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A DEA-BASED METHOD OF STEPWISE BENCHMARK TARGET SELECTION WITH PREFERENCE, DIRECTION AND SIMILARITY CRITERIA

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Abstract. *Data envelopment analysis (DEA) is a useful tool based on which inefficient decision-making units (DMUs) can perform a benchmarking process to improve their performance. However, several practical problems need to be addressed in benchmark target selection. One issue discussed in this research is that it might not be feasible for an inefficient DMU to achieve its target's efficiency in a single step, especially when the DMU is far from the benchmark target DMU. To resolve this problem, various methods of stepwise benchmarking have been proposed. Most of these methods, however, only consider the efficiency score in selecting benchmark targets and ignore various practical aspects that should be considered. In this paper, we propose a new method of stepwise benchmarking based on three criteria: preference, direction and similarity. The first criterion, preference, is used for selecting an ultimate benchmark target; the second criterion, direction is used in selecting intermediate benchmark targets which are located more closely to the improving path; and the third criterion, similarity is used for determining intermediate benchmark targets which are similar to the DMU under evaluation. Considering these three criteria, we develop a method of constructing a more practical and feasible sequence of benchmark targets.*

Keywords: Data envelopment analysis (DEA), Benchmarking, Efficiency

1. **Introduction.** The problem of benchmark target selection has been recognized as one of important factors that organizations need to consider in the process of improving their efficiency. This issue has been studied in previous research of various fields such as public administration [1], production and design [2,16], and business management [3]. In general, a benchmarking process consists of three steps. First, the best performer is identified. Second, the activities and objectives of benchmarking are set. Finally, best practices are implemented to achieve the benchmarking objectives [4]. Benchmarking requires an effective methodology for finding the best performer, which entails evaluation of the relative efficiencies of the competitors in terms of multiple input and output factors. Identifying the best performer is considered the most important step of benchmarking processes. To identity the best performer, data envelopment analysis (DEA), a methodology for measuring the relative efficiencies of homogeneous decision making units (DMUs), has been popularly used [5]. A DEA study provides a reference set of benchmark targets

for an inefficient DMU along with the corresponding efficiency gap (the degree to which that DMU must be improved so as to be rendered efficient). Several practical problems need to be addressed in benchmark target selection using DEA for inefficient DMUs. One of the problems to be discussed in this research is that it might not be feasible for an inefficient DMU to achieve its target's efficiency in a single step, especially when that DMU is far from the target DMU on the frontier. To resolve this problem, various methods of stepwise benchmarking have been proposed in the literature.

Alirezaee and Afsharian [6] proposed a layered efficiency evaluation model that provides a strategy by which an inefficient DMU can move to a better layer. This model, however, does not provide any information on how to choose the reference DMU in each layer. Shaneth et al. [7] proposed a proximity-based target selection method to provide the optimal path to the most efficient frontier DMU using self-organizing map (SOM) and reinforcement learning. This method, however, does not consider the reference set of inefficient DMUs, but focuses on practical target DMUs based on the similarity of input patterns for the benchmarking path. Park et al. [8] proposed a method of stepwise benchmarking which involves both stratifying DMUs into several performance levels and clustering DMUs based on the similarity of input patterns.

Stepwise benchmarking methods are considered to be more practical and more effective than conventional DEA based approaches, and various methods for stepwise benchmarking have been proposed in the literature. However, they are limited to some extent in that they do not consider various practical aspects that should be addressed for securing the practical feasibility of benchmarking process for inefficient DMUs.

In this paper, we propose a new method of stepwise benchmarking which incorporates three criteria for selecting a practical and feasible sequence of benchmark targets. Our approach considers multiple criteria (preference, direction and similarity) in selecting benchmark targets, while most of previous models considered only efficiency scores. This is the unique feature of the proposed approach compared with the previous ones. The first criterion, preference, is used for selecting an ultimate benchmark target; the second criterion, direction, is used for selecting intermediate benchmark targets which are located more closely to the improving path aimed for the ultimate benchmark target; and the third criterion, similarity, is used for determining intermediate benchmark targets which are similar to the DMU under evaluation in terms of the factor levels.

In order to illustrate the proposed method, we apply the proposed method to a set of East Asian container terminals and discuss the results. This paper is organized as follows. Section 2 provides an overview of DEA and SOM. Section 3 discusses the proposed method and Section 4 details our empirical study. Finally, Section 5 summarizes our work.

2. Background.

2.1. Data envelopment analysis (DEA).

DEA is a linear programming based model that evaluates the relative efficiencies of DMUs in terms of multiple inputs and outputs [9]. The mathematical model of DEA is given by the following:

$$\begin{aligned} &\max \frac{\sum_{r=1}^{s} u_r y_{rk}}{\sum_{i=1}^{m} v_i x_{ik}} \\ &\text{s.t.} \\ &\quad \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1; \quad j = 1, \dots, n \\ &\quad u_r, v_i \ge 0; \quad r = 1, \dots, s; \quad i = 1, \dots, m \end{aligned} \tag{1}$$

This is a basic DEA model developed by Charnes, Cooper and Rhodes [10], called CCR model. In this model, u_r is the weight given to the r-th output, v_i is the weight given to the i-th input, n is the number of DMUs, s is the number of outputs, m is the number of inputs, k is the DMU being evaluated, y_{rj} is the amount of the r-th output produced by DMU j, and x_{ij} is the amount of the i-th input used by DMU j. DEA models can be either input-oriented or output-oriented, depending on the rationale for conducting DEA. Input-oriented models minimize inputs while producing at least the same output levels, whereas output-oriented models maximize outputs while using at most the same input levels.

DEA is a useful tool for performance improvement through efficiency evaluation and benchmarking, specifically by providing a reference set which is a set of efficient units that can be utilized as benchmarks for improvement. The reference set can be obtained by dual model as shown in (2).

$$\begin{aligned}
&\min \theta - \varepsilon \left(\sum_{i=1}^{m} s_i^- + \sum_{r=1}^{s} s_r^+ \right) \\
&\text{s.t.} \\
&\quad \sum_{j=1}^{n} \lambda_j x_{ij} - \theta x_{ik} + s_i^- = 0, \quad i = 1, 2, \ldots, m, \\
&\quad \sum_{j=1}^{n} \lambda_j y_{rj} - y_{rk} - s_r^+ = 0, \quad r = 1, 2, \ldots, s, \\
&\quad \lambda_j, s_i^-, s_r^+ \geq 0, \quad j = 1, 2, \ldots, n
\end{aligned} \tag{2}$$

In model (2), θ is the efficiency score λ_j is the dual variable and ε is a non-Archimedean infinitesimal. By solving model (2), we can identify a composite DMU (a linear combination of DMUs) that utilizes less input than the DMU under evaluation while maintaining at least the same output levels. The optimal values of the dual variable λ_j are the coefficients for this linear combination of units. The set of units involved in the construction of the composite DMU can be utilized as benchmarks for improvement of the inefficient DMU under evaluation. If a DMU is given an efficiency score of '1', it is considered to be efficient; an efficiency score less than '1' indicates inefficiency.

2.2. **Stratification of DMUs in DEA.** In some DEA variants or applications, such as Seiford and Zhu [11], DMUs are stratified (or layered) into different efficiency levels. Let $J^1 = \{DMU_j, j = 1, \ldots, n\}$ be the set of all n DMUs and iteratively define $J^{l+1} = J^l - E^l$, where $E^l = \{DMU_k \in J^l | \theta^*(l,k) = 1\}$, and $\theta^*(l,k)$ is the optimal objective value of the following linear programming model in which DMU_k is under evaluation.

$$\begin{aligned}
&\theta^*(l,k) = \min_{\lambda_j, \theta(l,k)} \theta(l,k) \\
&\text{s.t.} \\
&\quad \sum_{j \in F(J^l)}^{n} \lambda_j x_{ij} \leq \theta(l,j) x_{ik} \\
&\quad \sum_{j \in F(J^l)}^{n} \lambda_j y_{rj} \geq y_{rk} \\
&\quad \lambda_j \geq 0, \\
&\quad j \in F(J^l)
\end{aligned} \tag{3}$$

Here, $j \in F(J^l)$ means $DMU_j \in J^l$, which is to say, $F(\cdot)$ represents the corresponding subscript index set and E^l consists of all the efficient DMUs on the l-th level best practice frontier.

When $l = 1$, model (3) becomes the original input-oriented CCR model, and the DMUs in set E^l define the first-level efficient frontier. When $l = 2$, model (3) yields the second-level efficient frontier after the exclusion of the first-level efficient DMUs. The model is solved iteratively until all of the DMUs are excluded. By this process, we can identify several levels of efficient frontiers. The following algorithm accomplishes the stratification process.

Step 1: Set $l = 1$, and J^l is the set of all DMUs.
Step 2: Evaluate the set of DMUs, J^l, by model (3) to obtain the l-th level efficient DMUs, set E^l.
Step 3: Exclude the efficient EMUs from future DEA runs. $J^{l+1} = J^l - E^l$. (If $J^{l+1} = \emptyset$ then stop.)
Step 4: Evaluate the new subset of "inefficient" DMUs, J^{l+1}, by model (3) to obtain a new set of efficient DMUs E^{l+1} (the new best practice frontier).
Step 5: Let $l = l + 1$. Go to *Step 2*.
Stopping rule: If $J^{l+1} = \emptyset$, the algorithm stops.

2.3. **Self-organizing map (SOM).** SOM developed by Kohonen [12], is an unsupervised clustering algorithm and the main feature is the visualization of its clustering results. It clusters high-dimensional data points into groups and depicts the relationships among the clusters on a map consisting of a regular grid of processing units called "neurons". Each neuron is represented by an n-dimensional weight vector, where n is equal to the dimension of the input features. The weight vector of each neuron is updated in the course of iterative training with input data points. SOM tends to preserve the topological relationship among the input data points so that similar input data points are mapped onto nearby output map units.

3. Methodology.

3.1. **Problems with the conventional DEA-based and the stratification DEA-based benchmarking.** In this section, we demonstrate some problems of the conventional DEA-based and the stratification DEA-based benchmarking, and then we propose a new stepwise benchmarking method to resolve the problems.

The sample data in Table 1 is utilized to explain the procedure proposed in this paper. The data set consists of 12 supermarkets and each supermarket consumes two inputs and yields one output. The two inputs are the number of employees (unit: 10) and the floor area (unit: 1000m^2) and the output is the sales (unit: \$100,000). We will apply the input-oriented CCR model to evaluate the efficiencies of the 12 supermarkets, where each supermarket is viewed as a DMU. Since the problem involves only two inputs and one output, we can depict the efficiency evaluation process on a two-dimensional plane, as shown in Figure 1.

Figure 1 shows the results of applying DEA to the set of DMUs. Let DMU L be a unit that wants to improve its performance and we will call this unit the 'evaluated DMU'. Then the rest of the DMUs are called 'compared DMUs'. The reference set of DMU L

TABLE 1. Supermarket example

Store	A	B	C	D	E	F	G	H	I	J	K	L
Employee (x_1)	2	4	8	3	4	5	5	6	7	6	6	7
Floor area (x_2)	4	2	1	6	3	2	6	3	3	9	4	7
Sales (y)	1	1	1	1	1	1	1	1	1	1	1	1

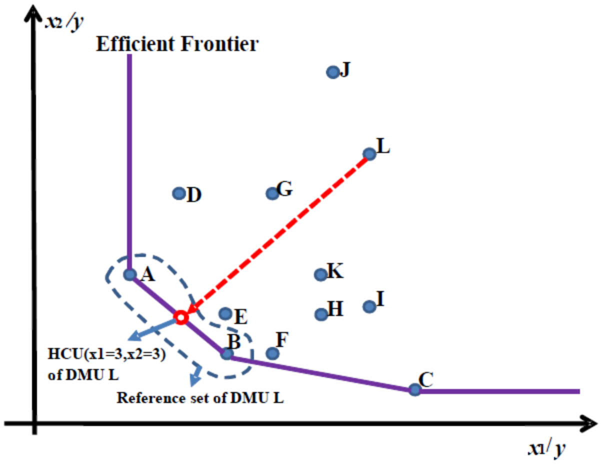

FIGURE 1. Benchmark targets provided by the conventional DEA

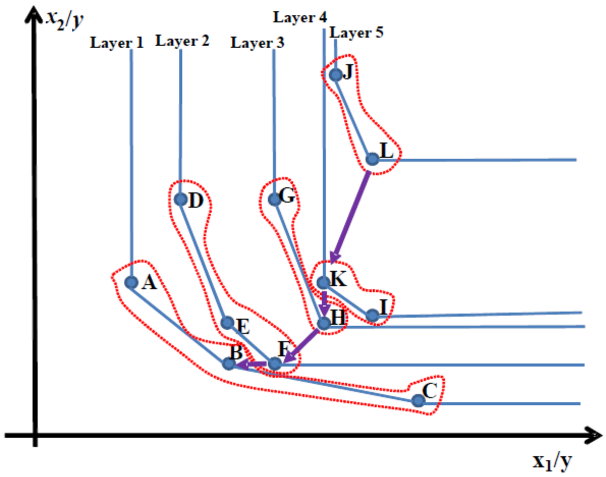

FIGURE 2. Benchmark targets provided by the stratification DEA

consists of efficient DMUs A and B and DMU L is compared with a hypothetical composite unit (HCU), a convex combination of DMUs A and B, to determine its efficiency score. DEA itself can be effective in that it provides benchmark targets for inefficient DMUs. In many practical situations, however, it might not be feasible for an inefficient DMU to reach its benchmark target at once especially when the inefficient DMU is far removed from the efficient frontier. To resolve this problem, various methods of stepwise benchmarking have been proposed in the literature based on a stratification of DMUs. If we apply the stratification method discussed by Zhu [9] to the supermarket example, we obtain the five layers as shown in Figure 2. DMU L can improve its efficiency by traversing a sequence of layers. Even though this approach may resolve, in part, the impracticality problem of the conventional DEA-based benchmarking, it does not provide any concrete criteria for selecting benchmark targets among the DMUs in each of the layers. We claim that three criteria can be used for that selection purpose which will be discussed in subsequent sections.

3.2. **Target selection based on preference structure.** The first criterion, 'preference', is used for determining the ultimate benchmark target. Thanassoulis and Dyson [13] proposed the incorporation of a weightbased preference structure into DEA models with fixed and controllable inputs which is represented by model (4). The preference model overcomes the limitation of the conventional input-oriented CCR model by attaching different degrees of importance to the individual input levels of inefficient DMUs in selecting benchmark targets. Here, z_r is the r-th output factor and p_i is the i-th input proportion; w_r^+ and w_i^- are user-specified weights to be attached to factor z_r and proportion p_i, respectively. The user specifies the weights w_r^+ and w_i^- that reflect the relative degree of improvement of the corresponding input-output levels. R_0 is the set of output factors, and I_{D0} and I_F are controllable input factors and exogenously fixed input factors, respectively. $\bar{I}_{D0}$ and $\bar{R}_0$ are the complements of I_{D0} and R_0, respectively. By changing the values of w_r^+ and w_i^- attached to z_r and p_i, the suitability of a benchmark target for the inefficient DMU can be changed.

$$
\begin{aligned}
\max & \sum_{r\in R_0} w_r^+ z_r - \sum_{i\in I_{D0}} w_i^- p_i + \varepsilon \left(\sum_{i\in \bar{I}_{D0}} d_i^- + \sum_{r\in \bar{R}_0} d_r^+ \right) \\
\text{s.t. } & z_r y_{rj_0} - \sum_{j=1}^{n} \beta_j y_{rj} = 0, \;\; r \in R_0, \\
& p_i x_{ij_0} - \sum_{j=1}^{n} \beta_j x_{ij} = 0, \;\; i \in I_{D0}, \\
& \sum_{j=1}^{n} \beta_j y_{rj} - d_r^+ = y_{rj_0}, \;\; r \in \bar{R}_0, \\
& \sum_{j=1}^{n} \beta_j x_{ij} + d_i^- = x_{ij_0}, \;\; i \in \bar{I}_{D0}, \\
& \sum_{j=1}^{n} \beta_j x_{ij} + d_i^- = x_{ij_0}, \;\; i \in I_F, \\
& z_r \geq 1 \;\; \forall r \in R_0, \;\; p_i \leq 1 \;\; \forall i \in I_{D0}, \;\; \beta_j \geq 0 \;\; \forall i, \\
& p_i, z_r \text{ free } \;\forall i \in I_0 \text{ and } r \in R_0, \\
& d_i^-, d_r^+ \geq 0 \;\; \forall i \in \bar{I}_0 \text{ and } r \in \bar{R}_0
\end{aligned}
\tag{4}
$$

In model (4), if $z_r^* = p_i^* = 1 \; \forall r \in R_0$ and $i \in I_{D0}$ as well as $d_r^{+*} = d_i^{-*} = 0 \; \forall r \in \bar{R}_0$ and $i \in \bar{I}_{D0}$ of $i \in \bar{I}_F$ then DMU_{j0} is relatively efficient. Otherwise DMU_{j0} is relatively inefficient and the suitable benchmark target for the inefficient DMU can be arrived at by Equation (5).

$$(x''_{ij_0}, i = 1, \ldots, m, y''_{rj_0}, r = 1, \ldots, s)$$

where

$$
\begin{aligned}
y''_{rj_0} &= z_r^* y_{rj_0} \;\; \forall r \in R_0, \\
y''_{rj_0} &= y_{rj_0} + d_r^{+*} \;\; \forall r \in \bar{R}_0, \\
x''_{ij_0} &= p_i^* x_{ij_0} \;\; \forall i \in I_{D0}, \\
x''_{ij_0} &= x_{ij_0} - d_i^{-*} \;\; \forall i \in \bar{I}_{D0} \text{ or } \forall i \in \bar{I}_F
\end{aligned}
\tag{5}
$$

3.3. **Target selection based on direction.** The second criterion, ‘direction’, is used in selecting intermediate benchmark targets that are located closer to the evaluated DMU’s improving direction towards the ultimate benchmark target. Two vectors from the evaluated DMU are computed. One is the direction vector from the evaluated DMU’s input patterns to the ultimate benchmark target’s input patterns. Another is the direction vector from the evaluated DMU’s input patterns to a compared DMU’s input patterns. To evaluate this criterion of the j-th DMU, the angle of these two vectors is calculated using the following formula:

$$\delta'_j = \cos^{-1} \frac{\sum_{r=1}^{m} (x_r^E - x_r^T)(x_r^E - x_r^C)}{\sqrt{\sum_{r=1}^{m} (x_r^E - x_r^T)^2} \sqrt{\sum_{r=1}^{m} (x_r^E - x_r^C)^2}} \tag{6}$$

δ_j' in model (6) is the angle between the two direction vectors from the evaluated DMU. x_r^E is the r-th input level of the evaluated DMU, x_r^C is the r-th input level of the compared DMU j, and x_r^T is the r-th input level of the ultimate benchmark target. When evaluating the direction criterion, we actually use δ_j, which is calculated by the following formula, instead of δ_j':

$$\delta_j = 1 - \left(\frac{\delta_j'}{\max(\delta_j')} \right), \tag{7}$$

where δ_j in model (7) indicates the relative magnitude of δ_j', which has the value between 0 and 1. DMU j, which has the maximum δ_j, means that it is closest DMU to the direction from the evaluated DMU to the ultimate benchmark target.

3.4. **Target selection based on similarity.** The third criterion, 'similarity', is used to select intermediate benchmark targets that have similar input patterns with the evaluated DMU. For this purpose, we classify DMUs into several similarity groups by SOM. The closer the locations of the two groups are on the map, the higher the degree of similarity between the two groups. We assume that the distance between the two DMUs belonging to the same group is 0.5 and the distance between two DMUs belonging to the adjacent groups is 1. Based on the above assumption, the distance can be calculated by Euclidean distance. For example, in Figure 3, the distance between Group 1 and Group 2 is calculated as 1 and the distance between Group 1 and Group 5 is calculated as $\sqrt{2}(= \sqrt{1^2 + 1^2})$.

Group 3	**Group 6**	**Group 9**
Group 2	**Group 5**	**Group 8**
Group 1	**Group 4**	**Group 7**

FIGURE 3. Example of SOM

The similarity between the evaluated DMU and DMU j is calculated using the following formula:

$$d_j = 1 - \frac{\sqrt{a^2 + b^2}}{P}, \tag{8}$$

where d_j in model (8) is the degree of similarity between the group containing the evaluated DMU and the group containing the j-th compared DMU, a is the horizontal distance between the group containing the evaluated DMU and the group containing the compared DMUs, and b is the vertical distance between the group containing the evaluated DMU and the group containing the compared DMUs. P is the maximum distance value among the groups (e.g., if the map generated by SOM is $4 * 4$, P is 4.24 $(= \sqrt{3^2 + 3^2})$). The formula $\frac{\sqrt{a^2+b^2}}{P}$ indicates the relative distance of each group and is the Euclidean distance between the group of the evaluated DMU and the group of the compared DMUs divided by the maximum Euclidean distance between all groups.

3.5. **The proposed benchmark selection method.** In this section, a method is proposed for the selection of stepwise benchmark targets considering preference, direction and similarity criteria. Direction and similarity criteria are used to find intermediate benchmark DMUs to benchmark ultimate target, and ultimate benchmark target is determined considering preference criterion. To find intermediate benchmark DMUs, a weighted average of the degrees of direction and similarity is calculated using the following formula:

$$\begin{aligned} &e_j = \delta_j w_1 + d_j w_2, \quad j \in F(J) \\ &w_1, w_2 \geq 0, \quad w_1, w_2 \leq 1, \quad w_1 + w_2 = 1, \end{aligned} \tag{9}$$

where $j \in F(J)$ means $DMU_j \in J$, i.e., $F(\cdot)$ represents the correspondence from a DMU set to the corresponding subscript index set J. w_1 and w_2 are weights attached to the direction and similarity criteria, respectively. Different weights can be given to the degree of direction or similarity to impart more emphasis, and the sum of each weight must be equal to 1. The procedure of the proposed method is described in detail below where J is a set of DMUs in higher efficiency levels than the evaluated DMU.

Step 1: Measure the relative efficiencies of DMUs and select the evaluated DMU.
Step 2: Select the ultimate benchmark target of the evaluated DMU using model (4).
Step 3: Cluster DMUs into several similarity groups in terms of input patterns by SOM.
Step 4: Measure δ_j and d_j using models (7) and (8) for all $j \in F(J)$.
Step 5: Evaluate e_j using model (9), for all $j \in F(J)$.
Step 6: Determine the next intermediate benchmark DMU by choosing the maximum value of e_j.
Step 7: Substitute the intermediate benchmark DMU determined in *Step 6* for the evaluated DMU.
Step 8: If the intermediate benchmark DMU is equal to the ultimate benchmark target, terminate the procedure. Otherwise, go to *Step 4*.

To illustrate the proposed method discussed in this section, we apply the method to the data in Table 1. NNclust which is an Excel-based SOM program is used to cluster DMUs into several similarity groups in terms of input patterns. The input variables for the SOM run are 'Floor Area' and 'Employee' from Table 1. The parameters chosen for the SOM run are that the training cycle is 100, the learning parameters are 0.9 for the starting point, and 0.1 for the ending point, and the map size is 4 by 4. After measuring the efficiencies of DMUs, DMU L is chosen to be the evaluated DMU. To determine the ultimate benchmark target, we use the DEA model with a preference structure, represented by model (4). We assume that the respective weights on x_1 and x_2 are 20 and 80, which means more preference is given to x_2. Using model (4) p_1^* and p_2^* are calculated to be 0.571 and 0.2857, respectively. If p_1^* and p_2^* are used in model (5), DMU B ($x_1 = 4, x_2 = 2$) is selected as the ultimate benchmark target for DMU L. The results of the SOM run are displayed in Figure 4.

The group numbers are shown at the bottom left corner of cells. We use the same weight, 0.5, both to the w_1 and w_2. The values of d_j, δ_j and e_j for DMUs in efficiency levels higher than DMU L are shown in Figure 5. The maximum value of e_j is attained by DMU K, and thus DMU K is determined to be the first intermediate benchmark target for DMU L. Now, DMU K becomes the evaluated DMU.

The values of d_j, δ_j and e_j for DMUs in efficiency levels higher than DMU K are shown in Figure 6. The maximum value of e_j in Figure 6 is attained by DMU B and thus DMU B is determined to be the second intermediate benchmark DMU for DMU L. Since DMU B is equal to the ultimate benchmark target of DMU L, the procedure is terminated.

On the other hand, if we give different weights 80 and 20 to x_1 and x_2, respectively, in order to give more preference to x_1, DMU A is selected as the ultimate benchmark target

K (0.60) H (0.67) I (0.63) C (1.00) 4	G (0.55) 8	A (1.00) B (1.00) E (0.86) D (0.67) 12 F (0.92)	16
L (0.43) 3	7	11	15
2	6	10	14
J (0.40) 1	5	9	13

FIGURE 4. Clustering of DMUs by SOM

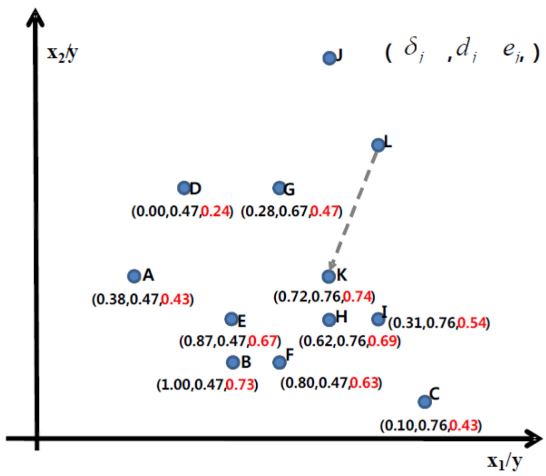

FIGURE 5. The values of e_j with DMU L being the evaluated DMU

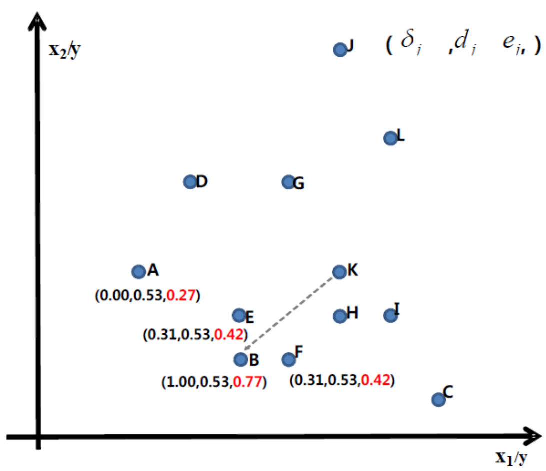

FIGURE 6. The values of e_j with DMU K being the evaluated DMU

for DMU L. Following the same procedure as described above, the intermediate benchmark DMUs for DMU L are determined to be DMU G and DMU A. In other words, DMU L should benchmark DMU G first and then DMU A. Figure 7 shows the two benchmarking paths which have different ultimate benchmark targets; L-K-B and L-G-A. If the ultimate

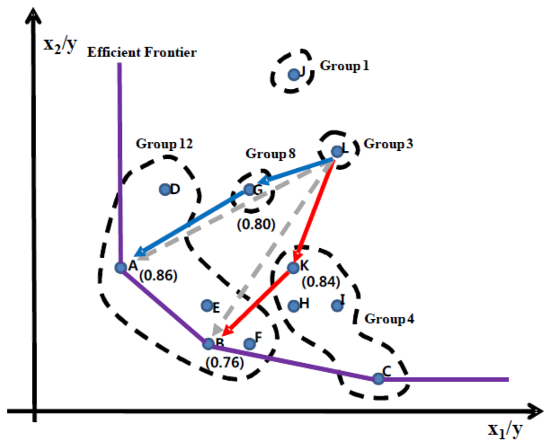

FIGURE 7. Benchmarking paths when ultimate benchmark targets are DMU A and DMU B

benchmark target determined is DMU B, then the first intermediate benchmark DMU for DMU L is DMU K in Group 4. Note that DMU K is more similar to DMU L in terms of input patterns than the others. And if the ultimate benchmark target determined is DMU A, then the first intermediate benchmark DMU is DMU G, which belongs to Group 8.

In the proposed method, different similarity groups can result depending on the values of the SOM parameters (learning parameters and training cycle), and then different benchmarking paths can be derived. In other words, if the values of the training cycle and learning parameters are increased, the number of intermediate benchmark DMUs is decreased, and if the values of the training cycle and learning parameters are decreased, the number of intermediate benchmark DMUs is increased. Also the intermediate benchmark DMUs can be changed according to the different weights that are given to the two criteria, direction and similarity.

4. **Case Study.** For a case study, relevant data are collected about 21 East Asian container terminals by accessing such data sources as *Containerization International Year Book 2005*. There have been many studies concerning operational efficiency assessment of ports and container terminals using DEA: Roll and Hayuth [14] used the CCR model to evaluate 20 ports with three inputs (manpower, capital and cargo uniformity) and four outputs (cargo throughput, level of service, user satisfaction, ship calls); Tongzon [15] evaluated four Australian and 12 international container ports using the CCR and an additive model with six inputs (number of cranes, number of container berths, number of tugs, terminal area, delay time and labor) and two outputs (cargo throughput and ship working rate). See also Hirashima [17]. In this paper, the efficiencies of the container terminals are evaluated in terms of the number of berths, the length of berths (m), the total port area (km^2) and the number of cranes as inputs, while the total container traffic (TEU) data are used as a output. Four terminals Hongkong, Shanghai, Shenzhen and Xiamen are determined to be efficient and the remaining 18 inefficient. Kobe, Kwangyang and Taizhong are particularly inefficient DMUs. Among these inefficient DMUs, Kwangyang is selected as the evaluated DMU. To determine the ultimate benchmark target for Kwangyang, the DEA model with a preference structure is used with the same weights (25%) on the four inputs. Shenzhen is determined to be the ultimate target DMU for Kwangyang. The SOM program, NNclust, is used to cluster DMUs into several similarity groups. The input variables used for the SOM run, are the number of berths, the length of berths, the

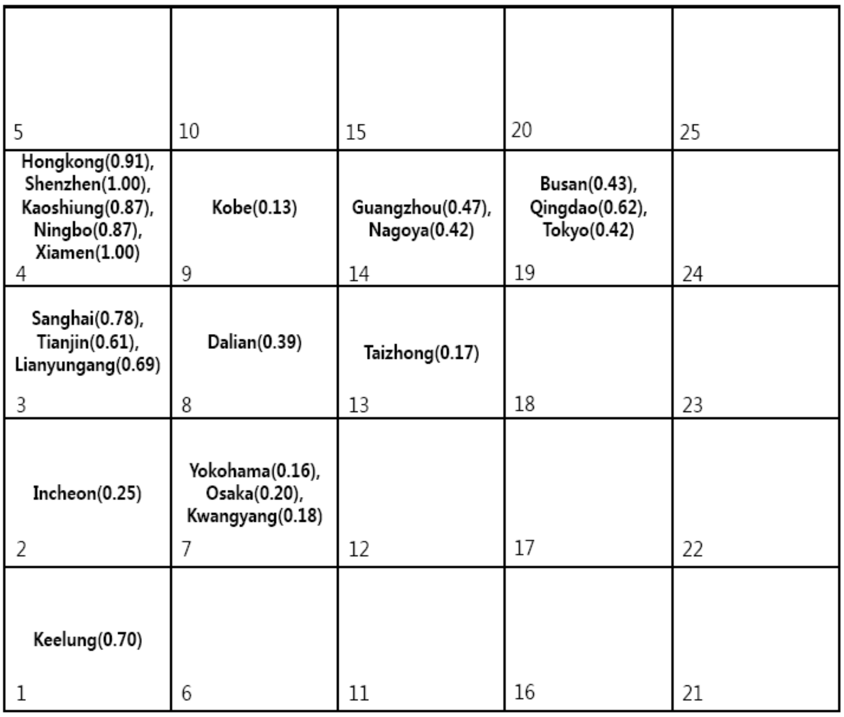

FIGURE 8. Clustering East Asian container terminals by SOM

total port area and the number of cranes. The results of the SOM run with 5 by 5 map configuration are shown in Figure 8.

We give the same weight, 0.5, to both of the criteria of direction and similarity. The values of d_j, δ_j and e_j for DMUs in higher efficiency levels than Kwangyang are shown in Table 2. Since Tianjin attains the maximum value of e_j, 0.87 it is selected as the first intermediate benchmark DMU for Kwangyang. Then, Tianjin now becomes the evaluated DMU. The values of d_j, δ_j and e_j for DMUs in higher efficiency levels than Tianjin are calculated and shown in Table 3. Since Lianyungang attains the maximum value of e_j, 0.94, it is selected as the second intermediate benchmark DMU for Kwangyang. Then, Lianyungang now becomes the evaluated DMU. The values of d_j, δ_j and e_j for DMUs in higher efficiency levels than Lianyungang are calculated and shown in Table 4. Since Shenzhen attains the maximum value of e_j, 0.91 among the compared DMUs, it is selected as the third intermediate benchmark DMU for Kwangyang. Since Shenzhen is the ultimate benchmark target for Kwangyang, the procedure is terminated. The benchmarking path for Kwangyang consists of firstly Tianjin, next Lianyungang and finally Shenzhen.

If we apply the conventional DEA approach to determining benchmark targets for Kwangyang, three benchmark targets including Hongkong, Shanghai, Shenzhen and Xiamen would be chosen because they are included in the reference set. However, it might be confusing for Kwangyang to benchmark simultaneously these four terminals and practically infeasible to achieve its efficiency improvement in a single step. The stepwise feature of the proposed methodology will be effective for overcoming this difficulty. If we apply the stepwise method proposed by Park et al. [8] to determining a benchmarking path for Kwangyang, three terminals including Tokyo, Ningbo and Shenzhen would be chosen as intermediate benchmark targets. Their method, however, does not have any systematic scheme for choosing intermediate targets that are more practically feasible for Kwangyang to benchmark. Actually, it is more practically feasible for Kwangyang to benchmark Tianjin and Lianyungang than Tokyo and Ningbo since those are more similar to Kwangyang

Table 2. The values of e_j with Kwangyang being the evaluated DMU

DMU j	**Hong kong**	**Shang hai**	**Shen zhen**	**Busan**	**Kaoh siung**	**Qing dao**	**Ningbo**	**Tianjin**	**Guang zhou**
δ_j	0.93	1.00	0.87	0.92	0.69	0.93	0.98	0.69	0.93
d_j	0.75	0.61	0.61	0.61	0.61	0.61	0.75	0.61	0.75
e_j	0.73	0.84	0.80	0.74	0.76	0.65	0.77	**0.87**	0.65
DMU j	**Tokyo**	**Xiamen**	**Dalian**	**Nagoya**	**Osaka**	**Keelung**	**Incheon**	**Lianyun gang**	
δ_j	0.68	0.90	0.48	0.43	0.24	0.22	0.60	0.74	
d_j	0.61	0.61	0.82	0.61	0.91	0.75	0.82	0.75	
e_j	0.64	0.75	0.65	0.52	0.58	0.49	0.71	0.75	

Table 3. The values of e_j with Tianjin being the evaluated DMU

DMU j	**Hong kong**	**Shang hai**	**Shen zhen**	**Busan**	**Kaoh siung**	**Qing dao**	**Ning bo**	**Kee lung**	**Lianyun gang**
δ_j	0.99	0.00	1.00	0.00	0.99	0.95	1.00	0.93	0.98
d_j	0.82	0.91	0.82	0.47	0.82	0.47	0.82	0.65	0.91
e_j	0.91	0.46	0.91	0.23	0.91	0.71	0.91	0.79	**0.94**

Table 4. The values of $e_j$with Lianyungang being the evaluated DMU

DMU j	**Hongkong**	**Shanghai**	**Shenzhen**	**Kaohsiung**	**Ningbo**	**Keelung**
δ_j	0.99	0.00	1.00	0.91	0.96	0.40
d_j	0.82	0.91	0.82	0.82	0.82	0.65
e_j	0.90	0.46	**0.91**	0.87	0.89	0.52

Table 5. Benchmarking paths obtained by varying weights

w_1	w_2	**Benchmarking path**	w_1	w_2	**Benchmarking path**
0.1	0.9	Kwangyang→ Dalian→ Tianjin→ Shenzhen	0.6	0.4	Kwangyang→ Tianjin→ Shenzhen
0.2	0.8	Kwangyang→ Tianjin→ Shenzhen	0.7	0.3	Kwangyang→ Tianjin→ Shenzhen
0.3	0.7	Kwangyang→ Tianjin→ Shenzhen	0.8	0.2	Kwangyang→ Tianjin→ Shenzhen
0.4	0.6	Kwangyang→ Tianjin→ Shenzhen	0.9	0.1	Kwangyang→ Shenzhen
0.5	0.5	Kwangyang→ Tianjin→ Shenzhen	1.0	0.0	Kwangyang→ Shenzhen

than these in terms of factor levels. The methodology proposed in this paper can resolve this issue by incorporating the multiple criteria, preference, direction, and similarity, in the stepwise benchmark target selection process.

Table 5 shows different benchmarking paths obtained for Kwangyang with varying weights given to the criteria of direction and similarity. As shown in the table, when the weights on direction and similarity criteria are 0.1 and 0.9, respectively, the stepwise benchmark targets for Kwangyang are firstly Dalian, next Tianjin and finally Shenzhen. By contrast, when the weights on direction and similarity are 0.9 and 0.1, respectively, Shenzhen is the only stepwise benchmark target for Kwangyang.

5. **Conclusions.** In this paper, we have proposed a new DEA-based method of stepwise benchmarking, which considers three criteria, preference, direction and similarity, for selecting benchmark targets. First, for the preference criterion, we consider weights that can be attached to each of the input factors to select the ultimate benchmark target of an inefficient DMU among the DMUs. Second, for direction we develop a target selection method that can find the closest efficient DMU in the direction in which the inefficient DMU targets the final predetermined benchmark. Third, similaritybased target selection by SOM is considered. As dictated by our method, we analyze the similarity based on the input factors of every DMU.

Considering these three criteria, we have developed a method of constructing a more practical and feasible sequence of benchmark targets. This is a new method that is formulated to remedy the drawbacks of the existing benchmarking methods which only consider the influence of efficiency when an inefficient DMU has to achieve its target using DEA. As an application of the proposed method, benchmarking of an East Asian container terminal was tested in the present study. The results show that the stepwise benchmarking path of an inefficient DMU can be found. This hybrid method is effective also in that it can suggest alternative benchmarking paths and targets according to changed condition variables and weights used for direction and similarity.

In spite of the above mentioned advantages of the proposed methodology, we find that it has two major deficiencies. First, this proposed method does not consider the number of benchmarking steps for an inefficient DMU to reach the ultimate target. If there are too many intermediate targets to benchmark on a benchmarking path for an inefficient DMU, it may create a significant practical difficulty for the DMU in accomplishing the benchmarking schedule. Therefore, how to control the number of targets on a benchmarking path could be a future research issue. Second, although the three criteria, preference, direction, and similarity, could be evaluated from both perspectives of input and output factors, the current paper focuses only on input factors. This issue is worth consideration.

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