the Japanese ones. Wen et al. [13] proposed an asset based business model for sustainability competitiveness and applied it to examining the Japanese semi-conductor industry. Goto et al. [14] discussed the deregulation issue between generation and transmission in the Japanese electric power industry. Sotome and Takahashi [15] indicated that Japanese employment systems influenced corporate productivity. They also discussed that their employment systems harmed the productivity improvements. Honma and Hu [16] discussed the total-factor energy efficiency in developed countries by comparing them with Japanese ones.

The third group was related to the energy and the environment. Sueyoshi et al. [17] contained 693 articles on DEA applications on energy improvement and environment protection. Sueyoshi and Goto [6] also included approximately 800 peer reviewed articles that discussed a use of DEA for environmental advancement and sustainability enhancement. Since both [6] and [17] summarize a long list of previous studies, this research does not need to specify them, except noting two findings on DEA applications. First, the electric power industry is the main research target in the early stage of DEA applications due to data accessibility to the industry. Second, the research on energy is classified into (a) electricity, (b) oil, (c) coal, (d) gas, (e) heat, (f) renewable and (g) energy efficiency and saving. The previous works on energy included 4 articles in the 1980s, 20 articles in the 1990s, 94 articles in the 2000s and 289 articles in the 2010s. Meanwhile, the environment and sustainability included 1 article in the 1980s, 6 articles in the 1990s, 41 articles in the 2000s and 222 articles in the 2010s. The applications in the two areas have been rapidly increasing during the past four decades.

This study methodologically belongs to the first and the third research groups. The DEA application belongs to the second group, but this study utilizes the method differently from the previous one used in the second group.

The proposed approach has four unique features. First, this research classifies outputs into two categories (i.e., desirable and undesirable). Then, we combine them for DEA-based performance assessment. Second, this study discusses how to identify a possible occurrence of undesirable congestion (UC, i.e., a limit on production) and that of desirable congestion (DC, i.e., eco-technology). Third, we reorganize DEA formulations under an occurrence of DC under the assumption that "undesirable outputs are the by-products of desirable outputs". Lastly, this study discusses an analytical rationale concerning why we can examine DC in the DEA environmental assessment.

3. Concepts

This section prepares underlying concepts for the methodological development used in this study.

3.1. Disposability

To examine the performance of Japanese manufacturing industries, this study introduces two disposability concepts, where each concept implies the elimination of inefficiency. One of them is "natural disposability" where the priority is economic success. The other is "managerial disposability" whose priority is pollution reduction.

To describe how we include the two disposability concepts in this research, we consider $X \in R_+^m$ as an input vector with m components, $G \in R_+^s$ as a desirable output vector with s components, and $B \in R_+^h$ as an undesirable output vector with h components. The subscript (j) indicates the j th decision making unit (DMU), whose components are strictly positive. Those components are specified by x, g and b.

Natural (N) disposability and managerial (M) disposability expresses unified production and pollution possibility sets as follows:

$$P_v^N(X)=\left\{(G,B): G \le \sum_{j=1}^{n} G_j\lambda_j,\ B \ge \sum_{j=1}^{n} B_j\lambda_j,\ X \ge \sum_{j=1}^{n} X_j\lambda_j,\ \sum_{j=1}^{n}\lambda_j = 1 \,\&\, \lambda_j \ge 0\ (j=1,..,n)\right\} \&$$
$$P_v^M(X)=\left\{(G,B): G \le \sum_{j=1}^{n} G_j\lambda_j,\ B \ge \sum_{j=1}^{n} B_j\lambda_j,\ X \le \sum_{j=1}^{n} X_j\lambda_j,\ \sum_{j=1}^{n}\lambda_j = 1 \,\&\, \lambda_j \ge 0\ (j=1,..,n)\right\}. \quad (1)$$

$P_v^N(X)$ indicates the set for natural disposability. Meanwhile, $P_v^M(X)$ is that of managerial disposability. The subscript (v) implies variable RTS or DTS. The two axiomatic expressions incorporate the addition constraint ($\sum_{j=1}^{n}\lambda_j = 1$) to express the variability on RTS or DTS. A difference between them is that the production technology under natural disposability has $X \geq \sum_{j=1}^{n} X_j \lambda_j$. The constraint implies that DMUs attempt to attain an efficiency frontier by reducing *X*. In contrast, the managerial disposability has an opposite direction of *X* in the constraint of $X < \sum_{j=1}^{n} X_j \lambda_j$.

3.2. Disposability Unification

The proposed assessment needs to classify outputs into desirable (good) and undesirable (bad) categories in this research because they are different in terms of their vector directions. After the output separation, we need to develop a conceptual guideline and its related computational process for unification.

Figure 1, separated from I to III, visually indicates the unification process. The three processes (I, II and III) are later integrated into the proposed DEA approach. The figure depicts a case of a single component of those vectors. Later, we extend the case to the case of multiple components in our framework.

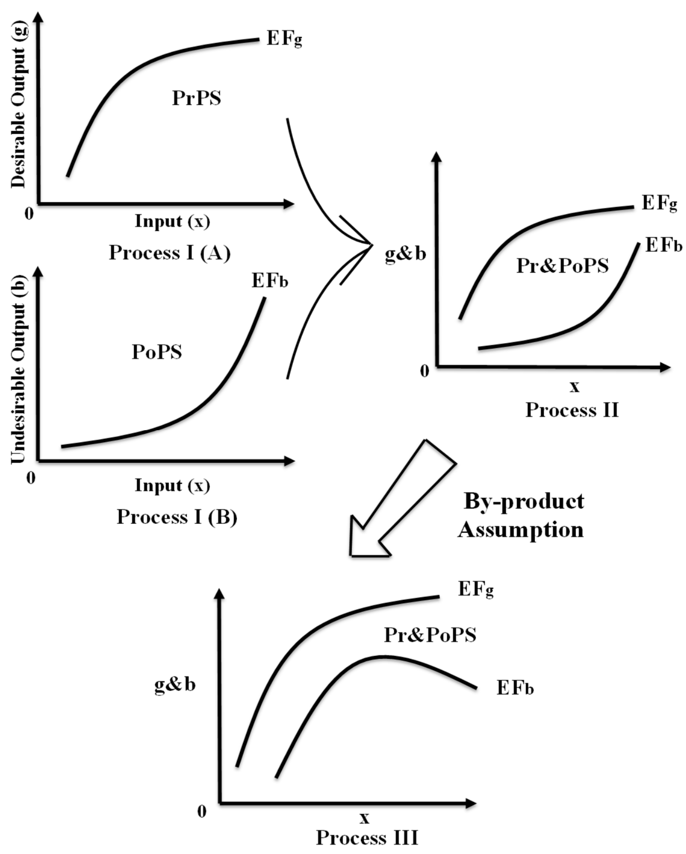

Figure 1. Unification between two groups of outputs. EF indicates an efficiency frontier. (a) The *g* and *b* stand for two different outputs. PrPS indicates a production possibility set, PoPS indicates a pollution possibility set. (b) Pr&PoPS indicate a production and pollution possibility set. (c) The last process (III) is for final unification by assuming that *b* is the by-product of g. This study considers the assumption under managerial disposability.

The first process (I) has two sub-processes: (A) and (B). Process I (A) shows the relationship between x and g. In this process, all DMUs have the same amount of b. The production possibility set (PrPS) locates below a curve, depicting an efficiency frontier (EF_g), in the x-g space. Most previous DEA investigations have considered the assessment within the PrPS. In the region, a DMU needs to decrease or maintain the current level of x for performance improvement along with an increase of g. Process I (A) depicts such a basis for measuring all conventional applications.

In environmental assessment, this research is conceptually different from the conventional DEA efforts. Such a difference may be found in Process I (B). A pollution possibility set (PoPS) locates above the curve, expressing an efficiency frontier (EF_b), in the x-b space. In this case, all DMUs produce the same amount of g. In depicted Process I (B), we consider that the PoPS is independent from the PrPS. The relationship between them is different from the reality of modern business because b may not exist without g.

Next, Process II unifies the two sets of Process I. In the process, the vertical axis indicates g and b. The unification process identifies a region for production and pollution possibility set (Pr&PoPS) between EF_g and EF_b. The set depicts the area where we can identify an existence of "sustainability" in which all DMUs increase X and decrease B.

Such a case is attained in Process III that is the final stage for unification in which we incorporate the by-product assumption. The assumption changes the two efficiency frontiers to be shaped by convex curves, as visually specified in the bottom of Figure 1. In the unification, the EF_g increase with the enhancement of x. Meanwhile, the EF_b increases and then decreases because of green technology innovation on b. Both curves are convex because of the by-product assumption. As a result of the assumption, the efficiency frontiers are structurally different from those of Processes I and II.

3.3. Undesirable Congestion (UC) and Desirable Congestion (DC)

Figure 2 illustrates the type of congestion that may occur on g and b. The concept is classified either UC or DC. The figure depicts dissimilarity between them. The left hand side shows the three types of UC on the horizontal axis (b) and the vertical axis (g). The right hand side shows the three types of DC in the space between g on a horizontal axis and b on the vertical axis.

The occurrence of UC can be identified on the slope of a supporting hyperplane. As depicted in the left hand side, the negative slope indicates an occurrence of "strong UC". The occurrence indicates a capacity limit on a production facility that lessens efficiency (e.g., transmission congestion in an electric power industry). In contrast, the positive slope implies an opposite case, or "no UC". The "weak UC" exists between them.

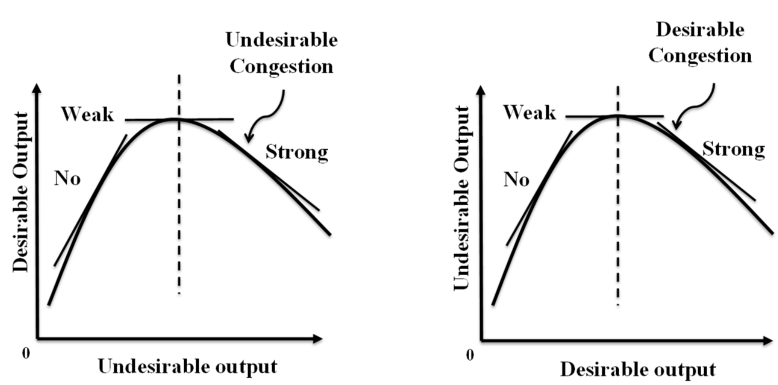

Figure 2. Undesirable congestion (UC) and desirable congestion (DC). (a) The left hand side indicates an occurrence of UC while the right hand side indicates that of DC. The UC implies a production capacity limit on g. The DC implies eco-technology innovation on b.

Admitting the importance of UC (e.g., Cooper et al. [18]) in production analysis, however, we are interested in the sustainability development by pollution prevention. This research pays attention to the occurrence of DC, not UC, because the DC implies a potential of green technology for sustainability enhancement. The right hand side of Figure 2, along with Process III of Figure 1, exhibits such a DC development. The negative slope indicates "strong DC". In contrast, the positive slope implies an opposite case, or "no DC". The "weak DC" exists between them.

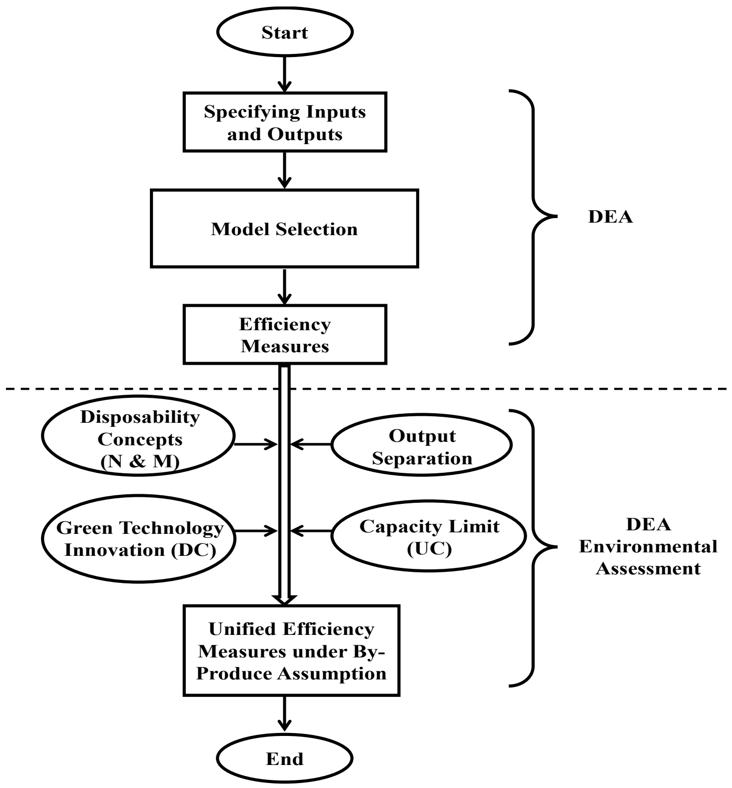

Figure 3. A conceptual flow incorporated into environmental assessment. (**a**) The upper part visually describes that DEA starts with specifying *X* and *G*. Then, it determines which models are used for the proposed research. The process excludes *B*. The part depicts a conventional use of DEA that assesses the performance of DMUs. (**b**)The lower part depicts how new proposed concepts are included into the proposed assessment. The process distinguishes between *G* and *B*. The separation needs two disposability concepts (i.e., N and M) for the unification between them. Then, we incorporate equality constraints on *G* or *B* to identify a potential of green technology innovation or that of a capacity limit on a production system, respectively. We also incorporate the new assumption that *B* is the by-product of G. Finally, the assessment produces three unified efficiency measures under the two disposability concepts and the by-product assumption.

After describing the DC, we return to the three processes of Figure 1 to specify the lower and upper bounds of an input change, because it is closely related to the scope of sustainability. First, in this research, a DMU can reduce *X* until it can reach EF_g. The frontier serves as a "lower bound" for the input reduction. In contrast, the DMU can increase *X* until it can reach EF_b. The frontier indicates an "upper bound" for the input increase. Thus, the sustainably is defined by the two frontiers depicted in Figure 1.

In other words, the sustainability is visually specified as Pr&PoPS surrounded by EF_g and EF_b. See the last stage of Figure 1. The frontier on the left hand in the region serves as the lower limit and the frontier in the right hand serves as the upper limit. In the sustainability development, the DEA assessment measures the lower limit by natural disposability where we need to reduce *X* (thereby reducing *B*) and increase *G*. In contrast, the assessment measures the upper limit by managerial disposability where we need to increase both X and G. For the purpose, green technology and pollution prevention (e.g., recycling) are necessary in reducing B.

Here, it is important to note that this research needs to discuss the economic activities of DMUs in terms of the sustainability measurement, but not considering their financial measures such as return on assets (ROA) and return on equity (ROE). Such financial measures are important in discussing corporate "survival" (e.g., avoiding bankruptcy), but they are not directly linked to B. So, we do not incorporate the financial measures in this research.

At the end of this section, Figure 3 shows a whole flow for computation incorporated into the proposed DEA models. The application starts with specifying inputs and outputs. Then, we determine which models are used for empirical investigation. The upper part depicts such a conventional use of DEA. The lower part depicts how new concepts are included into the proposed DEA assessment. The process classifies outputs into G and B. The distinction needs the two concepts (i.e., N and M) for unifying between them. The unification includes equality allocation on constraints related to G or B so that we can identify an occurrence of DC and/or that of UC. This study also incorporates the hypothesis that B is the by-product of G. Finally, our new assessment produces the three types of unified efficiency measures under the two disposability concepts and the by-product assumption.

4. Methodology

4.1. Formulations

An underlying assumption is that DEA relatively evaluates n DMUs, denoted by j. Each DMU uses m inputs, denoted by i, to yield s desirable outputs, denoted by r. The production process is associated with h undesirable outputs, denoted by f. The end of this article lists all variables used in this section.

DEA has three different models to measure the unified efficiencies of DMUs. Those are radial, non-radial and intermediate models (e.g., [19]). This research uses the non-radial model because it measures a level of unified efficiency by slacks on optimality, not depending upon an efficiency score, as found in the other two models. The type of measurement is referred to as the Pareto–Koopmans measure [20] and widely used in DEA-based assessment. Another benefit on the use is that the model makes it possible that we can evaluate DMUs, whose data contains zeros and/or negative values in a data set [21]. The analytical capability is important in assessing the attainment on various types of DMUs.

In the proposed model, this study needs to specify the following three types of data ranges (R) according to the upper and lower bounds on each factor:

$$\begin{aligned}
R_i^x &= \left(m+s+h\right)^{-1}\left(\max\left\{x_{ij} \mid j=1,\dots,n\right\}-\min\left\{x_{ij} \mid j=1,\dots,n\right\}\right)^{-1},\\
R_r^g &= \left(m+s+h\right)^{-1}\left(\max\left\{g_{rj} \mid j=1,\dots,n\right\}-\min\left\{g_{rj} \mid j=1,\dots,n\right\}\right)^{-1},\\
R_f^b &= \left(m+s+h\right)^{-1}\left(\max\left\{b_{fj} \mid j=1,\dots,n\right\}-\min\left\{b_{fj} \mid j=1,\dots,n\right\}\right)^{-1},
\end{aligned} \tag{2}$$

for all i, r and f. The rationale for them is that DEA can avoid the case where zero is found in a dual variable(s). They function as weights among production factors. The zero implies that the corresponding factor is not employed in the assessment. That is problematic. Aida et al. [22] first proposed the range allocation and referred to it as "range adjusted measure (RAM)". Thus, this research has originated from the RAM. Sueyoshi and Sekitani [23] mathematically compared RAM's strengths and drawbacks with the other DEA models.

4.1.1. Formulation for Natural Disposability

To compute the level of UEN under natural disposability, this research combines G and B regarding the k-th DMU under variable RTS. The resulting model becomes follows:

$$\begin{aligned} &\text{Maximize } \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right) \\ &\text{s.t.} \quad \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^{x-} = x_{ik} \ (all\ i), \\ &\sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g = g_{rk} \ (all\ r), \\ &\sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b = b_{fj} \ (all\ f), \\ &\sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0\ (all\ j), \\ &d_i^{x-} \geq 0\ (all\ i),\ d_r^g \geq 0\ (all\ r)\ \&\ d_f^b \geq 0\ (all\ f). \end{aligned} \quad (3)$$

The right hand side indicates an observed data concerning the *k*-th DMU. Meanwhile, the left hand side shows the formulations for the best practice measures which are identified on the two efficiency frontiers. They correspond to the first process (I) in Figure 1. Model (3) has the three types of slacks, denoted by *d*-related variables, for the proposed inefficiency measurement. Among them, the model includes input deviations ($+d_i^{x-}$) to attain the status of natural disposability.

The unified efficiency (UEN_v^{NR}) of the *k*-th DMU is measured by:

$$UEN_v^{NR} = 1 - \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x-*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}\right). \quad (4)$$

here, *NR* stands for non-radial and the three *d*-related slack variables are obtained from the optimality of Model (3). The equation within the parenthesis expresses the degree of unified inefficiency. As specified by the above equation (4), we subtract the inefficiency from unity to decide the degree of efficiency. The symbol (*) indicates optimality.

4.1.2. Formulation for Managerial Disposability

The managerial disposability compute the unified efficiency measure (UEM_v^{NR}) of the *k*-th DMU under variable DTS by the subsequent model:

$$\begin{aligned} &Maximize\ \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{r=1}^{s} R_r^g d_r^g + \sum_{f=1}^{h} R_f^b d_f^b\right) \\ &s.t. \quad \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x+} = x_{ik} \ (all\ i)\ \& \\ &same\ constraints\ in\ Model\ (3). \end{aligned} \quad (5)$$

Model (5) considers input deviations ($-d_i^{x+}$) to attain the status of managerial disposability. The other constraints in Model (5) are the same as those of Model (3).

The unified efficiency (UEM_v^{NR}) concerning the *k*-th DMU becomes

$$UEM_v^{NR} = 1 - \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x+*} + \sum_{r=1}^{s} R_r^g d_r^{g*} + \sum_{f=1}^{h} R_f^b d_f^{b*}\right). \quad (6)$$

where all the slacks are found on optimality. The equation within the parenthesis, obtained from the optimality, implies the degree of unified inefficiency. We subtract it from unity to decide the level of efficiency.

4.2. A Possible Occurrence of Undesirable Congestion (UC) or Desirable Congestion (DC)

As depicted in the left hand side of Figure 2, this study incorporates UC under natural disposability. To examine the occurrence, we use the following model that allocates equality constraints (i.e., no slack) on *B*:

$$
\begin{aligned}
\text{Maximize} \quad & \varepsilon\left(\sum_{i=1}^{m} R_i^{x-} d_i^{x-} + \sum_{r=1}^{s} R_r^g d_r^g\right) \\
s.t. \quad & \sum_{j=1}^{n} x_{ij}\lambda_j + d_i^{x-} = x_{ik} \ (all\ i\ ), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j - d_r^g \ = g_{rk} \ (all\ r), \\
& \sum_{j=1}^{n} b_{fj}\lambda_j \qquad = b_{fk} \ (all\ f), \\
& \sum_{j=1}^{n} \lambda_j = 1\ ,\ \lambda_j \geq 0 \ (all\ j), \\
& d_i^{x-} \geq 0 \ (all\ i) \ \&\ d_r^g \geq 0 \ (all\ r).
\end{aligned} \tag{7}
$$

Model (7) eliminates slacks related to *B*. These related constraints are considered as equality. The other constraints regarding *X* and *G* are structured by inequality because they have slacks in the formulation (7).

A unified efficiency, or $UEN(UC)_v^{NR*}$, of the *k*-th DMU becomes,

$$UEN_v^{NR} = 1 - \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x-*} + \sum_{r=1}^{s} R_r^g d_r^{g*}\right). \tag{8}$$

All variables used in Equation (8) are determined on the optimality of the Model (8). The equation within the parenthesis indicates the unified inefficiency. The efficiency is determined by subtracting it from unity.

As depicted in the right hand side of Figure 2, this study incorporates DC into managerial disposability. To examine the DC occurrence, we utilize the following model which allocates equality constraints (so, no slack) on *G*:

$$
\begin{aligned}
\text{Maximize} \quad & \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{f=1}^{h} R_f^b d_f^b\right) \\
s.t. \quad & \sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x+} = x_{ik} \ (all\ i), \\
& \sum_{j=1}^{n} g_{rj}\lambda_j \qquad = g_{rk} \ (all\ r), \\
& \sum_{j=1}^{n} b_{fj}\lambda_j + d_f^b \ = b_{fk} \ (all\ f), \\
& \sum_{j=1}^{n} \lambda_j = 1\ ,\ \lambda_j \geq 0 \ (all\ j), \\
& d_i^{x+} \geq 0 \ (all\ i) \ \&\ d_f^b \geq 0 \ (all\ f).
\end{aligned} \tag{9}
$$

The model eliminates slacks related to *G*. These related constraints are considered as equality. The other groups of constraints on *X* and *B* have slacks so that they are inequality constraints.

A unified efficiency, or $UEM(DC)_v^{NR*}$, of the *k*-th DMU becomes,

$$UEM(DC)_v^{NR} = 1 - \varepsilon\left(\sum_{i=1}^{m} R_i^x d_i^{x+*} + \sum_{f=1}^{h} R_f^b d_f^{b*}\right). \tag{10}$$

where all variables are determined on the optimality of Model (9). The equation within the parenthesis indicates the magnitude of unified inefficiency. The efficiency, along with a possible existence of DC, is determined by subtracting it from unity.

5. Extension: Formulation for By-Product Assumption

The structure of the final unification (III) incorporates the by-product assumption. The incorporation is important because *B* depends upon *G*. This assumption makes it possible that the production of *G* on EF_g increases with the *X* enhancement. Meanwhile, the pollution of *B* on EF_b increases and then decreases with the input increase due to the assumption. The increasing trend shifts to decreasing after the installation of new technology for environment protection. The green innovation may have such an impact on *B*.

Under the assumption on by-product assumption, Model (9) is reorganized as:

$$\begin{aligned} &Maximize \ \ \varepsilon(\textstyle\sum_{i=1}^{m} R_i^x d_i^{x+} + \sum_{f=1}^{h} R_f^b d_f^b) \\ &s.t. \quad \textstyle\sum_{j=1}^{n} x_{ij}\lambda_j - d_i^{x+} = x_{ik} \ (all\ i), \\ &\qquad \textstyle\sum_{j=1}^{n} g_{rj}\lambda_j = g_{rk} \ (all\ r), \\ &\qquad \textstyle\sum_{j=1}^{n} b_{fj}\lambda_j - d_f^b = b_{fk} \ (all\ f), \\ &\qquad \textstyle\sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0\ (all\ j), \\ &\qquad d_i^{x+} \geq 0\ (all\ i)\ \ \&\ \ d_f^b \geq 0\ (all\ f). \end{aligned} \tag{11}$$

The formulation (11) replaces the sign of $+d_f^b$ in Model (9) by negative ($-d_f^b$) in Model (11). The rationale is because both G and B have a similar (convex) structure on X as in the last unification process. That is, EF_g and EF_b become convex as depicted in Figure 1. Furthermore, Model (11) is prepared under managerial disposability and a possible existence of DC.

An efficiency score of the k-th DMU becomes $UEM(DC)_v^{NR} = 1 - \varepsilon(\sum_{i=1}^{m} R_i^x d_i^{x+*} + \sum_{f=1}^{h} R_f^b d_f^{b*})$ where all variables are determined on the optimality of Model (11). The equation within the parenthesis denotes a degree of unified inefficiency.

To describe an analytical rationale regarding why Model (11) measures the degree of efficiency in the last unification process, this research documents the following dual formulation that is originated from Model (11):

$$\begin{aligned} &Minimize \ \ -\textstyle\sum_{i=1}^{m} v_i x_{ik} + \sum_{r=1}^{s} u_r g_{rk} - \sum_{f=1}^{h} w_f b_{fk} + \sigma \\ &s.t. \quad -\textstyle\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} u_r g_{rj} - \sum_{f=1}^{h} w_f b_{fj} + \sigma \ \geq\ 0\ (all\ j), \\ &\qquad v_i \geq \varepsilon R_i^x\ (all\ i),\ u_r : URS\ \ (all\ r), \\ &\qquad w_f \geq \varepsilon R_f^b\ (all\ f)\ \ \&\ \ \sigma : URS. \end{aligned} \tag{12}$$

To describe the analytical implication of the dual formulation (12), we need to consider the complementary slackness conditions between (11) and (12). That is, they have the following conditions:

$$\left(-\textstyle\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} u_r g_{rj} - \sum_{f=1}^{h} w_f b_{fj} + \sigma\right)\lambda_j = 0 \ \text{ for all } j. \tag{13}$$

here, RS_k indicates a reference set for the k-th DMU that consists of efficient DMUs with $\lambda_j > 0$ for $j \in RS_k$ in Model (11). The supporting hyperplane is determined by,

$$-\textstyle\sum_{i=1}^{m} v_i x_{ij} + \sum_{r=1}^{s} u_r g_{rj} - \sum_{f=1}^{h} w_f b_{fj} + \sigma = 0 \ \text{ for } j \in RS_k \tag{14}$$

The slopes of the supporting hyperplane are determined by the marginal rate of transformation (MRT) of b_f to g_r. Sueyoshi and Yuan [24] provide a mathematical definition on MRT. The measure becomes $MRT_r^f = \partial b_f / \partial g_r = u_r^* / w_f^*$ for all r and all f. Since $w_f^* > 0$, the sign of u_r^* determines the direction concerning MRT. After solving Model (12), assuming a unique optimal solution, the MRT indicates a possible existence of DC by the following guideline:

(a) $u_r^* = 0$ for some (at least one) r indicates an occurrence of "weak DC",

(b) $u_r^* < 0$ for some (at least one) r indicates an occurrence of "strong DC" and (15)

(c) $u_r^* > 0$ for all *r* indicates "no" occurrence of DC.

Figure 4 depicts the whole computational flow that is utilized in this research.

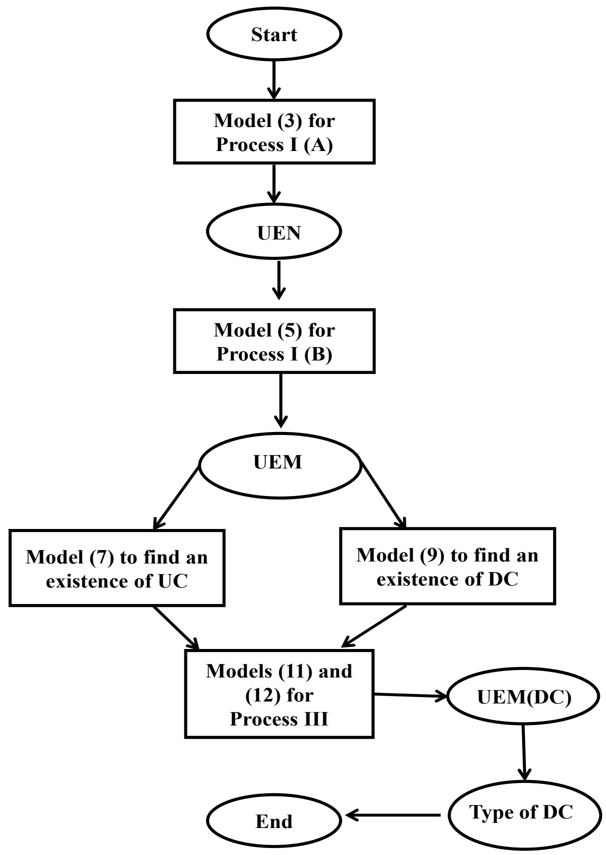

Figure 4. A computational flow for proposed assessment. (a) First, model (3) computes the degree of *UEN* as depicted in the process I(A). Second, model (5) calculates the degree of *UEM* as depicted in the process I(B). Third, the second process (II) is used to prepare the last process (III), Fourth, model (7) incorporates UC while model (9) incorporates DC. Fifth, the primal model (11) and its dual model (12) incorporate the by-product assumption and compute the degree of *UEM(DC)* as depicted in the process (III). Lastly, the classification rule (15) identifies the type of DC. (b) This research uses the third and fourth steps for the model development for the fifth step. Both the third and fourth steps do not maintain the by-product assumption. The fifth step includes the assumption to unify them under managerial disposability. The first and second steps compute *UEN* and *UEM* measures. The fifth and sixth steps compute *UEM(DC)* along with the DC classification.

6. Japanese Manufacturing Industries

To discuss the current situation in Japanese manufacturing industries, this study incorporates corporate resource and energy factors in the proposed assessment and compares their performance measures. Then, this study examines the following three research concerns:

First, Japanese firms look for their operational achievements to attain high sustainability [7]. Economic success is the first priority for them because it allows them to operate under natural disposability. They need capital accumulation to invest in green technology innovation.

Second, Japanese firms need to prevent their industrial pollutions. The assessment for environmental protection belongs to managerial disposability [6]. Large firms have capital accumulation at the level that becomes large enough to invest in green technology. In addition to the governmental regulation on environment, they need to pay attention to consumers' consciousness on various pollution issues [7].

Finally, we are interested in the influence of regulation. Japanese industrial policy regulates and controls all industries. Previously, it was believed that all manufacturing firms worked like a single entity, often referred to as "Japan Inc." However, recent fierce competition changes the business environment. The commutation is brought about by information technology incorporated into an advanced world-wide supply chain system. Corporate behaviors are driven by their survival strategies in a global market [6]. Consequently, a conventional relationship between government and business may not exist anymore in Japan. This study examines the current Japanese situation.

6.1. Data

This application examines the performance of Japanese manufacturing industries that include 13 industrial sectors with 110 companies during 2013 to 2015. The industrial sectors are food items (10), textile products (5), pulp and paper (3), chemicals (25), pharmaceutical products (9), gum products (3), glass, soil and stone products (2), iron and steel (3), non-ferrous metal and metal products (4), machinery (9), electrical equipment (23), transportation equipment and precision instrument (11), and other products (3), where the number in parentheses is that of companies per industrial sector. The total number of observations is 330 (the total number of companies = 110 firms × 3 years).

For the assessment, this study uses five input resources, two desirable outputs, and three undesirable outputs. We have collected economic data and environmental data from Toyo Keizai Inc. The database is well-known and often used for sustainability studies in Japan. All companies are listed in the first section of the Tokyo Stock Exchange. This study follows a guideline provided by the database in selecting the industrial groups and the three production factors.

Five inputs are the following items: (a) total assets: this item represents a total amount of each company's assets used for plant operation, office property, and equipment for production. Those are listed in a balance sheet; (b) total operating expenses: this is a total amount of company's incurred expenses used for day-to-day operation and production. Depreciation and amortization of assets are included but financial expenses are excluded from the item; (c) environmental protection cost: this is a company's cost used for environmental protection and investment; (d) total energy input: this is an amount of energy used for operation; and (e) total water resource input: this is the total amount of water resource inputs used per operation.

The inputs and desirable outputs are obtained from "Toyo Keizai Financial Data Digest," where Toyo Keizai is one of the well-known Japanese publishers. Undesirable outputs are from "Toyo Keizai CSR (Corporate Social Responsibility Souran (a comprehensive handbook in Japanese) that is the famous CSR database on Japanese firms.

6.2. Unified Efficiencies

Tables 2 and 3 represent unified efficiencies of pharmaceutical products and machinery industries which are obtained from Models (3), (5), and (11). The two industries are selected for illustration purposes. The dual variables for two desirable outputs and the type of DC are determined by Model (12).

Two desirable outputs are (a) revenues: total amount of sales gained from operation and (b) market capitalization: this represents a current aggregate value of a firm. It is calculated from a sum of current share price multiplied by the number of outstanding shares.

Three undesirable outputs are: (a) greenhouse gas emissions: a total amount of GHG emissions from an operation; (b) total waste discharges: this is an amount of waste discharged from an operation; and (c) total waste water discharges: this is an amount of waste water discharged from an operation.

Table 1. Descriptive statistics.

	Statistics	Total Assets	Total Operating Expenses	Environment Protection Cost	Total Energy Input	Total Water Resource Input	Revenues	Market Capitalization	Greenhouse Gas Emissions	Total Waste Discharges	Total Waste Water Discharges
	Unit	MioJPY	MioJPY	MioJPY	1000 GJ	1000 m^3	MioJPY	MioJPY	Ton-CO_2	ton	1000 m^3
Food item	Avg.	205,021	233,342	1359	3498	5579	237,625	154,392	199,638	42,185	3495
	Max.	470,664	786,036	4328	9978	19,309	791,426	564,672	592,150	235,320	17,487
	Min.	36,904	9176	46	411	360	13,603	19,017	19,469	3716	7
Textile product	Avg.	490,145	214,797	4146	15,716	76,315	226,570	405,796	2,394,267	40,691	74,013
	Max.	1,247,209	541,061	8475	31,000	184,000	566,259	1,642,901	21,900,000	135,000	180,000
	Min.	139,819	76,921	754	2455	4434	85,838	31,186	131,198	3086	164
Pulp and paper	Avg.	810,760	221,605	16,944	92,812	503,800	233,191	242,133	4,207,292	258,115	430,892
	Max.	1,265,110	633,641	29,807	150,000	933,000	653,979	523,675	6,680,000	762,000	881,000
	Min.	18,179	17,640	126	169	41	20,570	3454	8180	332	40
Chemical	Avg.	512,382	233,267	9596	22711	90,941	249,435	464,877	1,759,738	55,321	75,040
	Max.	2,015,977	887,848	41,861	127,842	1,430,000	900,723	3,392,037	9,144,000	422,200	1,036,000
	Min.	27,600	3526	97	121	107	18,625	16,652	6123	1026	6
Pharmaceutic al product	Avg.	741,641	260,881	1464	2112	8161	307,950	1,527,972	112,259	8575	7321
	Max.	2,728,528	682,766	4931	4874	47,072	796,512	4,738,751	266,490	24,506	47,050
	Min.	114,803	68,833	245	236	240	76,288	137,482	12,839	367	97
Gum product	Avg.	778,401	333,622	5083	6983	7800	412,491	1,219,445	423,810	20,747	5909
	Max.	2,011,618	801,291	13,887	17,673	21,722	1,006,602	3,414,216	1,001,939	40,163	18,627
	Min.	72,414	37,278	247	581	888	39,623	41,585	32,998	2961	598
Glass, soil and stone product	Avg.	419,618	277,026	2133	4306	2003	295,670	664,165	326,124	39,005	1651
	Max.	498,118	378,922	2995	7838	3182	398,595	840,191	707,687	57,400	2234
	Min.	336,726	158,345	1527	2366	1356	166,999	506,520	116,376	15,004	863
Iron and steel	Avg.	428,218	295,331	8155	15,933	13,836	307,727	314,304	837,498	342,558	10,024
	Max.	739,112	474,274	16,283	23,844	23,020	500,203	791,328	107,1000	886,000	22,490
	Min.	207,352	156,259	3342	12	4467	160,304	80,739	607,000	17,000	430
Non–ferrous metal and metal product	Avg.	865,761	511,186	3131	18,786	113,993	519,984	657,411	2,438,153	53,778	90,400
	Max.	1,252,174	930,390	5386	41,800	421,611	928,976	1,250,456	8,190,000	159,556	415,889
	Min.	415,388	2206	2080	4532	5862	8777	143,453	218,000	10,795	138
Machinery	Avg.	848,830	459,703	6448	4252	2414	491,945	775,660	210,223	50,113	1592
	Max.	3,476,067	1,917,326	26,635	15,451	9783	2,039,361	2,296,273	967,765	193,894	8250
	Min.	158,965	67,041	166	227	102	72,314	87,960	11,974	2098	67
Electrical equipment	Avg.	1,168,621	919,934	9179	16,302	7229	938,519	1,054,424	585,699	59,236	5116
	Max.	4,935,233	4,014,278	50,969	480,000	45,130	4,084,606	5,122,318	3,240,000	458,715	32,317
	Min.	16,867	26,900	43	62	38	27,204	3846	3217	88	23

Transportation equipment and precision instrument	Avg.	2,289,824	1,780,898	66,319	7925	3397	1,935,532	3,440,212	340,846	76,310	2815
	Max.	16,100,209	10,183,696	390,100	35,644	12,248	11,585,822	28,653,072	1,570,000	299,000	12,946
	Min.	50,905	5550	179	766	265	12,911	15,103	40,176	411	5
Other products	Avg.	551,684	348,077	3347	7390	5174	349,020	298,981	346,844	32,340	2830
	Max.	1,429,806	1,002,568	9838	21,275	15,300	1,001,026	818,161	999,000	51,300	11,800
	Min.	58,852	12,622	116	606	227	14,140	29,158	32,639	17,472	8
All	Avg.	870,005	569,704	12,758	15,035	46,014	603,631	983,674	963,046	63,571	38,398
	Max.	16,100,209	10,183,696	390,100	480,000	1,430,000	11,585,822	28,653,072	21,900,000	886,000	1,036,000
	Min.	16,867	2206	43	12	38	8777	3454	3217	88	5

Table 2. Unified efficiency measures on pharmaceutical product industry.

Pharmaceutical product							
Year	Company Name	*UEN*	*UEM*	*UEM(DC)*	Dual variables		DC
					Revenues	Market capitalization	
2013	Kyowa Kirin	0.985	0.967	0.756	0.133	−0.080	Strong
2014	Kyowa Kirin	0.981	0.965	0.759	0.133	−0.080	Strong
2015	Kyowa Kirin	0.984	0.964	0.792	0.138	−0.084	Strong
2013	Takeda	1.000	1.000	0.933	0.751	−0.081	Strong
2014	Takeda	1.000	1.000	1.000	0.751	−0.081	Strong
2015	Takeda	1.000	1.000	0.973	1.567	−0.129	Strong
2013	Astellas	1.000	0.989	0.847	0.268	−0.088	Strong
2014	Astellas	1.000	0.988	1.000	0.268	−0.088	Strong
2015	Astellas	0.997	0.985	0.955	1.933	−0.131	Strong
2013	Shionogi & Co., LTD.	0.994	0.981	0.735	0.133	−0.080	Strong
2014	Shionogi & Co., LTD.	0.997	0.985	0.798	0.138	−0.084	Strong
2015	Shionogi & Co., LTD.	1.000	0.990	0.830	0.150	−0.092	Strong
2013	Mitsubishi Tanabe Pharma	1.000	1.000	0.721	0.133	−0.080	Strong
2014	Mitsubishi Tanabe Pharma	0.995	0.988	0.749	0.133	−0.080	Strong
2015	Mitsubishi Tanabe Pharma	1.000	0.991	0.741	0.133	−0.080	Strong
2013	Nippon Shinyaku Co., LTD.	0.999	0.996	0.910	0.276	0.460	No
2014	Nippon Shinyaku Co., LTD.	1.000	1.000	0.844	2.901	0.313	No
2015	Nippon Shinyaku Co., LTD.	0.999	0.998	0.843	2.901	0.313	No
2013	Ono Pharmaceutical Co., LTD.	1.000	1.000	0.790	0.268	−0.088	Strong
2014	Ono Pharmaceutical Co., LTD.	0.997	1.000	0.877	2.178	−0.133	Strong
2015	Ono Pharmaceutical Co., LTD.	1.000	1.000	1.000	2.178	−0.133	Strong
2013	Santen	0.999	0.988	0.775	0.276	0.460	No
2014	Santen	1.000	0.991	0.760	0.133	−0.080	Strong
2015	Santen	0.999	0.991	0.755	0.133	−0.080	Strong
2013	Tsumura & Co.	0.996	0.978	0.882	0.276	0.460	No
2014	Tsumura & Co.	0.994	0.962	0.866	0.276	0.460	No
2015	Tsumura & Co.	0.994	0.962	0.874	0.276	0.460	No
Statistics	Avg.	0.997	0.987	0.843			
	S.D.	0.005	0.013	0.089			
	Max.	1.000	1.000	1.000			
	Min.	0.981	0.962	0.721			

DC stands for desirable congestion. Model (3) calculates a degree of *UEN* depicted in Stage I (A). Model (5) computes the magnitude of *UEM* depicted in Stage I (B). After incorporating the by-product assumption, Model (11) computes the degree of *UEM(DC)* as depicted in Stage III and Model (12) identifies the type of DC by applying Equation (15).

Table 3. Unified efficiencies on machinery industry.

Machinery							
Year	Company Name	*UEN*	*UEM*	*UEM(DC)*	Dual variables: Revenues	Dual variables: Market capitalization	DC
2013	Komatsu	0.988	0.947	0.768	0.133	-0.080	Strong
2014	Komatsu	0.987	0.943	0.778	0.202	-0.085	Strong
2015	Komatsu	0.986	0.949	0.766	0.268	-0.088	Strong
2013	Sumitomo Heavy Industries, Ltd.	0.989	0.973	0.865	2.901	0.313	No
2014	Sumitomo Heavy Industries, Ltd.	0.991	0.977	0.761	2.519	0.114	No
2015	Sumitomo Heavy Industries, Ltd.	0.989	0.974	0.826	2.901	0.313	No
2013	Komori	1.000	0.993	0.933	0.276	0.460	No
2014	Komori	0.998	0.995	0.927	0.276	0.460	No
2015	Komori	0.998	0.992	0.934	0.276	0.460	No
2013	Daifuku	0.998	0.994	0.881	2.385	0.336	No
2014	Daifuku	0.998	0.993	0.866	2.385	0.336	No
2015	Daifuku	0.998	0.995	0.823	0.276	0.460	No
2013	NSK	0.977	0.849	0.708	0.268	-0.088	Strong
2014	NSK	0.978	0.851	0.743	0.905	-0.094	Strong
2015	NSK	0.961	0.719	0.745	1.853	-0.045	Strong
2013	NTN	0.984	0.909	0.793	0.276	0.460	No
2014	NTN	0.984	0.912	0.733	2.901	0.313	No
2015	NTN	0.983	0.897	0.798	2.901	0.313	No
2013	JTEKT	0.990	0.924	0.655	0.268	-0.088	Strong
2014	JTEKT	0.989	0.916	0.666	0.546	-0.091	Strong
2015	JTEKT	0.989	0.916	0.657	0.905	-0.094	Strong
2013	Makita	1.000	0.999	0.767	0.202	-0.085	Strong
2014	Makita	1.000	0.999	0.769	0.202	-0.085	Strong
2015	Makita	1.000	1.000	0.782	0.931	-0.093	Strong
2013	Mitsubishi Heavy Industries	1.000	0.868	0.795	0.196	0.072	No
2014	Mitsubishi Heavy Industries	0.972	0.834	0.965	0.277	0.054	No
2015	Mitsubishi Heavy Industries	0.977	0.877	1.000	0.277	0.054	No
Statistics	Avg.	0.989	0.933	0.804			
	S.D.	0.010	0.068	0.092			
	Max.	1.000	1.000	1.000			
	Min.	0.961	0.719	0.655			

See notes of Table 2.

For illustration, in the two tables, all three efficiency measures on average include *UEN* = 0.997 for the pharmaceutical product and *UEN* = 0.989 for the machinery, *UEM* = 0.987 for the pharmaceutical product and *UEM* = 0.933 for the machinery, and *UEM(DC)* = 0.843 for the pharmaceutical product and *UEM(DC)* = 0.804 for the machinery. The pharmaceutical product industry is higher than the machinery industry on average in the three unified efficiencies. The lower averages of the machinery industry are partly because of these large standard deviations, compared to the pharmaceutical industry. For example, these standard deviations of *UEN* are 0.005 for the pharmaceutical product and 0.010 for the machinery.

Another finding is that *UEM(DC)* is generally lower than the other two efficiency measures. This is because Model (11) needs to assess not only unified efficiency but also a potential of green technology enhancement. Along with the high averages in the three efficiency measures, the pharmaceutical companies exhibit a high percentage of strong DC, compared to the machinery industry. This indicates that machinery companies have a high potential to handle pollution problems by enhancing their production amounts.

Table 4 is the extension of Tables 2 and 3 that summarize industry averages of the three efficiency measures. Table 4 indicates two implications concerning the first and second research concerns. One of them is that most industrial sectors have their high *UEN* measures. Those industries include the food item (*UEN* = 0.996), the pharmaceutical product (*UEN* = 0.997), the gum product (*UEN* = 0.997), the glass, soil and stone product (*UEN* = 0.990), the electrical equipment (*UEN* = 0.993), the transportation equipment and precision instrument (*UEN* = 0.994), and the other products (*UEN* = 0.991) on average. The standard deviations of those industrial sectors are relatively small. In contrast, the average *UEM* measures are generally lower than those of *UEN*. An exception is the pulp and paper industry, whose average *UEN* is 0.847, while average *UEM* is 0.923. The pulp and paper industry used to be an environmentally lagged industry. Their recent corporate efforts have changed the status of environmental protection.

Table 4. Unified efficiency averages of Japanese industrial sectors.

Industries	Statistics	*UEN*	*UEM*	*UEM(DC)*	Industries	Statistics	*UEN*	*UEM*	*UEM(DC)*
Food item	Avg.	0.996	0.935	0.880	Iron and steel	Avg.	0.950	0.714	0.875
	S.D.	0.005	0.080	0.091		S.D.	0.047	0.200	0.112
Textile product	Avg.	0.963	0.928	0.906	Non–ferrous metal and metal product	Avg.	0.966	0.921	0.818
	S.D.	0.039	0.089	0.074		S.D.	0.050	0.096	0.103
Pulp and paper	Avg.	0.847	0.923	0.999	Machinery	Avg.	0.989	0.933	0.804
	S.D.	0.125	0.108	0.002		S.D.	0.010	0.068	0.092
Chemical	Avg.	0.966	0.935	0.886	Electrical equipment	Avg.	0.993	0.939	0.866
	S.D.	0.054	0.097	0.099		S.D.	0.013	0.098	0.115
Pharmaceutical product	Avg.	0.997	0.987	0.843	Transportation equipment and precision instrument	Avg.	0.994	0.968	0.836
	S.D.	0.005	0.013	0.089		S.D.	0.012	0.057	0.137
Gum product	Avg.	0.997	0.958	0.866	Other products	Avg.	0.991	0.968	0.877
	S.D.	0.003	0.018	0.081		S.D.	0.010	0.024	0.153
Glass, soil and stone product	Avg.	0.990	0.934	0.741	All	Avg.	0.980	0.938	0.864
	S.D.	0.006	0.031	0.031		S.D.	0.045	0.095	0.109

Ave. indicates average and S.D. stands for standard deviation. DC stands for desirable congestion.

The other finding is that among the industrial sectors with high *UEN*, only the pharmaceutical product industry has exhibited higher *UEM* with 0.987 on average. It is followed by the transportation equipment and precision instrument as well as the other products with 0.968 in *UEM*. These measures indicate that companies with high *UEN* cannot always produce high *UEM*. The *UEM(DC)* also exhibits high average (0.999) in the pulp and paper as well as that (0.906) in the textile product, although the two industrial sectors do not exhibit high attainment in both *UEN* and *UEM*. This indicates, particularly for the pulp and paper sector, that companies of the sector put more weight on their environmental efficiencies than operational ones. The industry of glass, soil and stone products exhibits low average with 0.741 in *UEM(DC)*. The industry has a large space for efficiency improvement by introducing green technology. The iron and steel sector exhibits low *UEM(DC)* = 0.714, revealing a high potential to improve its pollution prevention by investing in green technology. Currently, this industry produces high CO_2 emissions among the manufacturing sectors.

The *UEN* outperforms the *UEM* in these degrees. This implies the implication that firms have first attempted to improve the sustainability by attaining their economic successes. To mitigate industrial pollution, they accumulate capital from their profits and invest it in green technology so that they can satisfy the minimum standard required by the government. It is indeed important that firms need to satisfy the environmental standard. However, it is difficult for them to follow the regulation guideline without economic sufficiency. The relatively low degree of *UEM(DC)* implies the current potential level for green technology innovation in Japanese manufacturing firms.

6.3. Statistical Test

Table 5 summarizes the rank sum test [25] on the three models i.e., *UEN, UEM, UEM(DC)*. The null hypotheses are related to the third research concern and summarized as follows:

(a) Ho: There is no difference among Japanese industrial sectors in their *UEN* measures;
(b) Ho: There is no difference among them in their *UEM* measures; and
(c) Ho: There is no difference among them in their *UEM(DC)* measures.

Table 5. Kruskal–Wallis rank sum test.

	Hypothesis 1	**Hypothesis 2**	**Hypothesis 3**
chi-squared with ties	72.31***	43.51***	42.522***
p-value	0.0001	0.0001	0.0001

(**a**) First Ho: there is no difference among Japanese industrial sectors in their *UEN* measures. Model (3) is used to compute *UEN* to examine the hypothesis. Second Ho: there is no difference among them in UEM. Model (5) measures *UEM* to examine the hypothesis. Third Ho: there is no difference among them in *UEM(DC)*. Model (11) calculates *UEM(DC)* to examine the hypothesis. (**b**) Holland and Wolfe [25] described the Kruskal–Wallis rank sum test. Sueyoshi and Aoki [26] described how to conduct the rank sum test for DEA.

The first and second hypotheses originate from [7]. The last examines the influence of DC and the by-product assumption. As indicated by Table 5, the rank sum test rejects the three hypotheses at the 1% significance by the chi-squared distribution. This indicates that there is a significant difference among Japanese industrial sectors in their unified efficiencies. Historically, the nation was often referred to as "Japan Inc." because the government carefully regulated and coordinated corporate operations. Such a government and business relationship has been admired and respected by the other industrial nations. However, Table 5 indicates that the strong relationship may not exist among different industrial sectors because firms are now facing fierce competition in a global market.

6.4. Desirable Congestion (DC)

Table 6 documents the percentage on a possible occurrence of DC, measured by Model (12) and the rule (15). The table indicates that 41% of firms have a potential of efficiency improvement by employing green technology for pollution prevention and the others (59%) do not have such a capability. Among them, a high percentage of strong DC is observed in the industrial sectors such as pharmaceutical products (74%), glass, soil and stone products (100%), and non-ferrous metal and metal products (67%). These sectors exhibit relatively low *UEM (DC)* in such a manner that these measures are 0.843, 0.741, and 0.818, respectively. Thus, investment in green technology in these industries becomes effective in reducing *B*.

Table 6. Type of desirable congestion.

Industries	Occurrence of Desirable Congestion		
	Strong	**Weak**	**No**
Food item	6 (20%)	0 (0%)	24 (80%)
Textile product	3 (20%)	0 (0%)	12 (80%)
Pulp and paper	2 (22%)	0 (0%)	7 (78%)
Chemical	25 (33%)	0 (0%)	50 (67%)
Pharmaceutical product	20 (74%)	0 (0%)	7 (26%)
Gum product	3 (33%)	0 (0%)	6 (67%)
Glass, soil and stone product	6 (100%)	0 (0%)	0 (0%)
Iron and steel	3 (33%)	0 (0%)	6 (67%)
Non–ferrous metal and metal product	8 (67%)	0 (0%)	4 (33%)
Machinery	12 (44%)	0 (0%)	15 (56%)
Electrical equipment	36 (52%)	0 (0%)	33 (48%)
Transportation equipment and precision instrument	12 (36%)	0 (0%)	21 (64%)
Other products	0 (0%)	0 (0%)	9 (100%)
All	136 (41%)	0 (0%)	194 (59%)

Desirable congestion implies an occurrence of green technology innovation. Using Model (12), we classify the type of congestion by Equation (15).

7. Concluding Comments

This study discussed how to enhance the sustainability of Japanese manufacturing firms by investing in green technology and other pollution prevention efforts (e.g., waste reduction) in their operations. The concept of sustainability is not clearly defined and, therefore, not analytically explored by previous studies. We have challenged the research task by DEA.

As the first step in our methodological development, this research separated outputs into two categories: desirable and undesirable. Second, we discussed how to unify them to compute their *UEN* and *UEM* scores. Finally, this research extended them for the development of a new measure, or *UEM(DC)*, under both the existence of DC and the by-product assumption. The assumption provided us with a new formulation for DEA-based environmental assessment.

To describe the applicability, we investigated the performance of Japanese 13 industrial sectors. The application obtained the following five implications: First, their *UEM(DC)* measures were generally lower than their magnitudes of *UEN* and *UEM* because the former needed to consider a potential for green technology innovation, recycling activities and other efforts for pollution prevention. Japanese companies with low *UEM(DC)* need to enhance green technology and other activities for environmental protection. Second, several sectors maintained their high *UEN* measures. Meanwhile, their standard deviations were relatively smaller than the magnitude of UEM and that of *UEM(DC)*. In other words, most industries now face different environmental surroundings. An exception was the pulp and paper industry. The industry used to be lagging in environmental protection, but its recent effort changed the current status on environmental protection. Third, among the industrial sectors with high *UEN* measures, only the pharmaceutical product sector exhibited high *UEM* with 0.987 on average. Transportation equipment and precision instrument were the second with 0.968 in *UEM*. The companies with high *UEN* may not necessarily lead to high *UEM*. This reveals a difficulty in balancing between operational and environmental efficiencies. Fourth, *UEM(DC)* exhibited high averages in the pulp and paper as well as the textile products, although they did not exhibit high achievement in both *UEN* and *UEM*. On the other hand, glass, soil and stone products presented low average with 0.741 in *UEM(DC)*. The industrial sector has a large space for sustainability improvement by implementing green technology investment. Finally, a high percentage of strong DC was observed in pharmaceutical products (74%), glass, soil and stone products (100%), and ferrous and non-ferrous metal products (67%). These industries exhibited relatively low in *UEM (DC)* in the manner that they were 0.843, 0.741, and 0.818, respectively. Investment in green technology and/or pollution prevention in these industries becomes effective in reducing *B*. The results on *UEM(DC)* indicate that firms in different sectors produce different results in green management even if they are strictly regulated by the Japanese government.

This research has four drawbacks, all of which need to explored in future. First, we have discussed how to compute a degree of sustainability under DC. However, this study does not discuss corporate implications derived from scale benefits such as RTS and DTS. These scale measures provide us with a strategic direction (e.g., increasing, decreasing and constant) by a scale change on inputs [27]. Second, we need to consider an efficiency change due to a time shift by a "Malmquist" index. The index examines a frontier shift among multiple periods. The shift indicates technology advancement and/or managerial improvement during the observed periods [28]. Third, the proposed approach is useful in measuring the performance of other types of manufacturing and service industries. Finally, this research needs a methodological comparison. That is, different methodology may produce empirical results which cannot be found in this research. This type of empirical issue is referred to as "a methodical bias" [29]. See also [30], which discussed the methodological problems that exist in many empirical studies.

In conclusion, it is hoped that this article may contribute to DEA environmental assessment applied to Japanese industrial sectors.

Nomenclature

Abbreviations

CO_2	The index of time Carbon Dioxide
DC	Desirable Congestion
DEA	Data Envelopment Analysis
DMU	Decision Making Unit
DTS	Damages to Scale
EF	Efficiency Frontier
GHG	Greenhouse Gas
M	Managerial
MRT	Marginal Rate of Transformation
N	Natural
NR	Non-Radial
RAM	Range Adjusted Measure
ROA	Return on Assets
ROE	Return on Equity
PoPS	Pollution Possibility Set

PrPS	Production Possibility Set
Pr&PoPS	Production and Pollution Possibility Set
RS	Reference Set
RTS	Returns to Scale
UC	Undesirable Congestion
UEN	Unified Efficiency under Natural Disposability
UEM	Unified Efficiency under Managerial Disposability
UEM(DC)	Unfired Efficiency under Managerial Disposability and Desirable Congestion
URS	Unrestricted
CSR	Corporate Social Responsibility

Variables

d_i^x	an unknown slack variable of the *i*-th input
d_f^b	an unknown slack variable of the *f*-th undesirable output
λ	an unknown column vector of intensity (or structural) variables
R_i^x	a data range related to the *i*-th input
R_r^g	a data range related to the *r*-th desirable output
R_f^b	a data range related to the *f*-th undesirable output
v_i	a dual variable of the *i*-th input
u_r	a dual variable of the *r*-th desirable output
w_f	a dual variable of the *f*-th undesirable output,
σ	a dual variable to indicate the intercept of a supporting hyperplane on a production and pollution possibility set
ε	a prescribed small number to control the magnitude of unified efficiency (e.g., ε = 0.1, 1 and 2). We use ε = 1 for this study. Thus, the number is not a non-Archimedean small number.

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