기술 평가 및 선정을 위한 AHP와 DEA 통합 활용 방법: 청정기술에의 적용

Integrated AHP and DEA method for technology evaluation and selection: application to clean technology

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ABSTRACT

Selecting promising technology is becoming more and more difficult due to the increased number and complexity. In this study, we propose hybrid AHP/DEA-AR method and hybrid AHP/DEA-AR-G method to evaluate efficiency of technology alternatives based on ordinal rating data collected through survey to technology experts in a certain field and select efficient technology alternative as promising technology. The proposed method normalizes rating data and uses AHP to derive weights to improve the credibility of analysis, then in order to avoid basic DEA models' problems, use DEA-AR and DEA-AR-G to evaluate efficiency of technology alternatives. In this study, we applied the proposed methods to clean technology and compared with the basic DEA models. According to the result of the comparison, we can find that the both proposed methods are excellent in confirming most efficient technology, and hybrid AHP/DEA-AR method is much easier to use in the process of technology selection.

Keyword : data envelopment analysis-assurance region, analytical hierarchy process (AHP), technology selection

Ⅰ. Introduction

Since technology develops fast, companies or countries should select and invest in promising technology from various technology alternatives. Due to the increasing number and complexity of technology, it is very difficult to select promising technology under various technology selection criteria in order to carry out R&D activities (Torkkeli & Tuominen, 2002). When selecting a technology, selection criteria should be identified (Khorramshahgol & Moustakis, 1988), then data/information of technology alternatives should be collected from various sources, and then evaluate the technology alternatives against each other based on the identified criteria (Lamb & Gregory, 1997). Therefore, the use of effective promising technology selection method is very important.

In order to make correct selection, whether a technology has good return of investment should be evaluated and considered. Some previous studies have employed data envelopment analysis (DEA) in order to select efficient technology (Lee

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et al., 2011; Moutaz, 1995). DEA is a non-parametric linear programming based technique to evaluate the relative efficiency of decision-making units (DMUs) that use multiple inputs to produce multiple outputs (Chang, 2011). When selecting a suitable technology among multiple technology alternatives, the various predefined criteria for the evaluation of technology alternatives can be categorized as the inputs and outputs in DEA. Inputs are the criteria that are related to the required resources of developing a technology and outputs are the criteria that are related to the results of applying a technology. DEA evaluates the efficiency of technology alternatives by comparing their inputs and outputs.

But there are some problems in the previous methods. Most previous methods used basic DEA models such as DEA-CCR and DEA-BCC for technology evaluation (Lee et al., 2011; Moutaz, 1995), which cannot analyze ordinal rating data (qualitative data collected through survey) accurately. In most cases, technology selection is usually carried out through survey to collect the expert's ordinal ratings to technology's predefined criteria. The previous methods using basic DEA models are also not excellent in confirming the most efficient technology because the DEA-CCR and DEA-BCC always select too many efficient technology alternatives, and accordingly make the selection of the most efficient technology difficult.

In order to solve the problems above, in this study, we propose hybrid AHP/DEA-AR method and AHP/DEA-AR-G method), which are hybrid methods of analytical hierarchy process (AHP) and data envelopment analysis-assurance region (DEA-AR). AHP/DEA-AR method uses DEA-AR model, which is developed based on basic DEA-CCR model to avoid the unreasonable weight distribution (Thompson et al., 1986). AHP/DEA-AR-G method uses data envelopment analysis-assurance region-global model (DEA-AR-G), which is derived from DEA-AR and can restrict weight more compactly (Allen, et al., 1997). In this study, in order to evaluate the efficiency of technology alternatives by analyzing ordinal rating data accurately, adjust the number of efficient technology alternatives flexibly, and select the most efficient technology alternative as promising technology, we used analytical hierarchy process (AHP) to derive the reasonable assurance region (AR) for using DEA-AR and DEA-AR-G, then used DEA-AR and DEA-AR-G to evaluate the efficiency of the technology alternatives by analyzing ordinal rating data collected through survey, and selected efficient technology alternative as promising technology. To demonstrate the effectiveness of the proposed hybrid methods, we applied them to the case of promising clean technology selection in a Korean company. We compared the application results of the proposed methods with the results of applying other DEA models such as DEA-CCR, DEA-BCC and DEA-supper efficiency and found that the proposed methods can make the technology selection become easier.

This study organizes the remaining structure as follows. In section 2, we review the literature of technology evaluation and selection, DEA models, AHP and hybrid use of AHP and DEA. In section 3, we describe the framework of AHP/DEA-AR and AHP/DEA-AR-G methods for selecting promising technologies accurately. In section 4, we apply the proposed methods to the case of promising clean technology selection in a Korean company and compare the results of the proposed methods with the results of applying other DEA models (DEA-CCR, DEA-BCC and DEA-supper efficiency). The last section provides conclusions.

Ⅱ. Literature review

1. Technology evaluation and selection

Early stage's technology evaluation focused on grasping possible positive and negative effect and uncertain effect due to impose of technology and minimizing negative effect through the analysis of causation between technology and effect (Daddario, 1968). However, nowadays, the purpose of technology evaluation is to use fundamental information and to identify future potential technology so as to create strategies for technology development and investment (Ryu & Byeon, 2011). Technology evaluation has been the essential ability to comprehend the values of technologies (Sung & Yang, 2005; Ho, 2011).

Technology selection is a process that involves identifying and evaluating alternatives and choosing among them (Shen et al., 2010). The process is becoming more and more difficult because the complex of technology is a list of elements from the 'physical' to the 'cultural' (James & John, 2001). In this process, information about technology alternatives should be collected through many channels, alternatives should be evaluated against each other or some criteria (Lamb & Gregory, 1997).

In technology selection, evaluating criteria are various. For example, Moutaz (1995) presented a decision method of technology selection considering 4 criteria: cost, load capacity, velocity and repeatability. Lee et al.(2011) evaluated hydrogen energy technologies considering 5 criteria: economic impact, commercial potential, inner capacity, technical spin-off, and development cost. Winebrake & Creswick (2003) evaluated hydrogen fuel processor technologies based on 17 criteria which can be grouped into five categories: (1) Fuel production and distribution, (2) Vehicle operation and performance, (3) Environmental impacts, (4) Resource issues and (5) Economics. Hajeeh & Al-Othman (2005) selected the most appropriate technology for seawater desalination based on 10 criteria: (1) Product water quality, (2) Recovery ratio, (3) Energy consumption per unit product water, (4) Equipment efficiency and type of energy utilization, (5) Available technology, (6) Plant capacity, (7) Total cost. Malladi & Min (2005) presented decision support models to select the high-speed access technologies under performance criteria (cost, quality and speed). Raju et al. (1995) selected suitable toilet soap-making technology under 7 criteria: (1) Capacity per day, (2) Capital per unit capacity, (3) Workers per unit capacity, (4) Hardware characteristics (5) Resources requirement, (6) Infrastructure requirement, (7) Environmental effects. Shen *et al.* (2010) proposed technology selection process considering 4 criteria: technological merit, business effect, technology development potential, and risk. Hsu *et al.* (2010) provided a systematic approach for technology selection considering 3 aspects' criteria: technology, economy and environmental protection. In this study, we consider 4 criteria (R&D capability, ease of production, marketability and technical extension).

Many research used DEA to select technology. A decision method for technology selection problems using a two-phase procedure was proposed

(Moutaz, 1995). In phase 1, data envelopment analysis is used to identify technologies that provide the best combinations of vendor specifications on the performance parameters of the technology. In phase 2, a multi-attribute decision making method is used to select a technology from those identified in phase 1. A integrated two-stage multi-criteria decision-making approach, including the hybrid fuzzy analytic hierarchy process (AHP) and data envelopment analysis (DEA) model was proposed to assess the relative efficiency of hydrogen energy technologies (Lee et al., 2011). Karsak & Ahiska (2005) proposed a novel practical common weight multi-criteria decision-making (MCDM) DEA approach for technology selection. DEA is used to evaluate efficiency of technologies in these studies.

But in researches above, the number of efficient technology is more than 1. This is difficult for decision makers to select only one suitable technology. In this research, we use DEA-AR to evaluate technologies and control the number of efficient technology by setting reasonable assurance region (AR) in AHP.

The previous studies on technology selection method focused on dealing with cardinal data, not ordinal data (Saen, 2006). In general, however, technology selection is conducted by carrying out surveys to several experts and then evaluating ordinal rating data collected through surveys. Thus, it is essential to have the technology selection method which can accurately analyze ordinal rating data. Some or all of the criteria in technology evaluation may be ordinal (qualitative), and should be treated as such (Saen, 2006). The addition of subjective judgements to the purely quantitative approach can provide a more realistic evaluation process (Sharon, 2008). In this study, technology alternatives are rated in ordinal data by experts.

2. 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 approach 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. The degree of inefficiency for a DMU is measured relative to a set of more efficient DMUs. However, a DMU identified as being efficient does not imply absolute efficiency. It is only relatively efficient to other DMUs that are being considered.

2.1. DEA-CCR model and DEA-BCC model

CCR method is introduced as the most basic DEA method (Charnes et al., 1978). 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):

$$Max\,h_0 = \frac{\sum_{r=1}^{s} u_r\, y_{ro}}{\sum_{l=1}^{m} v_i x_{i0}} \tag{1}$$

$$s.t.\ \frac{\sum_{r=1}^{s} u_r\, y_{rj}}{\sum_{l=1}^{m} v_i x_{rj}} \leq 1\,,\ j = 1, 2, \cdots, n$$

$$u_r \geq \epsilon > 0, \quad r = 1, 2, \cdots, s$$

$$v_r \geq \epsilon > 0, \quad i = 1, 2, \cdots, m$$

In Equation (1), h_0 is DMU 0's efficiency, u_r is the weight given to output r, v_i is the weight given to input i, y_{rj} is the amount of output r yielded by DMU j, x_{ij} is the amount of input i consumed by DMU j, ϵ is a positive non-Archimedean infinitesimal, n is the number of DMU, m is the number of input, s is the number of output. In Eqution (1), the first restrict equation means that the ratio calculated by using u_r and v_r should be less than 1 or equal to 1. x_j, y_j are the expert's rating data. Equation (1) is the ratio form of DEA. The numerator of Equation (1) is normalized by 1, the Equation (1) can be changed into multiplier form of DEA.

$$Max\ h_0 = \sum_{r=1}^{s} u_r\, y_{r0} \tag{2}$$

$$s.t. \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0\,,\ j = 1,2,\cdots,n$$

$$\sum_{i=1}^{m} v_i\, x_{i0} = 1$$

$$u_r\,, v_i \geq \epsilon\,,\ r = 1,2,\cdots,s\,;\, i = 1,2,\cdots,m$$

DEA-CCR model is deducted under the assumption of constant returns-to-scale (CRS), cannot distinguish the scale efficiency and the technical efficiency.

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:

$$\max h_0 = \sum_{r=1}^{s} v_r y_{r0} + u_0 \tag{3}$$

$$s.t.\ \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0,\ j = 1,2,...,n$$

$$\sum_{r=1}^{s} v_i x_{i0} = 1$$

$$u_r, v_i \geq \epsilon, r = 1,2,...,\ \forall\, r,i$$

In Equation (3), u_0 is scale indicator which is unrestricted. This is the difference with the DEA-CCR.

2.2. DEA-super-efficiency

To break the tie of efficient DMUs, the CCR model is modified by Anderson and Petersen (1993). The modified CCR model is called supper-efficiency model. It means that on same efficiency frontier, the remaining efficiency is included and the efficiency can exceed 1. Although the frontier exists, under the situation of weakly efficiency and not the extreme point, super-efficiency model (Equation (4)) can be used.

$$\min_{\theta k, s_r^+, s_i^-, \lambda_j} z_k(\theta_k, s_r^+, s_i^-) = \theta_k - \epsilon\left(\sum_{r=1}^{s} s_r^+ + \sum_{i \in D} s_i^-\right) \tag{4}$$

$$s.t. \quad \sum_{j=1, \neq k}^{n} \lambda_j y_{rj} - s_r^+ = y_{rk} \ \forall r$$

$$\theta_k x_{ik} - \sum_{j=1, \neq k}^{n} \lambda_j x_{ij} - s_i^- = 0 \ \forall \ i \in D$$

$$\theta_k free \in sign$$

$$s_r^+, s_i^-, \lambda_j \geq 0 \ \forall r, i \in D, j$$

$$\epsilon \infty innitesimal\, positive\, \nu ber$$

3. DEA-AR and DEA-AR-G

DEA-AR was developed based on basic DEA model (Thompson et al., 1986). In basic DEA model, the weights are not fixed in advance, but derived from the data. Each DMU chooses the assigned weights. In this case, an efficient DMU may be weighted a single input and a single output with the other inputs and outputs being weighted zero (Kong & Fu, 2012). The DEA-AR model can vary weights within a region by imposing constraints on the relative magnitudes of the weights for special items (Kong & Fu, 2012). DEA-AR was used to investigate the efficiency of Mexican banks (Taylor et al. 1997). DEA-AR was also employed to measure business college's performances in Taiwan's universities(Kong & Fu, 2012).

In DEA-AR model, for every pair (y_{r1k}, y_{r2k}) of measurement (input and output) the ratio w_{r1}/w_{r2} should be bounded by $L_{r1,r2}$ and $U_{r1,r2}$. Here, y_{r1k} and y_{r2k} are the $r1th$ and $r2th$ measurement of DMU k . w_{r1} and w_{r2} denotes the weight of y_{r1k} and y_{r2k}. $L_{r1,r2}$ and $U_{r1,r2}$ are the lower and upper bounds of the ratio. This constraint limits the region of weights to some special area. The equation is

$$L_{r1,r2} \leq \frac{w_{r1}}{w_{r2}} \leq U_{r1,r2} \qquad r1 \neq r2 \tag{5}$$

By adding Equation (5) into the equation of CCR method (Equation (1)), we can obtain the DEA-AR method.

DEA-AR-G model can set the restriction to each measurement's weight. The equation is as follows,

$$L_{r1} \leq \frac{w_{r1} \times \sum_{k=1}^{n} y_{r1k}}{w_{r1} \times \sum_{k=1}^{n} y_{r1k} + w_{r1} \times \sum_{k=1}^{n} y_{r2k}} \leq U_{r1} \tag{6}$$

By adding Equation (6) into the equation of CCR method (Equation (1)), we can obtain the DEA-AR-G method.

4. AHP

AHP is designed to solve complex multiple criteria decision making (MCDM) problems(Saaty, 1980; Kim, 2009). It can be used to reflect judgments on feelings, ideas, and emotions. The output of the AHP is a prioritized ranking, indicating the overall preference for each decision alternative. The AHP usually involves three stages of problem solving. These are the principles of decomposition, comparative judgments, and synthesis of priorities. The decomposition principle calls for constructing a hierarchy or network to represent a decision problem. The overall objective is located at the top of the hierarchy, and the criteria, sub-criteria, and alternatives are placed at each descending level of the hierarchy.

To apply the principle of comparative judgment, the user sets up a comparison matrix at each level by comparing pairs of criteria, or pairs of alternative at the lowest level. A scale of values ranging from 1(indifference) to 9 (extreme preference) is available for users to express their preferences. Once the matrix of pair-wise comparisons has been developed, one can estimate the relative priority for each of the alternatives in terms of the specific criterion.

Let $C_1,\ldots,C_m$ be m decision criteria and $W=(w_1,\ldots,w_m)^T$ be their normalized relative importance weight vector, which is to be determined by using pair-wise comparisons and satisfies the normalizing condition $\sum_{j=1}^{m} w_j = 1$ with $w_j \geq 0$ for $j=1,\ldots,m$. The pair-wise comparisons between the m decision criteria can be conducted by asking the decision maker (DM) or expert questions such as which criterion is more important with regards to the decision goal and by what scale (1-9). The answers to these questions form an $m \times m$ pair-wise comparison matrix which is defined as follows:

$$A=(a_{ij})_{m\times m} = \begin{array}{c} C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1m} \\ a_{21} & a_{22} & \cdots & a_{2m} \\ \vdots & \vdots & \cdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mm} \end{bmatrix} \qquad (7)$$

In Equation (7), a_{ij} represents a quantified judgment on w_i/w_j with a_{ii}=1 and $a_{ij}=1/a_{ji}$ for $i,j=1,\ldots,m$. If the pair-wise comparison matrix $A=(a_{ij})_{m\times m}$ satisfies $a_{ij}=a_{ik}a_{kj}$ for any $i,j,k=1,\ldots,m,$, then A is said to be perfectly consistent; otherwise it is said to be inconsistent.

From the pair-wise comparison matrix A, the weight vector W can be determined by solving the following characteristic equation:

$$AW=\lambda_{\max} w \qquad (8)$$

In Equation (8), λ_max is the maximum eigenvalue of A. Such a method for determining the weight vector of a pair-wise comparison matrix is referred to as the principal right eigenvector method (EM) (Saaty, 1980).

Since the DM may be unable to provide perfectly consistent pair-wise comparisons, it is demanded that the pair-wise comparison matrix A should have an acceptable consistency, which can be checked by the following consistency ratio (CR):

$$CR=\frac{(\lambda_{\max}-n)/(n-1)}{RI} \qquad (9)$$

In Equation (9), RI is a random inconsistency index, which value varies in the order of pair-wise comparison matrix.

Decision alternatives can be compared pair-wisely with respect to each decision criterion in the same way. After the weights of decision criteria and the weights of decision alternatives with respect to each criterion are obtained by using pair-wise comparison matrices, the overall weight (or called priority) of each decision alternative with respect to the decision goal can be generated by using the following simple additive weighting (SAW) method (Hwang & Yoon, 1981):

$$W_{A_i}=\sum_{j=1}^{m} W_{ij}W_j, \quad i=1,\ldots,n \qquad (10)$$

In Equation (10), $w_j(j=1,\ldots,m)$ are the weights of decision criteria, $w_{ij}(i=1,\ldots,n)$ are the weights of decision alternatives with respect to Criterion j, and $w_{A_i}(i=1,\ldots,n)$ are the overall weights of decision alternatives. Based upon the overall weights of decision alternatives, decision can be made and the alternatives can be ranked or prioritized. The best decision alternative will be the one with the biggest overall weight with respect to the decision goal. Sometimes, AHP is also used in technology selection. For example, Kim & Lee (2011) employed AHP in the method for determining an optimal LTPS(Low Temperature Polycrystalline Silicon) crystallization technology.

5. Hybrid DEA and AHP method

Lee *et al*[19] used the hybrid fuzzy analytic hierarchy process (AHP) and data envelopment analysis (DEA) model to assess the relative efficiency of hydrogen energy technologies. Abbas *et al.* (2010) proposed a new approach for information technology selection using balanced scorecard (BSC) and data envelopment analysis (DEA).

The integrated AHP and DEA method has been applied in many fields. For example, Sinuany-stern *et al.* (2000) proposed a hybrid AHP and DEA method using AHP to overcome the shortcoming of too many efficient DMUs, and DEA to overcome the shortcoming of AHP's subjectivity. Bowen (1990) suggested a two-step process of integrating DEA and AHP in site selection. They claimed that this combination would have the dual advantage of utilizing both objective and subjective data as well as reducing the number of paired comparison judgments required from the decision maker. Shang & Sueyoshi (1995) proposed a unified framework using AHP, simulation and DEA for the selection of the most appropriate flexible manufacturing system (FMS) for a manufacturing organization. Lee & Kim (2009) developed a combined AHP and DEA method for evaluating computer aided software engineering (CASE) tools. Seifert & Zhu (1998) investigated excess and deficits in Chinese industrial productivity for the years (1953-1990) by combining the DEA with other management science approaches such as Delphi, AHP and assurance region (AR) techniques. Their study demonstrated that DEA could be well combined with other methods. Zhang & Cui (1999) developed a project evaluation system using DEA and AHP method to manage investments in the various parts (sub-systems) of the State Economic Information System (SEIS) of China. Ertay *et al.* (2006) suggested a similar decision-making methodology based on the DEA and AHP for evaluating facility layout design. Takamura & Tone (2003) presented a site evaluation model based on AHP and DEA method for relocating Japanese government agencies out of Tokyo.

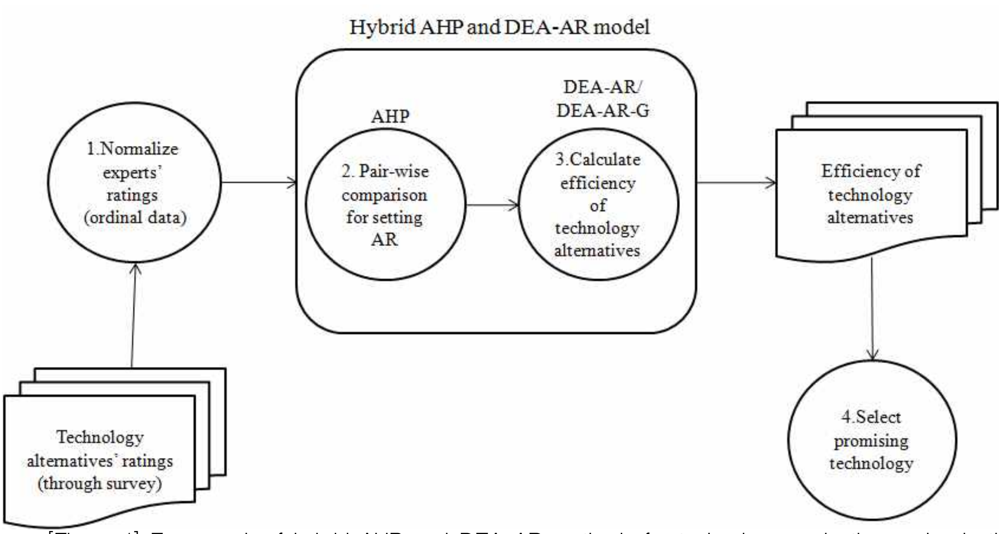
From the above studies, we can see that the integrated AHP and DEA method has also been applied on site selection, evaluation system selection, project evaluation, evaluating facility layout design, and so on, but seldom used on technology selection. In this study, we propose hybrid AHP and DEA methods of technology evaluation and selection. In order to analyze ordinal data correctly, we use DEA-AR model instead of basic DEA model.

III. Hybrid AHP and DEA methods for technology evaluation and selection

In this study, the 2 proposed hybrid methods analyze ordinal rating data of the 4 criteria (R&D capability, ease of production, marketability, technical extension) collected through survey to technology experts. In the 4 criteria, R&D capability is the required R&D capability of a technology. The required R&D capability means the comprehensive resources which need to be inputted in the R&D process. The resources contain human resource, physical resource and financial resource. Ease of production is the ease of using a technology to producing products. It means that the inputted comprehensive resources, such as material resource, human resource and so on. Marketability is the marketability of a product using a technology. It actually means a technology's marketability. Marketability is an important criteria to evaluate whether a technology can bring output. Technical extension is a technology's extension to other products or fields. It is used to evaluate whether a technology has a long-term future, also a criteria to forecast whether a technology can bring more output in the future. R&D capability and ease of production evaluate the inputs to a technology from development to commercial practice. Marketability and technical extension are results of applying a technology, evaluate a technology's short-term and long-term outputs. According to described above, the 4 criteria contains the broadest measure of inputs and outputs to a technology, and can measure the efficiency more accurately. These 4 criteria are usually considered by companies in the process of technology selection also. Therefore, we selected the 4 criteria, and defined R&D capability as input 1, ease of production as input 2, marketability as output 1, and technical extension as output 2 in DEA.

In this study, we proposed hybrid AHP and DEA methods for technology evaluation and selection based on systematical process and practicability. In this study, the proposed methods use DEA-AR and DEA-AR-G which can adjust AR's range to calculate efficiency of technology alternatives. The two DEA models can adjust the number of efficient technology alternative using the AR's range, insure the reasonable variation range of the weights, limit the variation range and insure the analysis's reliability through the normalization of criteria' values.

Figure 1 shows the framework of hybrid AHP and DEA method for technology evaluation and selection.



[Figure 1] Framework of hybrid AHP and DEA-AR methods for technology evaluation and selection.

As shown in Figure 1, in order to select the suitable technologies, we first normalized the experts' ratings (ordinal data) to technology alternatives, then, calculate reasonable weights by using AHP to set the AR's range for DEA-AR and DEA-AR-G. DEA-AR and its derived model

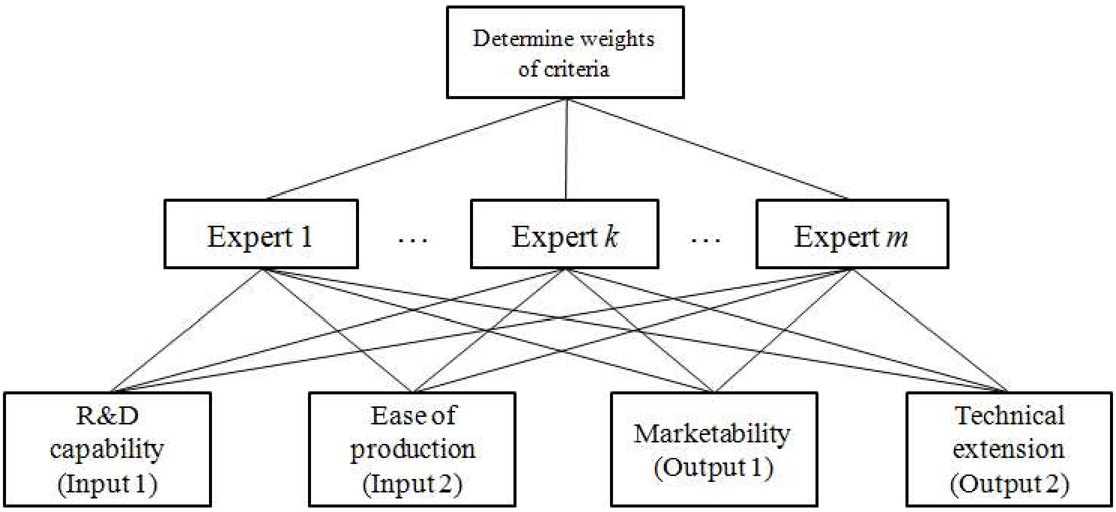
DEA-AR-G have the same theory, but are different in the method of setting AR. It will be introduced in section 3.2. Then we use DEA-AR model and DEA-AR-G model to calculate the efficiency of technology alternatives. At last, we select the technology with the highest efficiency value as the promising technology.

1. Normalize ordinal data

When process questionnaires, the qualitative data measured with Likert scale can be processed like quantitative data. But in order to make all variables compare with each other easily, normalization is needed. In this study, we use the normalization method proposed by Roll and Golany (1993). According to their method, each rating value is divided by the mean of the ratings to the criteria. For example, to n technology alternatives, the ratings to the s th output are $y_{s1},\ldots,y_{sn}$, the mean is $\overline{y_s}=\frac{\sum_{j=1}^{n} y_{sj}}{n}$, the normalized value of n the technology alternative's s the output's rating is $\frac{y_{sn}}{\overline{y_s}}$.

2. Set assurance region (AR) by AHP

Before using the DEA-AR model, assurance region (AR) should be set. In this step, we use pair-wise comparison in AHP to get the weights of inputs and outputs and set AR for using DEA-AR and DEA-AR-G. First, we conducted a survey to experts and elicit their subjective judgements on the importance of the 2 inputs (R&D capacity and ease of production) and 2 outputs (technical extension and marketability). Then, the analytic hierarchy process (AHP) proposed by Saaty (1980) is used to get the every expert's weights of inputs and outputs.



[Figure 2] AHP hierarchy for determining weights of inputs and outputs.

In Figure 2, at the top, is the goal of the hierarchy (determining weights of criteria). At the second level, m experts give their ratings to the importance of the 4 criteria (2 inputs and 2 outputs), and make pair-wise comparison of the 4 criteria. Then AHP uses eigenvector scaling to convert the pair-wise comparisons into weights. So we can get m sets of the criteria's weights given by the m experts. The weights of inputs and outputs obtained from the AHP analysis will be used for setting AR.

Before using the DEA-AR model, assurance region (AR) should be set. AR for using DEA-AR model is set by ratio between measurement (input and output)'s weight. In order to set AR for DEA-AR model, the weights of inputs and outputs are used to calculate each expert's input weight ratio and output weight ratio and find the largest and the smallest values of each weight ratio; then, set upper and lower bound of the ratio (as shown in Equation (11)).

$$OL_{i,k} \leq \frac{w_i}{w_k} \leq OU_{i,k} \qquad (11)$$

In Equqtion (11), w_i is the weight of output i, w_k is the weight of output k. $\frac{w_i}{w_k}$ is the output weight ratio. $OL_{i,k}$ is the smallest value among the m sets of output weight ratio, and set as the lower bound of the output weight ratio(OL). $OU_{i,k}$ is the largest value among the m sets of output weight ratio, and set as the upper bound of the output weight ratio(OU). The upper and lower bound of the input weight ratio should be set by the same way.

In DEA-AR, the lower and upper bounds play the most central function in setting the number of final efficient DMU. We can adjust the range between the lower and upper bounds to set the number of efficient technology we want to select.

DEA-AR-G model is the model named DEA-AR Global model derived from DEA-AR model. DEA-AR-G model has the same theory with DEA-AR, but different in the method of setting AR. AR for using DEA-AR-G is set to each measurement to enhance the restricting elaboration, and has the advantage of directly adjusting the restricting degree.

DEA-AR-G model can set the restriction to each measurement's weight. The equation is as follows,

$$OL_i \leq \frac{w_i \times \sum_{j=1}^{n} y_{ij}}{w_i \times \sum_{j=1}^{n} y_{ij} + w_k \times \sum_{j=1}^{n} y_{kj}} \leq OU_i \qquad (12)$$

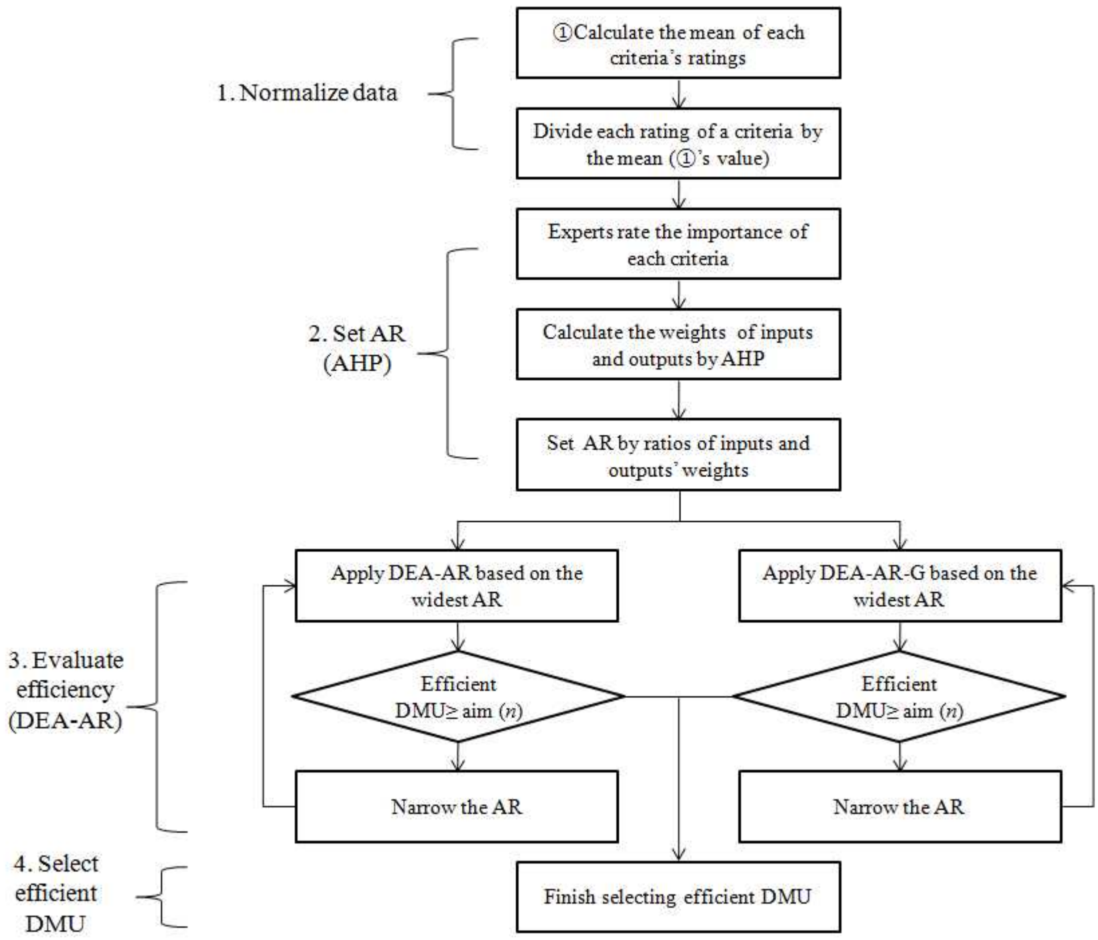
In Equation (12), y_{ij} is the amount of output i consumed by DMU j. y_{kj} is the amount of output k consumed by DMU j.

3. Calculate efficiency of technology alternatives

After setting AR, in this step, we employ DEA-AR model and DEA-AR-G model evaluate the efficiency of technology alternatives by comparing their ratings in inputs (R&D capability and ease of production) and their ratings in outputs (marketability and technical extension). Then, we can get evaluation results. In the results, the DEA efficiency of efficient technology is 1, on the other hand, the DEA efficiency of inefficient technology is less than 1. If the number of efficient technology evaluated by DEA is more than the required number, we should narrow the assurance region to reduce the number of efficient technology until getting required number of efficient technology.

4. Select promising technologies

If we set the number of final selected technology (DMU) is n, the process can be shown in Figure 3,



[Figure 3] The process of selecting n technologies using hybrid AHP and DEA-AR methods

As shown in Figure 3, if we use the hybrid AHP and DEA-AR methods to select n technologies, we should normalize the experts' ratings first. Before applying DEA-AR model and DEA-AR-G model, we have to set the AR by using AHP. After that, we apply the obtained AR to DEA-AR model and DEA-AR-G model to evaluate technology alternatives' efficiency. If the number of efficient technology is larger than n, we should narrow the AR gradually to until we get n efficient technologies.

Ⅳ. Application study

1. Introduction

In this section, we applied the 2 proposed methods to the case of selecting promising clean technology. In the process of AHP analysis, 3 experts were invited to rate the 185 clean technology alternatives under the consideration of 4 criteria (R&D capability, ease of production, marketability and technical extension). All the ratings were made on a five-point scale (1 being a "very low" and 5 being a "very high" level). Although this application has limitations, it put the focus on applying the proposed methods, and confirmed that the proposed method can be used in practice. Therefore, compared with the selection result, this is more significant.

Generally, when government evaluates technologies, except the 4 considered criteria, other criteria such as urgency, government support and so on are also considered, but in this study, duo to the unclear distinction as input and output in DEA, we don't consider the criteria such as urgency, government support and so on. This is for avoiding the complexity and focusing on the illustration of the proposed hybrid methods.

2. Normalize the experts' ratings

In this step, we need to normalize experts' ratings. First, we should calculate each criteria's mean value. The R&D capability's mean value is 3.7, the ease of production's mean value is 3.65, the marketability's mean value is 3.78, the technical extension's mean value is 3.85. Then, we use each technology's rating values to divide the corresponding criteria's mean value to get the normalized values.

3. Set assurance region (AR) by AHP

In order to use DEA-AR model and DEA-AR-G model to evaluate efficiency of the 185 clean technology alternatives, we should calculate the weights of inputs and outputs and set assurance region (AR) according to their ratios.

To calculate the weights of inputs and outputs, we conducted a survey to 3 experts and collected their ratings to the importance of the 2 inputs and 2 outputs. All the ratings were made on a five-point scale (1 being a "very low" and 5 being a "very high" level).

[Table 1] Experts' ratings to the importance of 2 inputs and 2 outputs.

		Expert 1	Expert 2	Expert 3
Input	R&D capability(Input1)	4.5	4	4
	Ease of production(Input2)	3	3	2
Output	Marketability(Output1)	4	4.5	3.5
	Technical extension(Output2)	2	3	2.5

Table 1 shows the 3 experts' ratings to the importance of the 2 inputs and 2 outputs. Then we make pair-wise comparisons of the ratings to get the weights of inputs and outputs. Table 2 shows the weights of inputs and outputs rated by each expert.

[Table 2] The weights of inputs and outputs rated by each expert.

		Expert 1	Expert 2	Expert 3
Input	R&D capability (Input1)	0.6	0.57	0.67
	Ease of production (Input2)	0.4	0.43	0.33
Output	Marketability(Output1)	0.67	0.6	0.58
	Technical extension(Output2)	0.33	0.4	0.42

After getting the weights of inputs and outputs, we should calculate each expert's input weight ratio and output weight ratio. Table 3 shows the weight's ratios:

[Table 3] Each expert's weight ratios.

	Expert 1	Expert 2	Expert 3
Input1/Input2	1.5	1.33	2.0
Output1/Output2	2.0	1.5	1.38

Then, we need to find the smallest and largest values of each weight ratio and construct the upper and lower bound values of weight ratio to set the assurance region (AR). Table 4 shows the lower and upper bounds of assurance region (AR):

[Table 4] The lower and upper bounds of assurance region (AR)

	Lower	Middle	Upper
Input1/Input2	1.33	1.5	2.0
Output1/Output2	1.38	1.5	2.0

In Table 4, among the ratios of inputs, 1.33 is used as the lower bound of inputs' weight and 2.0 is used as the upper bound of inputs' weight in DEA. 1.38 is used as the lower bound of outputs and 2.0 is used as the upper bound of outputs' weight. The weights of inputs and outputs are allowed to vary within the region of the lower and upper bounds. If the number of efficient technology evaluated by DEA is more than the number of expert's aim, we should narrow the assurance region to reduce the number of efficient technology. For example, we can set 1.5 as the lower bound for inputs, 1.5 as the lower bound for outputs and keep the upper bounds of both inputs and outputs unchanged.

Above all is the process of setting AR for DEA-AR model. The process of setting AR for DEA-AR-G is similar. We use the weights in the weights in Table 2 and Equation (6) to set AR for DEA-AR-G model. Table 5 shows the weights of inputs and outputs.

[Table 5] The weights of inputs and outputs rated for DEA-AR-G

	Expert 1	Expert 2	Expert 3
Input 1	0.603	0.573	0.673
Input 2	0.397	0.427	0.327
Output 1	0.666	0.596	0.576
Output 2	0.334	0.404	0.424

The same with DEA-AR, DEA-AR-G model's assurance region (AR) could be set by arranging the weights in order of value. Table 6 shows the assurance region (AR) of DEA-AR-G.

[Table 6] The lower and upper bounds of assurance region (AR) for DEA-AR-G

	Lower	Middle	Upper
Input 1	0.573	0.603	0.673
Input 2	0.327	0.397	0.427
Output 1	0.576	0.596	0.666
Output 2	0.334	0.404	0.424

In Table 6, we can see that every measurement' weight has lower bound and upper bound. If the number of efficient technology evaluated by DEA-AR-G is more than the required number, we should narrow the assurance region to reduce the number of efficient technology.

4. Evaluate efficiency of clean technologies by DEA

4.1. Apply DEA-AR

In this step, we use DEA-AR model to evaluate efficiency of the185 clean technology alternatives with the assurance region (AR) set in Table 4. Table 7 shows the DEA-AR efficiency of clean technology alternatives.

[Table 7] DEA-AR efficiency of clean technology alternatives

Rank No.	Tech No.	Efficiency value
1	CT96	1
2	CT155	0.995
3	CT14	0.993
4	CT68	0.955
5	CT86	0.938
6	CT30	0.938
7	CT98	0.933
8	CT32	0.930
…	…	…
184	CT135	0.705
185	CT132	0.673

In Table 7, CT96 means the 96th clean technology alternative. CT96 (DB construction technology of clean production technologies) has the highest efficiency value (1.000), and is ranked the first. There is only 1 efficient technology (efficiency value is 1), so we need not to narrow the range of AR.

4.2. Apply DEA-AR-G

The difference between DEA-AR and DEA-AR-G is the method of setting AR. Unlike DEA-AR use the ratio of inputs and outputs' weights to set AR, DEA-AR-G model set AR using the ratio of each input or output's values and all inputs or outputs' values, and can assign weights more detailed. In this study,

We use DEA-AR-G model to evaluate efficiency of the 185 clean technology alternatives with the assurance region (AR) set in Table 6, and can get 2 efficient technologies (CT155 and CT96). In order to get only 1 efficient technology, we narrow the assurance region range by setting middle values (0.603, 0.397, 0.596 and 0.404) as the lower bounds and keeping the upper bounds of both inputs and outputs unchanged. Table 8 shows the revised DEA-AR-G efficiency of clean technology alternatives.

[Table 8] Revised DEA-AR-G efficiency of clean technology alternatives

Rank No.	Tech No.	Efficiency value
1	CT96	1
2	CT14	0.993
3	CT155	0.982
4	CT68	0.959
5	CT98	0.938
6	CT86	0.937
7	CT30	0.937
8	CT33	0.935
…	…	…
184	CT135	0.713
185	CT132	0.682

As shown in Table 8, after narrowing the AR, CT 96 technology is also evaluated as the efficient technology. Compare the Table 7 and Table 8, we can find that although they have same efficient technology (CT96), the other technology alternatives' efficiency values and rank's sequence are different.

4.4.3. Apply other DEA models

We also use the clean technology data on other DEA models (DEA-CCR, DEA-BCC and DEA-Super-efficiency) for comparison. The comparison of efficient technology in different DEA models can be shown in Table 9.

[Table 9] Comparison of efficient technology in different DEA models

Model	Number of efficient technology	Tech No.	Tech name	Efficiency value
DEA-CCR	8	CT168	Integrated Air Pollution forecasting technology	1
		CT166	Indoor air quality of new building management technology	
		CT165	VOCs (Volatile Organic Compounds) characterization technology	
		CT155	Life Cycle Costing Analysis technology	
		CT118	Byproduct Applied technology	

		CT96	DB construction technology of clean production technologies	
		CT32	Environmental material technology	
		CT14	Hazardous substances thermosetting plastic technology	
DEA-BCC	28	CT170	Process control and distribution technology	1
		CT168	Integrated Air Pollution forecasting technology	
		CT167	Urban atmospheric O-zone forecasting and management technology	
		CT166	Indoor air quality of new building management technology	
		CT165	VOCs (Volatile Organic Compounds) characterization technology	
		CT5	No-use hazardous Materials technology	
		CT157	Equipment intelligent technology	
		CT155	Life Cycle Costing Analysis technology	
		CT143	Chemical DB construction technology	
		CT134	Disposal process automation technology	
		CT118	Byproduct Applied technology	
		CT106	End separation technology	
		CT105	Standard packaging technology	
		CT104	RFID logistics management technology	
		CT14	Hazardous substances thermosetting plastic technology	
		CT96	DB construction technology of clean production technology	
		CT79	complex inter CMS building technology	
		CT78	Material Flow Analysis technology	
		CT77	Eco-Industrial Complex modeling technology	
		CT75	Water network construction technology	
		CT74	Energy network building technology	

		CT73	Resource network construction technology	
		CT72	New functional Materials Development technology	
		CT68	Composite materials recycling technology	
		CT66	Frontera alternative recycling technology	
		CT64	Substances regulated alternative technology	
		CT32	Environmental material technology	
		CT30	Advanced catalytic oxidation technology	
DEA-Super-efficiency	8	CT96	DB construction technology of clean production technologies	1.077
		CT155	Life Cycle Costing Analysis technology	1.056
		CT32	Environmental material technology	1.027
		CT14	Hazardous substances thermosetting plastic technology	1.006
		CT168	Integrated Air Pollution forecasting technology	1
		CT166	Indoor air quality of new building management technology	1
		CT165	VOCs (Volatile Organic Compounds) characterization technology	1
		CT118	Byproduct Applied technology	1
AHP/DEA-AR	1	CT96	DB construction technology of clean production technologies	1
AHP/DEA-AR-G	2	CT155	Life Cycle Costing Analysis technology	1
		CT96	DB construction technology of clean production technologies	1

As shown in Table 9, the proposed two methods (AHP/DEA-AR method and AHP/DEA-AR-G method) and other DEA models select CT96 technology as the efficient technology. In AHP/DEA-AR and AHP/DEA-AR-G, CT96 technology has the highest efficiency value. Especially, in DEA-Super-efficiency, the CT96 technology also has the highest efficiency value (1.077). The selected efficient technology (CT96) is also selected as efficient technology by other DEA models. But in DEA-CCR and DEA-BCC, except CT96 technology, there are 7 and 27 other technologies which also have the same efficiency value (1), DEA-super-efficiency also selected 7 technologies as efficient technologies except CT96, so it is difficult for decision makers to select a most suitable technology among them by using the basic DEA models. But in AHP/DEA-AR method, only CT96 is selected as efficient technology, in AHP/DEA-AR-G method, only CT155 and CT96 are selected as efficient technologies. This greatly reduces the selecting scope, and facilitates selection. Especially, in DEA-AR-G model, we can get 2 efficient technologies at first, in order to get only 1 efficient technology, we should narrow the AR, then CT96 technology is evaluated as the most efficient technology also. From this case, we can see that the number of efficient technology can be controlled through the resetting of AR. From the above, we can conclude that both the AHP/DEA-AR method and AHP/DEA-AR-G method are excellent in selecting the most efficient technology, and the CT96 technology (DB construction technology of clean production technologies) is the most efficient technology in 185 clean technologies. We can also conclude that the both proposed methods can reflect experts' intents actively, and can be used flexibly, are excellent at selecting the most efficient technology. On the other hand, although DEA-AR-G model set AR through setting lower and upper bounds of each measurement's weight, has higher AR's adjusting elaboration compared with DEA-AR model, but in this case, it has to narrow the AR to fix the final efficient technology (CT96). This makes the process of selection become complex compared with DEA-AR model. Therefore, in this case, AHP/DEA-AR method is easier to use than AHP/DEA-AR-G method.

Ⅴ. Conclusion

In this study, in order to evaluate survey data and select promising technology accurately, we proposed two hybrid methods, AHP/DEA-AR and AHP/DEA-AR-G. Compared with the technology selecting methods using basic DEA models, the proposed hybrid methods combinedly used normalization, AHP, DEA-AR and DEA-AR-G to evaluate ordinal rating data more accurately. We applied the 2 proposed methods on the case of selecting promising clean technology for Korean companies. The result showed that the 2 proposed methods are much better in confirming the most efficient technology than the methods of using basic DEA models. It also showed that the proposed methods make the technology selection more convenient. Especially, the AHP/DEA-AR method has better performance although AHP/DEA-AR-G method has higher AR's adjusting elaboration than AHP/DEA-AR method.

The 2 proposed methods normalize technology rating data (ordinal data), can more accurately analyze them. Especially, instead of the normal DEA model, we use DEA-AR model and DEA-AR-G model to void the unreasonable weight distribution. It makes the weights can be restricted within a reasonable region which reflect experts' intention when using DEA, and the number of efficient technology can be set flexibly. The application of the proposed methods on clean technology selection validated the practicability of the proposed methods. Compared with the method of adding the criteria' values simply, the 2 proposed methods has more objectivity and theoretical excellence, present an improving direction for promising technology selection. But in this study, we proposed technology selection methods considering 4 criteria categorized by input and output. In the complex environment for technology selection, more criteria should be considered, and setting input criteria and output criteria can also affect the final selected technology. So how to set input criteria and output criteria reasonably is another topic which should be discussed. Only 3 experts were invited to rate the technology alternatives. In order to enhance the rating value's reliability, more experts should be invited to do the survey.

Therefore, in future research, methods considering various criteria and evaluating alternatives more accurately should be proposed.

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