신흥 기술의 단계적 벤치마킹을 위한 SOM, DEA와 AHP 방법의 순차 활용

Sequential use of SOM, DEA and AHP method for the stepwise benchmarking of emerging technology

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ABSTRACT

Emerging technologies have significant implications in establishing competitive advantages and are characterized by continuous rapid development. Efficient benchmarking is more and more important in the development of emerging technologies. Similar input level and importance are two necessary criteria need to be considered for emerging technology's benchmarking. In this study, we proposed a sequential use of self-organizing map(SOM), data envelopment analysis(DEA) and analytical hierarchy process(AHP) method for the stepwise benchmarking of emerging technology. The proposed method uses two-level SOM to cluster the emerging technologies with similar required input levels together, then, in each cluster, uses DEA-BCC model to evaluate the efficiencies of the emerging technologies and do tier analysis to form tiers. On each tier, AHP rating method is used to calculate each emerging technology's importance priority. The optimal benchmarking path of each cluster is established by connecting the emerging technologies with the highest importance priority. In order to validate the proposed method, we apply it to a case of biotechnology. The result shows the proposed method can overcome difficulties in benchmarking, select suitable benchmarking targets and make the benchmarking process more efficient and reasonable.

Keyword : benchmarking, emerging technology, data envelopment analysis-BCC (DEA-BCC), analytical hierarchy process (AHP) rating method

1. Introduction

Benchmarking is a search for companies' or industry's best practices that will lead to superior performance or organizational success. Benchmarking has been widely adopted by manufacturing and service industries, and other industries around the world since its development by Xerox in 1979 (Camp, 1989). It has influenced organizational competitive advantage and success in many ways (Lai et al., 2011). Effective benchmarking requires standards for the measurement of performance across a broad range of organizations, and often the most relevant benchmarking information to improve operations arises from industry-level

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comparisons (Johnson et al., 2010). Comparing technologies to move from one technical state to another one, will also involve benchmarking (Marie Dou, H. J., 2004). Emerging technologies, as the potential of changing the basis of competition (Hung & Chu, 2006), are always in rapid development and absorbing new ideas and technologies (Van der Valk, Moors & Meeus, 2009). Therefore, in order to keep the continuous improvement and explore the growth potential to enhance performance, benchmarking is an essential process in the development process of emerging technologies.

Due to the complexity and importance of the benchmarking processes, data envelopment analysis (DEA) is one of tools used in support of benchmarking implementation (Lai et al., 2011). DEA is a non-parametric linear programming method to evaluate the efficiencies of decision making units (DMUs) with multiple inputs and outputs (Charnes et al., 1978). Efficient DMU's score is 1 whereas inefficient DMU's score is less than 1. An inefficient DMU can be yield an efficient DMU as a reference target to benchmark (Shaneth et al., 2009). The efficiency of emerging technology can be evaluated in DEA by comparing emerging technology's input resource and output result. After evaluation, efficient emerging technologies and inefficient emerging technologies are determined. An inefficient emerging technology should be yield an efficient emerging technology as a reference target to benchmark.

In this study, in order to make the emerging technology's benchmarking more effective and reasonable, we propose a sequential use of self-organizing map(SOM), data envelopment analysis(DEA) and analytical hierarchy process(AHP) method for the stepwise benchmarking of emerging technology to make the emerging technology not only consider the benchmarking target's required input levels, but also consider the target's importance when selecting benchmarking target. The proposed method integrated two-level SOM, DEA-BCC model and AHP rating method. Two-level SOM is a clustering method which is composed of self-organizing map (SOM) and K-means method (Vesanto & Alhoniemi, 2000). DEA-BCC(Banker, Charnes and Cooper) model (Banker et al., 1984) is proposed by Banker, Charnes and Cooper, so this DEA model uses their names' first characters as the model's name, abbreviated as BCC. DEA-BCC is a slightly modified version of the CCR(Charnes, Cooper and Rhodes) model, assumes a variable return-to-scale by adding a constraint on the weights of inputs and outputs. AHP (Saaty, 1980) is a useful method designed for solving complex multiple criteria decision making (MCDM) problems. In this study, AHP rating method is used to avoid impracticable pair-wise comparison when there are a large number of alternatives (Sueyoshi et al., 2009). The proposed method uses two-level SOM to cluster emerging technologies based on similar input levels, then, in each cluster, employs DEA-BCC model to evaluate the efficiency score of the emerging technologies, and form several tiers according to the efficiency scores, after that, on each tier, uses AHP to evaluate the importance priority of efficient emerging technologies based on the selected importance criteria. When establishing a benchmarking path across the sequence of tiers, the most preferable emerging technology on each tier is the one with the highest importance priority score. According to this selection rule, an optimal path to the most efficient emerging technology on the frontier through importance-based target selection process is provided. We illustrate the proposed method on with biotechnologies. The result shows that the proposed method can effectively overcome the problems mention above and provide a much more reasonable benchmarking process for emerging technologies.

The rest of the paper is organized as follows. Section 2 presents the related literature reviews about benchmarking, emerging technology, two-level SOM, DEA and AHP. Section 3 describes the procedure of the proposed method. Section 4 illustrates the proposed method with biotechnologies. Finally, section 5 summarizes the conclusions and makes recommendations to the future works.

Ⅱ. Literature review

1. Emerging technology

The emerging technologies add values and establish competitive advantages for newly established companies. They are necessary to product, production, or services of the industry (Hung & Chu, 2006). They can significantly shape and change social life of present and future (Dewick et al., 2004; van Merkerk & van lente, 2005). Rapid development in terms of new ideas or technologies' significance and development rate are emerging technology's characteristics (van der Valk et al., 2009). Therefore, when selecting or developing any emerging technology, it is very important and necessary to identify the technology fields considering strategic importance (Shen et al., 2010). In the benchmarking process, importance is also a significant selecting criteria.

Recently, emerging technology has been researched by many researchers. For example, Sahoo et al. (2007) introduced the chief scientific and technical aspects of nanotechnology, and discussed some of its potential clinical applications. Hung and Hsu (2011) examined the relationship between the macroeconomic business cycle and the TFT-LCD crystal cycle in China and the US. Janssen and Rutz (2011) provided an overview of bio-fuel's situation in Latin America. Some other researches discussed how emerging technologies have evolved, solved problems and created new opportunities and how they have raised additional challenges to society in emerging markets (Hall et al., 2008; Melillo et al., 2009).

In this study, we propose an integrated benchmarking method for emerging technology to effectively take the benchmarking activity.

2. Benchmarking

Benchmarking is a process of measuring and comparing a broad range of organizations to identify paths to improve business processes and organizational performance (Keehley et al., 1997). Benchmarking is first adopted by Xerox Corporation in the late 1970s. Benchmarking allows an organization to evaluate its processes objectively and thoroughly to mine the potential improvement (Kline, 2003).

Data, methods and media are 3 major components of a benchmarking study (Johnson et al., 2010). Data are the key performance indices (KPIs) or measures describing a set of comparable organizations. Methods are the employed analyzing tools to analyze and transform the collected data to useful information or managerial suggestions. Media are the channels by which the data is collected and the results are delivered. The 3 components can be used as follows. Data is usually collected by phone interviews, online surveys, questionnaire mailed to users or experts, or face-to-face interviews. Partial productivity method is commonly used to compare the level of output to the level of input to evaluate an organization's performance. Finally, the evaluation results are disseminated in various forms to help an organization improve performance.

It has been proved that DEA is a powerful tool for performance evaluation and benchmarking (Lai et al., 2011). The DEA has been successfully used in benchmarking researches. For example, Martin and Romin (2006) used DEA to do benchmarking analysis of Spanish commercial airports; Min and Joo (2006) benchmarked the operational efficiency of logistics providers using data envelopment analysis; Shaneth et al.(2009) proposed a stepwise benchmarking method which employed DEA as evaluation tool; Lim et al. (2011) presented a method designed based on DEA for selecting effective benchmarking paths; Seol et al. (2007) proposed a framework using DEA for benchmarking service process, and so on. In this study, we also use DEA as the evaluation tool to evaluate emerging technologies for benchmarking.

In the benchmarking process, selecting a suitable benchmarking path is very important to make the benchmarking activity more effective. When selecting a benchmarking path, there are several problems (Lim et al., 2011). First, an inefficient DMU selects a reference target without considering the difference between its own actual input levels and the selected reference target's required input levels. Different DMUs have different requirements in input levels. When an inefficient DMU selects a reference target, the difference between the inefficient DMU's input levels and the selected reference target's input levels should be considered. Because it is very difficult for an inefficient DMU to be efficient when they benchmark a reference target DMU which has different input levels (Shaneth et al., 2009). Second, the reference target might be a hypothetical DMU which doesn't exist actually. The efficiency of an inefficient DMU is evaluated relative to an efficient DMU or a combination of efficient DMUs on the efficient frontier. If the reference point of an inefficient DMU does not overlap any efficient DMU on the efficient frontier, the reference target is not an actual existing DMU, but a hypothetical one. Benchmarking a hypothetical DMU is very difficult and unrealistic. Third, it is difficult to benchmark multiple efficient DMUs simultaneously. When the reference set of an inefficient DMU has multiple efficient DMUs, the inefficient DMU will face a confounding situation of benchmarking multiple efficient DMUs. A selection rule should be provided. Fourth, it is difficult for an inefficient DMU to achieve the reference target in a single step. Especially, if the inefficient DMU is far from the efficient frontier, it is impossible to achieve the frontier in a single step, a stepwise improvement is much more reasonable.

In this study, we proposed a input level based stepwise benchmarking method for emerging technology to solve the problems mentioned above.

3. Two-level SOM

Two-level self-organizing map (2-level SOM) is a clustering method combining self-organizing map (SOM) and K-means (Vasanto & Alhoniemi, 2000). Two-level SOM first uses the original SOM (Kohonen, 1990) to cluster data set, then, the produced prototypes by SOM are clustered by K-means. SOM is a sophisticated unsupervised clustering method (Vasanto & Alhoniemi, 2000). K-means method is also a popular and widely used clustering method (Kalyani & Swarup, 2011). DB (Davies-Bouldin) index is used to test the validity of 2-level SOM. DB index is the ratio of the sum of within-cluster scatter to between cluster separations as shown in equation (1).

$$DB(U) = \frac{1}{c}\sum_{i=1}^{c} \underset{i \neq j}{Max}\left\{\frac{\triangle(x_i) + \triangle(x_j)}{\delta(x_i, x_j)}\right\} \qquad (1)$$

The sum of inner cluster, Δ(Xi) can be obtained through equation (2) and the distance between Xi and Xj is calculated by equation 3. Here, Zi represents the center of the i-th cluster.

$$\triangle X_i = \frac{1}{|c_i|}\sum_{x \in c_i}\{\, \| x - z_i \| \,\} \qquad (2)$$

$$\delta(X_i, X_j) = \| z_i - z_j \| \qquad (3)$$

Accordingly, when DB index is minimized, the proper clustering can be conducted. Although, there are several other index(Dunn, 1973; Calinski & Harabasz, 1974; Maulik & Bandyopadhyay, 2002) that can be used to test validity, the DB index is appropriate for examining the result of clustering by k-means algorithm, because lower values of the DB index indicates better result of spherical cluster (Vesanto & Alhoniemi, 2000). So we use DB index to test the validity of two-level SOM model.

The previous literatures also shows that two-level SOM is better than other methods such as K-means and SOM respect to the rate of misclassification, and the real-world data on the basis of Wilk's Lambda and descriptive analysis (Kuo et al., 2002; 2006). Thus, two-level SOM is a novel two-stage clustering method for clustering variables of research field such as marketing, biology and medicine(de Castro Le?o et al., 2009; Godin et al., 2005). In this study, we use two-level SOM to cluster homogeneous emerging technologies.

4. Data envelopment analysis (DEA)

DEA is a popular mathematical programming methodology based on the Efficiency Frontier (Charnes et al., 1978). DEA evaluates the relative efficiencies of a homogeneous set of decision making units (DMUs) having multiple inputs and outputs. The DEA identifies a set of weights (all weights must be positive) that individually maximizes each DMU's efficiency while requiring the corresponding weighted ratios (i.e., using the same weights for all DMUs) of the other DMUs to be less than or equal to 1. A DMU is considered relatively inefficient if its efficiency score is less than 1.

4.1. DEA-CCR

Charnes et al. (1978) introduced the CCR or constant returns-to-scale (CRS) model that assumes that the increase of outputs is proportional to the increase of inputs at any scale of operation. When there are n DMUs utilizing m inputs and producing s outputs, the relative efficiency score of a test DMU k is obtained by solving the following linear programming model proposed by Charnes et al.(1978):

$$\max \sum_{r=1}^{s} v_r y_{rk} \qquad (4)$$

$$s.t. \sum_{i=1}^{m} u_i x_{ik} = 1, \qquad (5)$$

$$\sum_{r=1}^{s} v_r x_{rj} - \sum_{i=1}^{m} u_i x_{ij} \le 0, \quad \forall j, \qquad (6)$$

$$u_i \ge \epsilon,\ v_r \ge \epsilon,\ \forall i,r \qquad (7)$$

Where y_{rk} is the amount of output r yielded by DMU k, x_{jk} is the amount of input i consumed by DMU k, v_r is the weight given to output r, u_i is the weight given to input i, and ε is a positive non-Archimedean infinitesimal.

4.2. BCC model

Banker et al. (1984) developed the BCC model to estimate the pure technical efficiency of decision making units with reference to the efficient frontier. It also identifies whether a DMU is operating in increasing, decreasing or constant returns to scale. So CCR model is a specific type of BCC model. The

BCC model evaluates the efficiency of DMU by solving the following linear program:

$$\max \sum_{r=1}^{s} v_r y_{rk} - v_0 \quad (8)$$

$$s.t. \sum_{i=1}^{m} u_i x_{ik} = 1 \quad (9)$$

$$\sum_{r=1}^{s} v_r x_{rj} - v_0 - \sum_{i=1}^{m} u_i x_{ij} \leq 0, \quad \forall j, \quad (10)$$

$$v_o,\ free \quad (11)$$
$$u_i \geq \epsilon,\ v_r \geq \epsilon,\ \forall i, r$$

When we add a constraint on the convexity of weights given to inputs and outputs to the CCR model, we can obtain the BBC model(Lim et al., 2011).

In this study, because BCC model can not only estimate pure technical efficiency, but also evaluate the DMUs at the same scale fairly, so DEA-BCC model is used to evaluate efficiencies of emerging technologies and do the tier analysis.

5. Analytical hierarchy process (AHP)

AHP is designed to solve complex multiple criteria decision making (MCDM) problems (Saaty, 1980; Kim, 2011; Normatov et al., 2011). The output of the AHP is a prioritized ranking which indicates the overall preference of each alternative. AHP is usually in technology selection. For example, Kim and Lee (2011) employed AHP in the method for determining an optimal LTPS (Low Temperature Polycrystalline Silicon) crystallization technology. The AHP has two measurement modes, absolute and relative (Saaty, 1994).

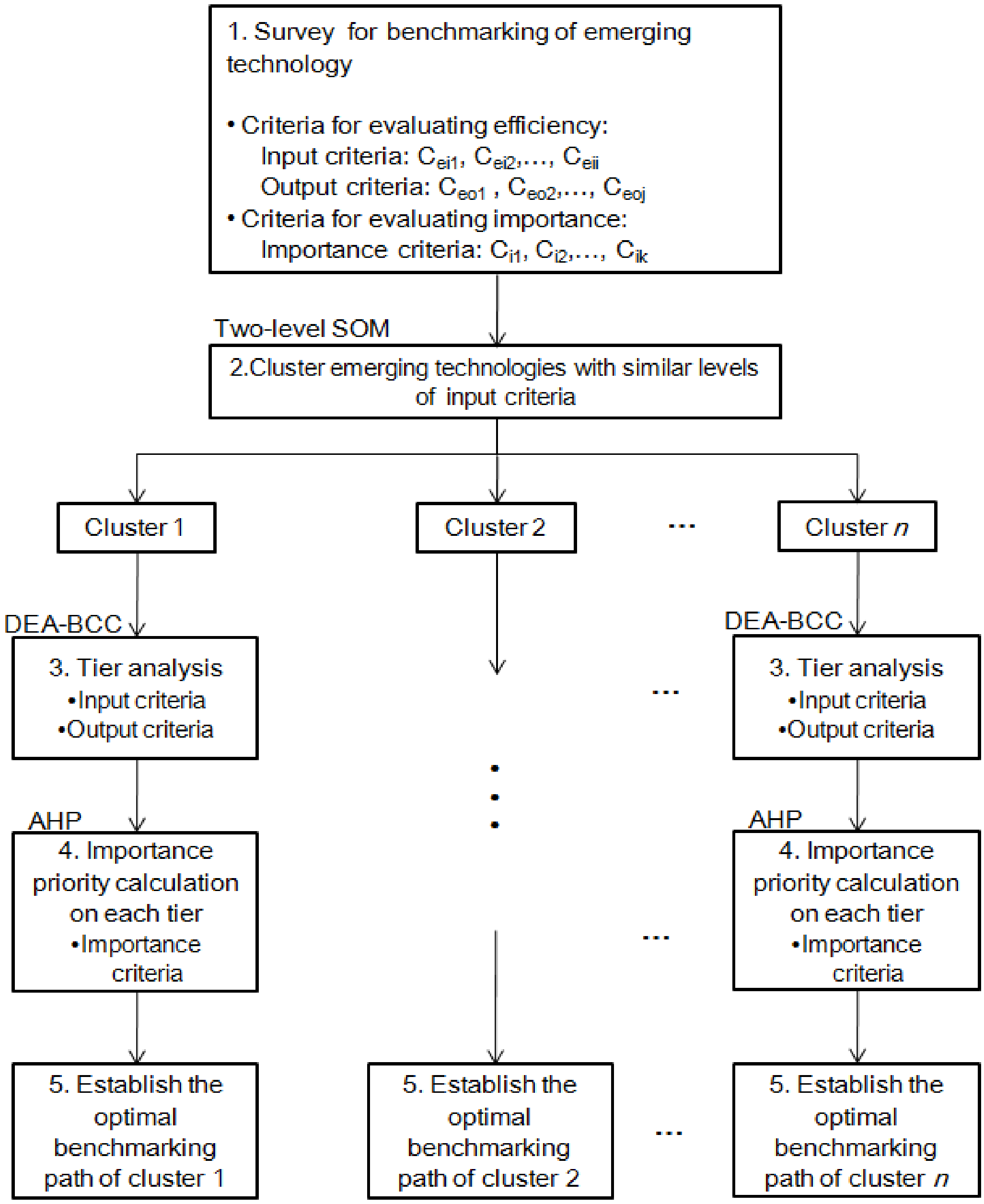
In AHP relative measurement (pair-wise comparison), a comparison matrix at each level can be set up. A ranking scale ranging from 1 (indifference) to 9 (extreme preference) can be used to express user's preference. After setting a matrix of pair-wise comparisons, each alternative's relative priority can be calculated. The AHP absolute measurement method (AHP rating method) differs from the traditional AHP relative measurement method (AHP pair-wise comparison).

Absolute measurement (or rating) is defined as a set of intensity levels (or categories) that serves as a base to evaluate the performance of the alternatives in terms of each criterion and/or sub-criterion (Duarte & De Souza, 2005). The procedure of AHP rating method is as follows: (1) get experts' subjective ratings on the importance of criteria; (2) make pair-wise comparison of the ratings to get the weights of criteria; (3) fix the number of element level, use pair-wise comparison to derive the original score for each level and normalize them; (4) generate the final values of the alternative priorities.

The main advantage of AHP rating method is decreasing the number of necessary comparisons when there are a large number of alternatives and pair-wise comparison is impracticable (Sueyoshi et al., 2009; Simoes da Silva et al., 2010; Ainapur et al., 2011). In this study, we also use this method to calculate the importance priorities of the emerging technologies on each tier.

Ⅲ. Sequential use of SOM, DEA and AHP method for the stepwise benchmarking of emerging technology

In this study, we propose a sequential use of SOM, DEA and AHP method for the stepwise benchmarking of emerging technology to make the emerging technology's benchmarking more effective and reasonable. Figure 1 shows the procedure of the proposed method.



[Figure 1] The procedure of the proposed method

In Figure 1, before making survey, we identify $i+j+k$ criteria for benchmarking. i criteria are criteria of input resource of applying a emerging technology, and are identified as input criteria. Ceii means the i th input criteria for evaluating efficiency. j criteria are criteria of results of applying a emerging technology, and are identified as output criteria. Ceoj denotes the j th output criteria for evaluating efficiency. Experts' ordinal ratings to the input criteria and output criteria are used to evaluate efficiencies of emerging technologies for tie analysis. For calculating the importance priorities of emerging technologies on each tier, we identify k criteria as importance criteria. The experts' ordinal ratings to the importance criteria are used to evaluate importance priorities of emerging technologies on each tier. After identifying the criteria, a survey is carried out to get experts' ordinal ratings to these identified criteria of emerging technologies. Then, we use two-level SOM to cluster emerging technologies based on ordinal ratings of *i* input criteria. After that, in each cluster, DEA-BCC model is used on experts' ordinal ratings to input criteria and experts' ordinal ratings to output criteria to evaluate efficiency of technology alternatives, and form tiers. Next, on each tier, AHP is applied to experts' ordinal ratings to importance criteria to calculate the importance priorities of emerging technologies on the tier. Until now, in each group, there is only one emerging technology with the highest importance priority on each tier. These emerging technologies can be selected as benchmarking targets. A benchmarking path across the sequence of tiers in each group can be established. The benchmarking path in each group consists of a sequence of the benchmarking targets.

1. Step 1: Identify criteria and survey emerging technologies for benchmarking

In this step, for evaluating efficiencies of emerging technologies, we identify $i+j$ criteria (i input criteria, j output criteria); for calculating importance priorities of emerging technologies, we identify k importance criteria. We use the ordinal ratings to the $i+j$ criteria to evaluate emerging technologies' efficiencies to form tiers, and use the ordinal ratings to the k criteria to calculate emerging technologies' importance priorities. After that, we carry out a survey to experts to collect their ordinal ratings to the identified criteria of emerging technologies.

2. Step 2: Employ two-level SOM to cluster emerging technologies with similar levels of input criteria

In this study, first, we use clustering method to group the technology alternatives with similar input levels to guarantee the benchmarking practicable. As mentioned by Shaneth et al. (2009) in section 2.2, benchmarking should take input level into consideration seriously, because the benchmarking will be impracticable if the required input level of an inefficient alternative is different with the required input level of the benchmarking target alternative, the benchmarking is difficult, even impracticable. When a technology benchmarks other technologies, input level should be considered first. Therefore, clustering based on the input level should be applied at the very beginning.

In this step, two-level SOM is employed to cluster emerging technologies based on similar levels of ordinal ratings to input criteria. Two-level SOM is a better clustering algorithm than other methods such as SOM or K-means because of low misclassification. After using two-level SOM, emerging technologies with similar ratings of input criteria will be clustered together.

3. Step 3: Use DEA-BCC model to evaluate efficiencies of emerging technologies and do tier analysis

In this step, in each cluster, DEA-BCC model is used to evaluate the efficiencies of emerging technologies to assist the tier analysis. The tier analysis in this study is based on a technique proposed by Seiford and Zhu (2003) that cluster DMUs together based on their efficiency levels.

Define $J^l=\{DMU_j,\ j=1,\cdots,n\}$ as the set of all n DMUs. We iteratively define $J^{l+1}=J^l-E^l$, where

$E^l=\{DMU_k \in J^l \mid DMU_k$ has a DEA efficiency score of 1$\}$. Identifying multiple efficient frontiers can be realized following steps below:

Step 1: Set l =1, then evaluate the DMU set, J^l, to get the efficiency set, E^l, of first-level frontier DMUs (i.e. when l= 1, the DEA model runs on all the n DMUs and the DMUs in E^l are defined as the first-level efficient frontier).

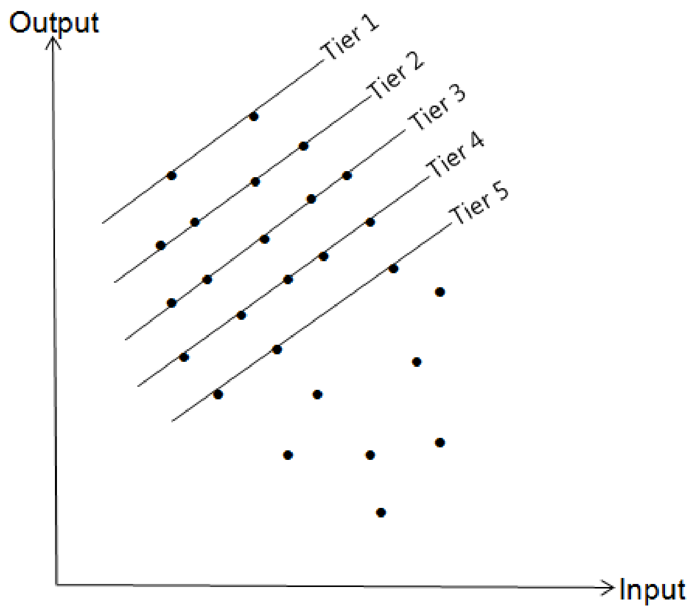
Step 2: Exclude the efficient DMUs from the efficient frontier, and set $J^{l+1} = J^l - E^l$.

Step 3: If J^{l+1} is less than three times of the sum of the input criteria's number and output criteria's number, then stop. Otherwise, evaluate the remaining DMUs, J^{l+1} to obtain a new efficient frontier E^{l+1}.

Step 4: Let l=l+1, and go to step 2.

Stopping rule: If J^{l+1} is less than three times of the sum of the input criteria's number and output criteria's number, the algorithm stops (Banker et al., 1984).

After applying the algorithm above, we can obtain result of tier analysis illustrated in Figure 2.

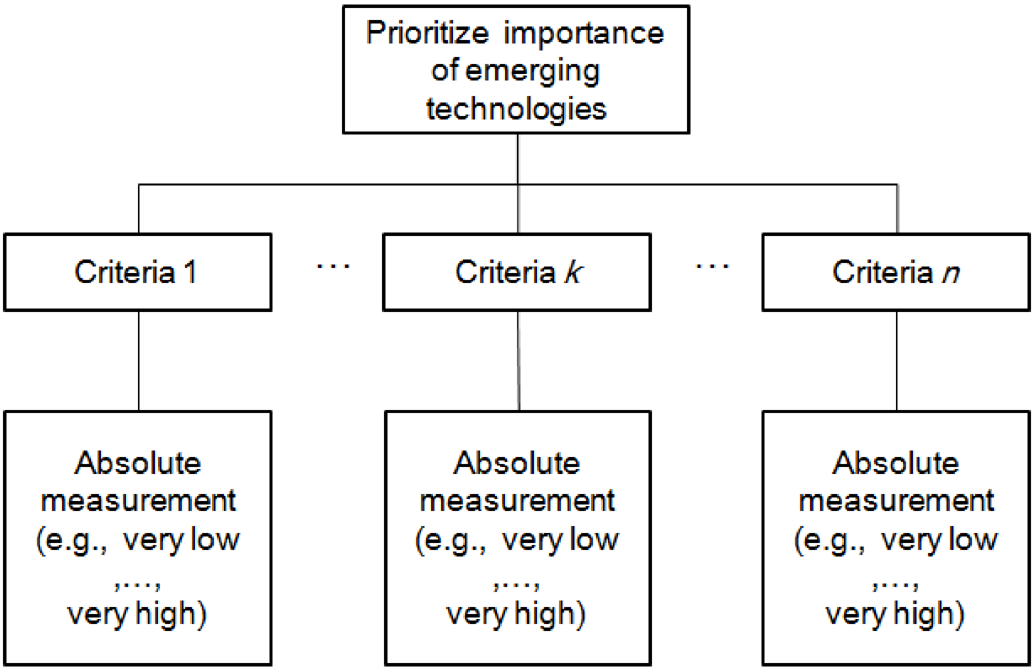


[Figure 2] The result of tier analysis.

In Figure 2, the first round of the tier analysis reveals the most efficient DMUs. These DMUs form 'tier 1'. In the second round, the remaining DMUs are analyzed and the derived efficient DMUs form 'tier 2'. Similarly, 'tier 3' and 'tier 4' can be obtained. In other words, the DMUs on tier 1 are superior to the DMUs on tier 2, and the DMUs on tier 2 are superior to the DMUs on tier 3, and so on.

4. Step 4: Use AHP rating method to calculate the importance priorities of emerging technologies on each tier

In this step, in each cluster, AHP rating method is used to calculate the importance priorities of emerging technologies on each tier. This method can avoid the impracticable pair-wise comparison caused by a large number of alternatives. Figure 3 shows the hierarchy of AHP rating method for prioritizing emerging technologies within each cluster.



[Figure 3] Hierarchy of AHP rating method for prioritizing importance of emerging technologies within each cluster

In Figure 3, m experts' ratings to the importance of criteria are used to derive weights of criteria. The number of intensity levels (or categories) and variation levels of each criteria (e.g., from "very high" to "very low") are fixed in advance.

Pair-wise comparison is used to derive the original score for each level and normalize them by dividing each original score by the largest value among them. After applying AHP rating method in each cluster, the importance priorities of emerging technologies on each tier can be calculated.

5. Step 5: Establish the optimal benchmarking path of each cluster

In this step, in each cluster, according to the calculated importance priorities of emerging technologies on each tier, we can establish the optimal benchmarking path of each cluster. In each cluster, we should select the emerging technology with the highest importance priority on each tier as the tier's benchmarking target. In case of multi highest importance priorities, the one with the highest sum of importance criteria' ratings should be selected as the tier's benchmarking target. These selected targets can form the cluster's optimal benchmarking path.

Ⅳ. Illustration study

1. Illustration study introduction

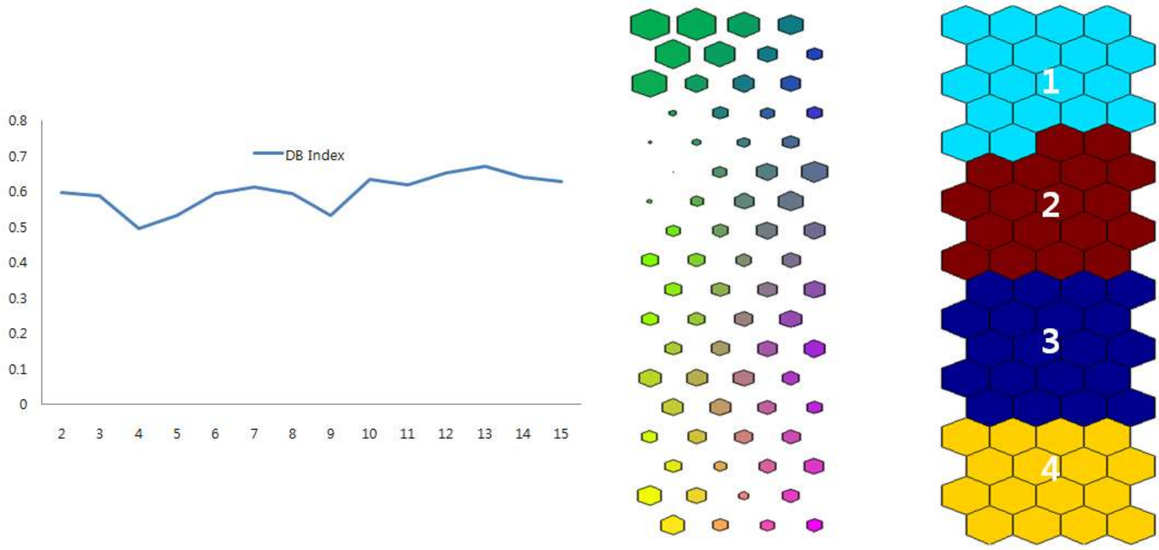
In this section, in order to illustrate the proposed method, we apply it to a case of biotechnology. Biotechnology is a kind of emerging technology, and is under increasing scrutiny. In order to evaluate the biotechnologies and establish an efficient and reasonable benchmarking method, we identified 6 criteria for evaluation. They are R&D capability, ease of production, technical extension, marketability, urgency and conformance level to national policy. Generally speaking, when evaluating technologies, efficiency and importance are usually evaluated. When evaluating technology's efficiency and importance, the 6 criteria mentioned above are usually used. Therefore, we select the 6 criteria as the evaluating criteria also. R&D capability evaluates the levels of the input resources for developing a technology. Ease of production evaluates the levels of utilizing input resources to realize a technology. Marketalility evaluates a technology's output level from an economic point. Technical extension evaluates a technology's extend output level from an technical point. conformance level to national policy evaluates a technology's matching level with national development policy. Urgency evaluates a technology's urgency level with the market needs. The 6 criteria can comprehensively evaluate a technology's levels of efficiency and importance. Specific to biotechnology, R&D capability is used to evaluate how much R&D costs or resources are required in the biotechnology's R&D process. If we produce a product using a biotechnology, ease of production is used to evaluate whether the production process is simple and easy. If the products using a biotechnology are put on the market, marketability is used to evaluate whether the products can be sold well. Technical extension is used to evaluate whether a biotechnology can be extended to other products. Urgency means whether a biotechnology is needed by market or necessary to society urgently. conformance level to national policy means whether the R&D and popularization of a biotechnology matches the country's developing policy.

After identifying the 6 criteria, we invited 3 experts in biotech field to do a survey to 189 biotechnologies on the 6 criteria. The survey used a five-point scale (1 being a "very low" level and 5 being a "very high" level). The average ratings of the 3 experts are used in the whole evaluation process. In the 6 criteria, R&D capability and ease of production are resources of applying a technology, marketability and technical extension are results of applying a technology, so we identify the 4 criteria as input criteria 1(R&D capability), input criteria 2(ease of production), output criteria 1(marketability) and output criteria 2(technical extension). Then, we apply DEA-BCC on experts' ordinal ratings to the 4 criteria to calculate the efficiency of biotechnologies, and do the tier analysis. The other 2 criteria (Urgency and conformance level to national policy) are related with the importance of biotechnologies. In order to evaluate importance priorities of biotechnologies on each tier, we apply AHP rating method on experts' ordinal ratings to the 2 criteria to derive the corresponding importance priority values.

2. Result of clustering based on similar ratings of input criteria

In this study, the two-level SOM method is used to cluster biotechnologies based on similar levels of 2 input criteria (R&D capability and ease of production). Figure 4 shows the result of applying two-level SOM.

In Figure 4, a 4×18 matrix map consisted by 72 prototypes from 189 biotechnologies is built. Then, the 72 prototypes are clustered by K-means method. As a result, 4 is the proper number of cluster because of the lowest DB index value (0.4973). Table 1 shows the result of two-level SOM clustering.



[Figure 4] Result of two-level SOM clustering

[Table 1] The result of two-level SOM clustering

Cluster No.	Number of biotechnology	Cluster center	
		R&D capability	Ease of production
1	37	2.80	2.35
2	73	2.00	1.04
3	40	3.26	2.95
4	39	2.48	1.98
Total	189		

In Table 1, the 189 biotechnologies are clustered into 4 clusters, 37 biotechnologies in cluster 1, 73 biotechnologies in cluster 2, 40 biotechnologies in cluster 3, 39 biotechnologies in cluster 4. The center value of each cluster represents the mean of biotechnologies' required levels of input criteria in that cluster. For example, cluster 2 has the lowest cluster center value in terms of R&D capability and ease of production, (2.00, 1.04). It means that the biotechnologies in cluster 2 have the lowest requirement at the 2 input criteria. On the other hand, the biotechnologies in cluster 3 have highest requirement at the 2 input criteria.

3. Result of the tier analysis and importance priority calculation

As mentioned in section 2.4, the DEA is used to measure the efficiency of a DMU which has one or multiple inputs or one or multiple outputs. The efficiency is a ratio of total weighted outputs to total weighted inputs (Korpela et al., 2007). In this study, the efficiencies of emerging technologies are calculated by comparing the weighted experts' ratings to the output criteria and the weighted experts' ratings to the input criteria. A emerging technology alternative is considered efficient if its efficiency score is equal to 1, otherwise, if its efficiency score is less than 1, the alternative is inefficient. We used a software named DEA solver to calculate the efficiencies of biotechnologies. In DEA solver, we input the experts' ratings to input criteria and output criteria, selected DEA-BCC model, and obtain efficiencies of biotechnologies in each cluster. We also calculated each group's standard deviation. The standard deviation of alternatives' efficiencies in group 1 is 0.035. The standard deviation of alternatives' efficiencies in group 2 is 0 because all the biotechnology alternatives' efficiency values are 1. The standard deviation of alternatives' efficiencies in group 3 is 0.058. The standard deviation of alternatives' efficiencies in group 4 is 0.041. According to the method proposed by Seiford and Zhu (2003), tiers are formed. After that, on each tier, we used a software named Expert choice to apply the AHP rating method to the experts' ratings to the 2 importance criteria to evaluate the importance priorities of biotechnologies. The overall inconsistency appears as 0.00 in the Expert choice software, less than 0.1, so it means that the AHP result is reasonable and reliable. Table 2 shows result of cluster 1's tier analysis and importance priority calculation.

[Table 2] Result of cluster 1's tier analysis and importance priority calculation

Biotechs on tier1	Importance priorities of biotechs on tier 1	Inefficient biotechnologies
9	0.502	4
13	0.816 (7)	32
15	**0.816 (7.33)**	52
27	0.693	65
29	0.502	66
30	0.502	82
36	0.502	135
49	0.816 (7)	183
51	0.625	187
55	0.502	
56	0.502	
64	0.625	
67	0.497	
72	0.625	
73	0.497	
86	0.502	
98	0.502	
134	0.625	
137	0.625	
164	0.625	
166	0.625	
167	0.375	
170	0.497	

180	0.497
181	0.375
185	0.625
188	0.497
189	0.625

In Table 2, according to the tier analysis rule and the stopping rule, 28 biotechnologies were evaluated as efficient biotechnologies and formed 1 tier. The remaining 9 biotechnologies are inefficient, and should select a target on tier 1 to benchmark. According to the importance priority calculated by AHP rating method, No. 13, 15 and 49 biotechnologies have the highest importance priority value on tier 1, and should be selected as the benchmarking target alternatives on tier 1. Among the 3 alternatives, we finally selected the No. 15 as the final benchmarking target because of the highest sum (7.33) of importance criteria (urgency: 4.00; conformance level to national policy: 3.33). Table 3 shows the result of cluster 2's tier analysis.

[Table 3] Result of cluster 2's tier analysis

Biotechs on tier 1	Bioteches on tier 1	Bioteches on tier 1	Bioteches on tier 1
2	106	127	154
5	108	128	155
23	109	129	156
40	110	138	157
41	111	139	158
42	112	140	159
43	113	141	160
44	115	142	161
77	116	143	162
78	117	144	163
79	118	145	174
80	119	146	175
99	120	147	176
100	121	148	177
101	122	149	178
102	123	150	179
103	124	151	
104	125	152	
105	126	153	

In table 3, all the 73 biotechnologies were evaluated as efficient technologies, and formed tier 1. Therefore, in cluster 2, there is no biotechnology which need to benchmark. Table 4 shows the result of cluster 3's tier analysis and importance priority calculation.

[Table 4] Result of cluster 3's tier analysis and importance priority calculation

Biotechs on tier 1	Importance priorities of biotechs on tier 1	Biotechs on tier 2	Importance priorities of biotechs on tier 2	Bioteches on tier 3	Importance priorities of biotechs on tier 3	Inefficient biotechs
1	0.625	3	0.625	**132**	**0.625(7)**	19
12	0.502	11	0.625	136	0.625(6)	22
14	0.502	26	0.502			68
24	**1(8.66)**	35	0.625			70
25	0.625	50	0.625			75
33	0.625	53	0.816			84
34	0.809	71	0.625			85
57	0.502	83	0.625			87
58	0.502	92	0.625			88
69	0.625	93	0.625			89
96	1(8)	94	0.625			90
130	0.816	95	0.625			91
131	0.375	**97**	**1.000**			

In Table 4, according to the tier analysis rule and the stopping rule, 28 biotechnologies were evaluated as efficient biotechnologies and formed 3 tiers. The remaining 12 biotechnologies are inefficient, and should select a target on each tier to benchmark. According to the importance priority calculated by AHP rating method, No. 132 and 136 biotechnologies have the same importance priority value on tier 3, and should be selected as the benchmarking target alternatives on tier 3. Among the 2 alternatives, we finally selected the No. 132 as the final benchmarking target because of the highest sum (7) of importance criteria (urgency: 3.50; conformance level to national policy: 3.50). No. 97 biotechnology has the highest importance priority value on tier 2, and should be selected as the benchmarking target on tier 2 directly. No. 24 biotechnology is selected as the benchmarking target on tier 1. Table 5 shows the result of cluster 4's tier analysis and importance priority calculation.

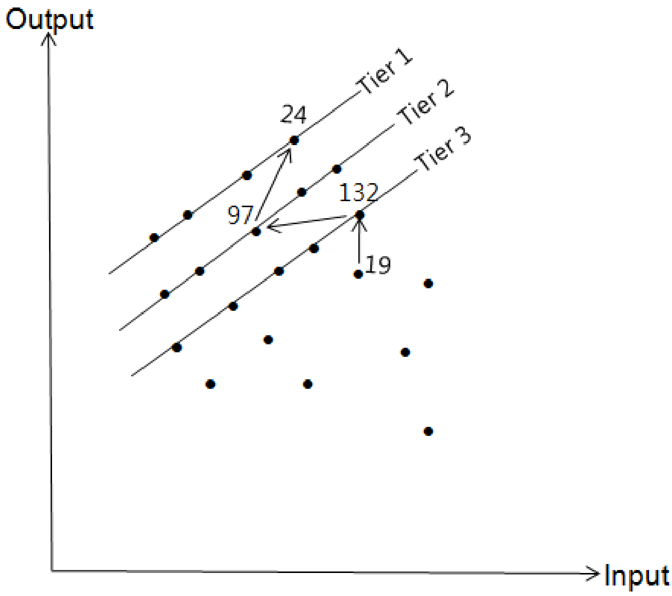
[Table 5] Result of cluster 4's tier analysis and importance priority calculation

Biotechs on tier 1	Importance priorities of biotechs on tier 1	Biotechs on tier 2
54	**0.625(6.67)**	6
81	0.502	7
107	0.625(6)	8
114	0.625(6)	10
133	0.375	16
165	0.625(6)	17
168	0.497	18
169	0.625(6)	20
171	0.502	21
172	0.375	28
182	0.625(6)	31
184	0.497	37
186	0.625(6)	38
		39
		45
		46
		47
		48
		59
		60
		61
		62
		63
		74
		76
		173

In Table 5, according to the tier analysis rule and the stopping rule, all the 39 biotechnologies were evaluated as efficient biotechnologies and formed 2 tiers. Because there is no inefficient biotechnology left.

4. Establish a benchmarking path in each cluster

After selecting benchmarking targets in each cluster, we can connect these targets and establish a benchmarking path in each cluster. Let us take cluster 3 for example, Figure 5 shows a benchmarking path of cluster 3.



[Figure 5] A benchmarking path of cluster 3

In Figure 5, tier 1 is the most efficient frontier, and is more efficient than tier 2. It means that the emerging technology alternatives on tier 1 are superior to the alternatives on tier 2. Likewise, tier 2 is more efficient than tier 3. The alternatives on tier 2 are superior to the alternatives on tier 3. The inefficient emerging technology alternatives should first benchmark an alternative on tier 3, then benchmark an alternative on tier 2, at last, benchmark an alternative on tier 1 to realize a stepwise benchmarking to get to the most efficient frontier. In each step, the inefficient emerging technology alternative should select the most important alternative(the alternative which has the highest importance priority) of the tier as the benchmarking target. A path formed by the most important alternative on each tier can be defined as a benchmarking path. For example, in Figure 5, if the No. 19 inefficient biotechnology wants to benchmark to the efficiency frontier (tier 1), it should benchmark the No.132 biotechnology on tier 3, because No. 132 biotechnology is the most important alternative on tier 3, after that, benchmark the No. 97 biotechnology on tier 2, because No. 97 biotechnology is the most important alternative on tier 2, at last, benchmark the No. 24 biotechnology on tier 1, because No. 24 biotechnology is the most important alternative on tier 1. This path (132→97→24) is a benchmarking path of cluster 3. Following this path, an inefficient biotechnology can benchmark the most important biotechnology on each tier to avoid benchmarking the unimportant biotechnology to waste resource and time.

Ⅴ. Conclusion

Benchmarking is a necessary activity for emerging technology to keep improvement. When emerging technologies carry out benchmarking activities, benchmarking target's required input resource levels and importance should be considered seriously to prevent unnecessary waste of time and resources. In order to make the emerging technologies to benchmark effectively and reasonably, we proposed a sequential use of SOM, DEA and AHP method for the stepwise benchmarking of emerging technology.

The proposed method clusters emerging technologies based on ratings to the required input levels of the emerging technologies by two-level SOM, then, in each cluster, used DEA-BCC to evaluate efficiencies of emerging technologies and do the tier analysis to form tiers. After that, in each cluster, the proposed method used AHP rating method on the ratings to importance criteria of emerging technologies to calculate each tier's emerging technologies' importance priorities. On each tier, the emerging technology with the highest importance priority is selected as the benchmarking target of the tier. Finally, in each cluster, the optimal benchmarking path is established by connecting the selected benchmarking targets from the lowest efficiency tier to the highest efficiency tier.

The proposed method has several salient points. First, by the proposed method, the emerging technologies can benchmark a target which has similar input levels. This will make the benchmarking practicable and avoid unnecessary waste of time and resource. Second, the proposed method can make an emerging technology select a suitable benchmarking target considering a target alternative's importance. This is very important for emerging technologies to identify the development strategic and establish the competitive advantages. Third, the proposed method provides a stepwise benchmarking process. This can make the emerging technologies improve efficiency gradually, and develop stably. Fourth, the benchmarking targets provided by the proposed method are all actual existing emerging technologies. This can avoid the difficulties of benchmarking a hypothetical emerging technology.

This study also has some limitations. First, only 6 criteria are considered in our study. In future work, more criteria should be taken into consideration. Especially, some specific criteria related with emerging technology, such as technical barrier, technical maturity and so on. Second, the criteria used for clustering were only criteria of input resource. In future work, other criteria could also be taken into consideration for clustering to provide a new benchmarking perspective. In addition, combining other methods or approaches to develop new benchmarking models for emerging technology can be another research direction.

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