An AHP/DEA Hybrid Model for Measuring the Relative Efficiency of Energy Efficiency Technologies

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Abstract – **Due to the expiration of the national energy and resources plan, established in 1997, and Korean government needs to build a new one coping with 10 years from 2006 through 2015 strategically. In this paper, we prioritize the relative weights of energy technologies in the sector of the national energy efficiency plan by using the AHP/DEA hybrid model, which is one of the multi-criteria decision making (MCDM) method composed of the analytic hierarchy process and data envelopment analysis. We suggest a scientific procedure to measure the relative efficiency and priorities of energy efficiency technologies as decision maker and energy policy makers make a national decision and energy policy.**

Keywords – **AHP, DEA, energy policy, energy efficiency**

I. INTRODUCTION

The Korean Government made a 10-year period program of national energy and resource technology R&D (NERP) in 1997. The Government needs to make a strategic long-term NERP to cope with the forthcoming 10-year period as the previous plan is set to expire. It is also time to establish an efficient energy and resource technology R&D strategy due to a steady increase in the energy technology R&D budget.

The new NERP aims to improve the energy intensity, reduce the emission of greenhouse gases within the United Nations Framework Convention on Climate Change, and contribute to the economic development of the country. The new NERP considers the energy environment including high oil prices, the United Nations Framework Convention on Climate Change, and the hydrogen economy.

In this paper, we apply the analytic hierarchy process (AHP) and data envelopment (DEA) hybrid model to weight the relative preferences of energy efficiency technologies. The Analytic Hierarchy Process (AHP) is a subjective method for analyzing qualitative criteria to generate a weighing of the operating units. Saaty has proposed AHP as a decision making method to solve unstructured problems since 1977 [1]. In general, Saaty indicated that decision making involves tasks such as planning [2], generating a set of alternatives, setting priorities, choosing a best policy after evaluating a set of alternatives, allocating resources, determining requirements, predicting outcomes, designing systems, measuring performance, ensuring the stability of a system, optimizing and resolving conflict [3].

Saaty introduced four principles of the AHP: decomposition, prioritization, synthesis and sensitivity analysis. In the AHP, a decision making process is modeled as a hierarchical structure. At each level in the hierarchy, the decision maker is required to make pairwise comparisons between decision alternatives and criteria using a scaling ratio for the weighing of attributes. The AHP determines the relative ranks or priorities of the decision alternatives.

The DEA is an analytical procedure, based on mathematical programming, developed by Charnes et al. (1978) for measuring the relative efficiency of decision making units (DMUs) in a set. It is used to access the relative efficiency of DMUs. After evaluating the efficiency of energy technology development, a DMU is classified as efficient or inefficient.

We established criteria for evaluating the priorities in energy technologies of energy efficiency plan from a long-term point of view. We applied AHP to generate the relative weights of criteria and alternatives in energy efficiency plan. And then, the relative weights are used to apply for data for measuring the efficiency of the DEA method. We determine the priorities for energy technologies of energy efficiency plan applied to the AHP/DEA hybrid model for the first time. The results of the AHP/DEA hybrid model not only provide the government with an effective decision-making tool as the government makes a strategic energy and resource R&D policy, but also represent a consensus of experts in the sectors of energy efficiency plan.

The remainder of this paper is structured as follows. In section 2, we describe the methodology, which is the AHP and DEA methods including the execution flow chart. Section 3 and 4 then present the results and discussions. Finally, conclusions of this paper are made in Section 5.

II. METHODOLOGY

A. *Execution flow chart*

The execution flow chart is composed of 6 phases. Fig. 1 shows the schematic of the execution flow chart. In the first phase, we analyze the energy policy, the energy environment, short list of energy efficiency technologies. The 2nd phase makes a criteria list to weigh the relative importance of criteria and alternatives. In the 3rd phase,

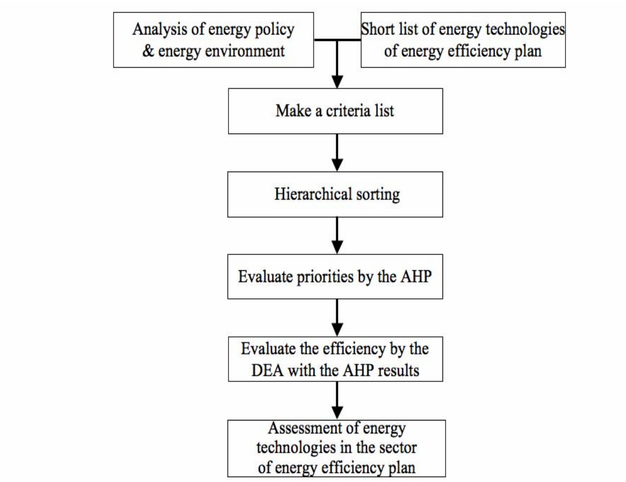

Fig. 1 Execution flow chart

we establish the hierarchy structure and sorts the criteria. In the 4th phase, we evaluate the priorities in energy technologies by the AHP process. The 5th phase evaluates the efficiency of energy technologies by the DEA approach. Finally, the 6th phase evaluates and aggregates the efficiency values resulted from the 5th phase. We focus on prioritizing energy technologies in the sector of the national energy efficiency plan and weigh the priorities of energy efficiency technologies by the AHP/DEA hybrid model.

B. AHP method

The AHP enables the decision makers to structure a complex problem in the form of a simple hierarchy and to evaluate a large number of quantitative and qualitative factors in a systematic manner under multiple conflicting criteria. The AHP makes use of pairwise comparisons matrix, hierarchical structures, and ratio scaling to apply weights to attributes. Problems are decomposed into the hierarchy of a goal, attributes, and alternatives by using the AHP process, shown in Fig. 2. The criteria and alternatives, and the 3rd stage structures the hierarchy, which breaks down the complex problem into a number of small constituent elements and structures the elements

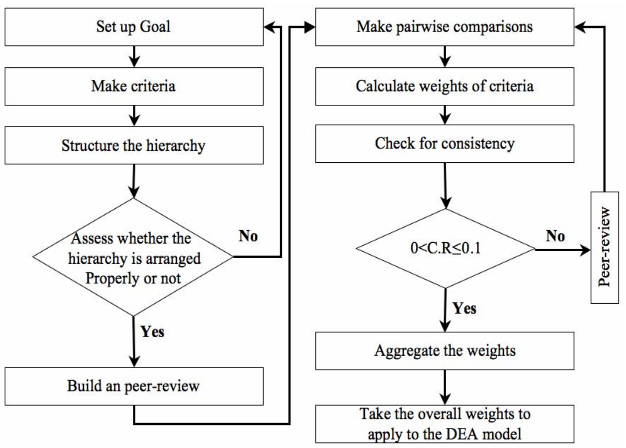

Fig. 2 The AHP process

TABLE I
SCALE FOR PAIRWISE COMPARISIONS

Important scale	Definition	Explanation
1	Equal important	Two elements contribute equally
3	Moderate important	One element is slightly favored over another
5	Strong important	One element is strongly favored over another
7	Very strong important	An element is very strongly favored over another
9	Extreme important	One element is the most favored over another

in a hierarchical form. The 4th stage evaluates whether the hierarchy is arranged properly or not by considering the target. After assessing the hierarchy, we execute peer-review in the 5th stage, which aggregates the weights of experts. In the 6th stage, we make pairwise comparisons, and we then calculate the weights of the criteria and check for consistency in the 7th and 8th stages. Then, in the 9th stage, we review the consistency ratio (CR), which should be between 0 and 0.1. If the CR is greater than 0 and less than 0.1, we move to the 10th stage which aggregates the weights. Finally, we take the overall weights of energy efficiency technologies, which will be applied to the DEA model.

Table 1 shows the scale for pairwise comparisons. The numbers 1, 3, 5, 7 and 9 are used as scaling ratios, corresponding to the strength of preference for one element over another. For example, number 9 represents extreme importance over another element. Generally, the 9-point scale is used because the qualitative distinctions are meaningful in practice and have an element of precision when the items are compared with one another. The ability to make qualitative distinctions is well represented by the 5 possible attributes of equal, moderate, strong, very strong, and extreme.

When we apply the AHP process to take the weights of criteria and alternatives, the decision maker should be consistent in the preference ratings. Formula 1 describes the process of taking the overall weights of alternatives.

$$\begin{pmatrix} \frac{w_1}{w_1} & \frac{w_1}{w_2} & \cdots & \frac{w_1}{w_n} \\ \frac{w_2}{w_1} & \frac{w_2}{w_2} & \cdots & \frac{w_2}{w_n} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{w_n}{w_1} & \frac{w_n}{w_2} & \cdots & \frac{w_n}{w_n} \end{pmatrix} \begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = \begin{pmatrix} nw_1 \\ nw_2 \\ \vdots \\ nw_n \end{pmatrix} \Rightarrow AX = nX \tag{1}$$

If a_{ij} represents the importance of alternative i over alternative j and a_{ik} represents the importance of alternative i over alternative k, $a_{ij} \cdot a_{jk}$ must be equal to a_{ik} that is an estimate of the ratio W_i / W_k for the judgments.

TABLE II
RANDOM INDEX

Matrix index	RI value	Matrix index	RI value
1	0	6	1.24
2	0	7	1.32
3	0.58	8	1.41
4	0.9	9	1.45
5	1.12	10	1.49

If Matrix *A* is not a non-zero vector, there is a λ_{max} of $Ax = \lambda_{max}$, which is the largest eigenvector of Matrix *A*. If the pairwise comparisons matrix is perfectly consistent, then λ=n and CR is 0. For each alternative, the Consistency Ratio is measured by the ratio of Consistency Index (CI) to Random Index (RI). Formula 2 provides the process of calculating the CI values. The values of RI are also described in Table 2.

$$CI = \frac{\lambda_{max} - n}{n-1} \quad (2)$$

$$CR = \frac{CI}{RI} \quad (3)$$

CR≤0.10 implies a satisfactory degree of consistency in the pairwise comparisons matrix, but if C.R.>0.10, serious insistencies might exist and AHP might not yield meaningful results.

The AHP criteria are composed of 2-tier hierarchy. The hierarchy structure of criteria is shown in Fig. 3. At the top of the control hierarchy, the goal is to weigh the energy technologies in the sector of the national energy efficiency plan.

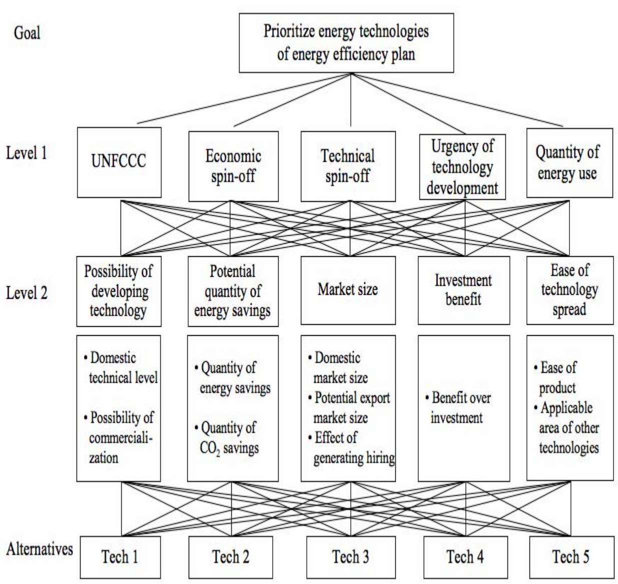

Fig. 3 AHP hierarchy structure

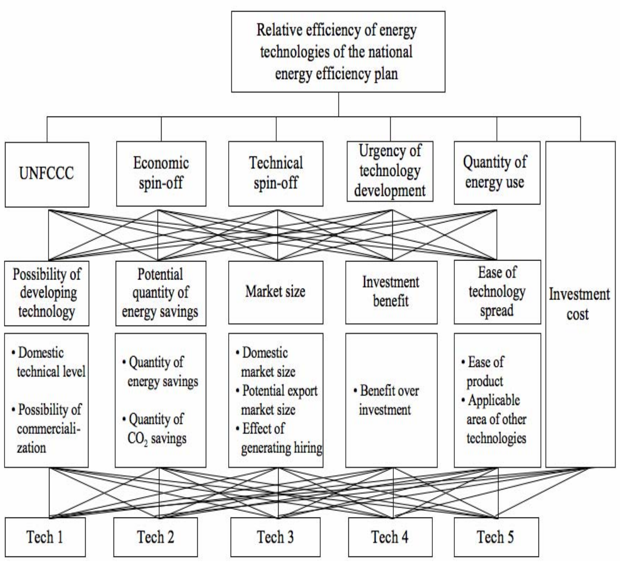

Fig. 4 Hierarchy structure of the DEA process

In Level 1, there exist 5 criteria, which are UNFCCC, economical spin-off, technical spin-off, urgency of technology development, and quantity of energy use. Level 2 is composed of the 5 sub-criteria of possibility of developing technologies, potential quantity of energy saving, market size, investment benefit, and ease of energy use.

C. DEA method

Data envelopment analysis is an evaluation tool for decision making units (DMUs) and solves many decision making problems by integrating multiple inputs and outputs simultaneously. This mathematical method has been applied in a wide range of applications since 1978. The DEA is generally applied not only to assess the service productivity related to banks [4], insurance (Mahajan et al, 1991), hospitals [5], Universities [6] and restaurants, but also to evaluate the efficiency of R&D programs [7].

Fig. 4 shows the hierarchy structure of The DEA process, which is composed of single input factor and multiple output factors. The input factor is composed of investment cost for developing energy efficiency technologies. The output factors are composed of 5 factors, which are possibility of developing technology, potential quantity of energy savings, market size, investment benefit, and ease of technology spread, multiplied from the weights of the UNFCCC, economic spin-off, technical spin-off, urgency of technology development, and quantity of energy use. The relative weights, resulted from the AHP approach, are used to the output factors for the DEA approach.

The DEA ration form, proposed by Charnes, Cooper and Rhodes (1978) [8], is designed to measure the relative efficiency or productivity of a specific DMU_k. The DEA formulation is given as follows. Suppose that there is a set of *n* DMUs to be analyzed, each of which uses *m* common inputs and *s* common outputs. Let *k* (*k*=1, …, n) denote the DMU whose relative efficiency or productivity is to be maximized.

$$\text{Max} \quad h_k = \frac{\sum_{r=1}^{s} u_{rk} Y_{rk}}{\sum_{i=1}^{m} v_{ik} X_{ik}} \tag{4}$$

$$\text{s.t} \quad \frac{\sum_{r=1}^{s} u_{rk} Y_{rj}}{\sum_{i=1}^{m} v_{ik} X_{ij}} \leq 1, \quad \text{for } j = 1, \dots, n \tag{5}$$

$$u_{rk} > 0, \quad \text{for } r = 1, \dots, s \tag{6}$$

$$v_{ik} > 0, \quad \text{for } i = 1, \dots, m \tag{7}$$

Where u_{rk} is the variable weights of given to the r^{th} output of the k^{th} DMU, v_{ik} is the variable weights of given to the i^{th} input of the k^{th} DMU, u_{rk} and v_{ik} are decision variables determining the relative efficiency of DMU_k, Y_{rj} is the r^{th} output of the j^{th} DMU, and X_{ij} is the i^{th} input of the j^{th} DMU. It also assumes that all Y_{rj} and X_{ij} are positive. h_k is the efficiency score and is less than and equal to 1. When efficiency score of h_k is 1, DMU_k is called the efficient frontier. There are two types of CCR model. One version is input oriented model, which minimizes the inputs, and the other is output oriented model maximizing the outputs. In this paper, we apply the output oriented CCR model since we focus on maximizing the multiple outputs.

III. RESULTS

The aim of using the AHP approach is to take the relative weights of criteria and alternatives, which will be the input and output values for measuring the efficiency of energy efficiency technologies in the sector of the national energy efficiency plan by the DEA approach.

As shown in Table 3, multiple outputs and single input are resulted from the AHP approach. Possibility of developing technology, potential quantity of energy savings, market size, investment benefit, and ease of technology spread are multiple outputs respectively and investment cost is the single input for the DEA approach. The unit of investment cost is million US dollar in 2006.

The results of the DEA approach are shown in Table 4. The efficiency score 1.000 means the DMU is the relatively highest efficient and is included on the efficient frontier group comparing with the other DMUs.

TABLE Ⅲ
INPUT AND OUTPUT DATA

Technology	Possibility of developing technology	Potential quantity of energy savings	Market size	Investment benefit	Ease of energy use	Investme nt cost
High-efficiency drying tech	0.019	0.022	0.016	0.015	0.021	99
Fine chemical processing	0.016	0.017	0.022	0.020	0.015	94
Energy conversion tech	0.022	0.021	0.022	0.021	0.020	126
Unutilized energy tech	0.018	0.019	0.019	0.018	0.017	105
Energy material tech	0.022	0.021	0.021	0.022	0.020	178
High efficiency dying tech	0.016	0.014	0.014	0.016	0.016	47
Process automation and intelligence tech	0.025	0.023	0.024	0.029	0.023	47
Supercritical fluid process tech	0.013	0.012	0.011	0.012	0.012	68
Evaporation and distillation tech	0.030	0.028	0.029	0.022	0.024	52
Adsorption separation tech	0.020	0.018	0.018	0.019	0.020	105
Membrane separation tech	0.022	0.030	0.027	0.027	0.029	157
Crystallization tech	0.016	0014	0.017	0.016	0.018	94
Green building tech	0.036	0.052	0.042	0.033	0.044	105
Building renovation tech	0.023	0.021	0.022	0.032	0.022	58
High-efficiency HVAC [a] tech	0.036	0.024	0.027	0.027	0.029	105
CHP [b] tech	0.026	0.025	0.030	0.029	0.026	345
Energy efficiency improvement policy	0.023	0.023	0.023	0.023	0.023	47
High− efficiency low-emission vehicle tech	0.005	0.005	0.005	0.005	0.005	73
Superconductor tech	0.025	0.032	0.019	0.015	0.024	63
Electric power conversion tech	0.052	0.041	0.051	0.057	0.051	230
High efficiency electric heating tech	0.034	0.035	0.042	0.038	0.037	63
Energy storage tech	0.047	0.045	0.049	0.038	0.041	324
Standby power saving tech	0.032	0.036	0.029	0.041	0.038	68
Heat pump tech	0.020	0.025	0.017	0.012	0.013	147
Heat exchange tech	0.018	0.014	0.016	0.014	0.020	47
Boiler tech	0.011	0.010	0.012	0.015	0.013	52
High-efficiency furnace tech	0.011	0.009	0.010	0.009	0.008	47
Burner tech	0.007	0.008	0.010	0.015	0.013	52
Motor tech	0.020	0.021	0.017	0.016	0.018	52
Lighting tech	0.009	0.010	0.010	0.011	0.009	68
Fluid machine tech	0.005	0.006	0.006	0.006	0.008	152
6 major appliances [c]	0.025	0.021	0.027	0.028	0.026	47
DSM tech	0.007	0.007	0.006	0.005	0.004	52

[a] Heating, ventilation and air conditioning [b] Combined heat and power unit
[c] TV, refrigerator, washing machine, air-conditioner, computer, electric rice cooker

TABLE VI
DEA EFFICIENCY SCORE

Technology	Efficiency score	Rank	Technology	Efficiency score	Rank
High-efficiency drying tech	0.384	18	High− efficiency low-emission vehicle tech	0.112	32
Fine chemical processing	0.347	19	Superconductor tech	0.916	6
Energy conversion tech	0.317	25	Electric power conversion tech	0.416	16
Unutilized energy tech	0.325	24	High efficiency electric heating tech	1.000	1
Energy material tech	0.223	30	Energy storage tech	0.258	28
High efficiency dying tech	0.616	12	Standby power saving tech	0.996	3
Process automation and intelligence tech	0.995	4	Heat pump tech	0.297	26
Supercritical fluid process tech	0.347	20	Heat exchange tech	0.747	10
Evaporation and distillation tech	1.000	1	Boiler tech	0.470	15
Adsorption separation tech	0.341	21	High-efficiency furnace tech	0.407	17
Membrane separation tech	0.340	22	Burner tech	0.476	14
Crystallization tech	0.325	23	Motor tech	0.710	11
Green building tech	0.880	8	Lighting tech	0.268	27
Building renovation tech	0.905	7	Fluid machine tech	0.095	33
High-efficiency HVAC tech	0.596	13	6 major appliances[c]	0.989	5
CHP tech	0.139	31	DSM tech	0.254	29
Energy efficiency improvement policy	0.873	9			

Evaporation and distillation tech and high efficiency electric heating tech are on the efficient frontier group, as followed by standby power saving tech, process automation and intelligence tech, and 6 major appliances. The other 29 energy technologies are inefficient. 7 energy efficiency technologies, evaporation and distillation tech, high efficiency electric heating tech, standby power saving tech, process automation and intelligence tech, and 6 major appliances, have over 90% of efficiency scores.

IV. DISCUSSION

In this paper, we prioritize the relative efficiency or productivity by using the AHP and DEA hybrid model. We can take the overall efficiency scores related to energy efficiency technologies in the sector the national energy efficiency plan. The AHP is a powerful tool to decompose the complex problem into a simple hierarchy structure. And the DEA addresses many MCDM problems without the limitation of the units of multiple inputs and outputs. There are various DEA methods. We applied the output oriented CCR model for measuring the relative efficiency scores of energy efficiency technologies.

V. CONCLUSION

This paper describes how to prioritized energy technologies in the sector of the national energy efficiency plan based on the AHP and DEA hybrid approach. This empirical illustration suggests that the energy efficiency technologies can be weighted by MCDM methods efficiently. As a result of the AHP/DEA approach, 2 energy efficiency technologies such as evaporation and distillation tech and high efficiency electric heating tech are efficient comparing with other 29 efficiency technologies. With this hybrid model, we can take the relative efficiency scores of energy efficiency technologies efficiently due to the merits of DEA, which is non-parametric method.

This paper suggests the decision makers and policy makers in the sector of energy that MCDM problems can be addressed by the scientific procedure such as the hybrid model of the AHP and the DEA approaches.

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