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Improving Organizational Efficiency by Combining Tier Analysis and Neural Clustering Method

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Abstract: In this article, I propose a hybrid data envelopment analysis (DEA) system that utilizes a methodology combining the tier analysis with the neural clustering method. I aim to show that the hybrid system can be used to evaluate the inter-organizational efficiency in the life insurance companies. The application is unfolded in two phases. In the first phase, DEA is repetitively used to evaluate the efficiency of DMUs and cluster them together according to their efficiency levels (tier analysis). In the second phase, the system utilizes a self organizing map to group similar DMUs, selects benchmarking targets within a reference set, and provides the guidelines on the stepwise enhancements for the inefficient ones.

Key-words: Hybrid system, Data mining, Neural clustering, Tier analysis, Data envelopment analysis.

1 Introduction

DEA was developed by Charnes et al. [8] as a generalization of the framework of Farrell [13] on the measurement of productive efficiency. DEA, as a non-parametric approach, evaluates relative efficiency of inputs and outputs and determines a set of Pareto-efficient DMUs with an objective of calculating a discrete piecewise frontier.

DEA has been introduced in operational research [8] and economic literatures [12] as a method for assessing the efficiency of activity units. It has been used extensively for assessing the relative efficiency of activity units of non-profit (e.g. education [6][15], courts [17], hospitals [7][9]) and for-profit (e.g. banks [18][19][22], hotel [10], restaurants [1], public houses [2], corporate performance [20]) organizations. Details of the methodology as well as description of DEA can be found in Boussofiance et al., [4] and Fried et al., [14].

As the earlier list of applications suggests, DEA can be a powerful tool used widely. But, despite of its extensive applications and merits, some features of DEA remain bothersome. So, this article presents a hybrid DEA system that utilizes a methodology combining the conventional DEA with the machine learning technology in order to complement drawbacks of the conventional DEA. The application is divided into two phases.

In the first phase, the hybrid system applies DEA to evaluate the efficiency of DMUs with their multidimensional inputs and outputs. After that, the system clusters the DMUs together through the tier analysis, which applies the DEA again to the remaining inefficient DMUs.

In the second phase, the hybrid DEA system derives the stepwise strategies improving the efficiency of a DMU and finds, so-called, the efficiency improvement path for any inefficient DMU. The conventional DEA offers no guidelines about the efficiency improvement, since a reference set for inefficient DMUs just contains several efficient ones. Hence, the system utilizes a technique for dividing DMUs into similar segments. The basic idea is that DMUs within the same segment share similar management environment and, therefore, it is easy for a less inefficient DMU to become more efficient if it tries to follow the management strategy or operation of more efficient ones in the same segment. With the tiers identified by the tier analysis, the segment knowledge is used to find improvement paths for inefficient DMUs.

To verify the usefulness of the proposed methodology, I apply the system to evaluating the inter-organizational efficiency of 29 life insurance companies in Korea. The market for life insurance has become saturated. Participation of foreign life insurance companies into Korean market has made the management environment worse. In fact, small life insurance companies became bankrupt during last couple of years. Therefore, in order to survive in such a highly competitive market, they are eagerly pursuing the productivity improvement in the management and management strategies, which result in improving the efficiency of operation and gaining a competitive advantage. In doing so, life insurance companies need appropriate tools to precisely measure their operational efficiency. Based on these measurements, they can establish their improvement strategies to make themselves more efficient.

2 Data Envelopment Analysis (DEA)

Several characteristics that make DEA powerful are as follows: First, DEA can handle simultaneously multiple inputs and outputs of a DMU. Second, it does not require the assumption of a functional form relating inputs to outputs. Third, DEA directly compares DMUs with a peer or combination of peers, and it provides management with a procedure to differentiate between efficient and inefficient DMUs. Fourth, it pinpoints the degree of deficiency and causes for each inefficient DMU. Fifth, it can detect specific inefficiencies that may not be detectable through other techniques such as linear regression or ratio analysis. Finally, inputs and outputs can have different units of measurement.

Despite of its extensive merits and applications, some features of DEA remain bothersome. First, though DEA is good at estimating 'relative' efficiency of a DMU, it only tells us how well we are doing compared with our peers but not compared with a 'theoretical maximum'. Thus, in order to measure efficiency of a new DMU, we have to entirely develop new DEA with the data of previously used DMUs. We cannot predict the efficiency level of the new DMU without another DEA analysis. Second, because DMUs are directly compared with a peer or combination of peers, DEA offers no guidelines where relatively inefficient DMUs improve. Finally, it does not provide stepwise paths for improving the efficiency of each inefficient DMU.

3 Hybrid DEA System

In this section, I present a hybrid DEA system that combines the tier analysis and the neural clustering method in order to complement drawbacks of the conventional DEA.

3.1 Phase I - tier analysis

The hybrid DEA system uses DEA to evaluate the efficiency of DMUs. DEA determines the most productive group of the DMUs and the less-productive group. The DMUs are clustered into an efficient group or an inefficient one by DEA. A similar approach for clustering DMUs by DEA was presented by Thanassoulis [21]. However, that study made the clusters by the characteristics of the input resource mix not by their efficiency levels. Tier analysis here is a technique that can cluster DMUs according to their efficiency levels.

In the first application of DEA, the hybrid system obtains the efficiency scores of entire DMUs. The results reveal the most efficient group by indicating their scores are equal to 1. I call this group 'tier 1'. Then, the system proceeds DEA again only with the inefficient DMUs which are not on tier 1. DMUs whose efficiency scores are equal to 1 are set 'tier 2' in the second application. I repeat the same procedure while the number of remaining inefficient DMUs is at least three times multiple of that of input plus output variables, as Banker and Kemerer [3] have proposed. I call this procedure *tier analysis*. The hybrid DEA system divides DMUs into several tiers by applying this tier analysis (refer to Fig. 1).

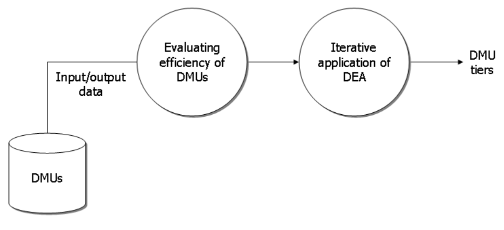

Fig. 1. A procedure of tier analysis.

3.2 Phase II - efficiency improvement path

In the second phase, the hybrid system identifies the stepwise path for improving the efficiency of each DMU, except the most efficient DMUs on the tier 1.

In doing so, the set of DMUs used in the first phase is clustered into a number of segments by using SOM. With the DMU segments by SOM and the DMU tiers by the tier analysis, a set of benchmarking target DMUs are determined. I call this set *enhancement improvement path*, which inefficient DMUs can follow in order to improve their efficiency levels (refer to Fig. 2).

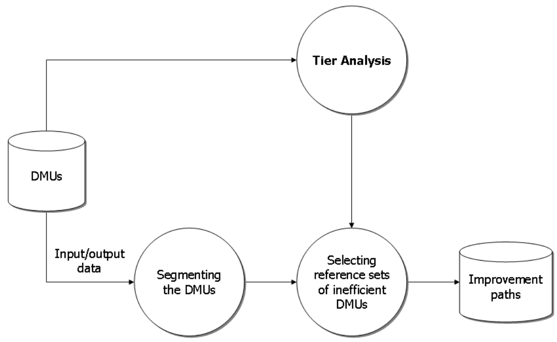

Fig. 2. A procedure of finding stepwise efficiency improvement paths.

4 Application Results

In order to verify the usefulness of the hybrid DEA system, I apply it to the evaluation of the efficiency of 29 life insurance companies (Inter-organizational efficiency).

4.1 Characteristics of life insurance industry

In general, a method of analyzing productivity of a life insurance company is to represent the relationship of inputs and outputs to be a generalized Leontief profit function and to estimate parameters of the function [24]. However, the life insurance industry has such an uncertain management environment as inaccuracy of price information on inputs and outputs, unbalance of the amount of inputs and outputs due to monopoly or duo-poly, the exit from or entry into the industry, and government regulations on insurance rate. These limitations prevent the parametric method, which needs strict assumptions on a population, from being used.

Several researches have been made to measure the efficiency of life insurance companies by using DEA [5][11][23]. However the difficulty of those efficiency studies lies in measuring the productivity of the insurance industry. As Hornstein and Prescott [16] explain, there is not even a conceptual definition of the output to guide the construction of a reasonable measure of its product. Without it, it is not clear what data should be collected and how they should be used to compute an output measure. Therefore two alternatives are often suggested: on one hand, premiums or incurred losses, and on the other hand, the number of policies contracted appropriately. In recent papers, losses and financial investments, and premiums earned are used as a proxy for nominal output.

In this article, I propose an evaluation model of life insurance companies with four input and two output variables, as shown in Table 1.

Table 1. Input and output variables for evaluating life insurance companies.

Variable		Measurement
Input	net operating expenses (NOE)	Subtracting income expenses from such expenses as labor wages, general administration, welfare, and salesman recruiting expenses
	number of office workers (NOW)	The number of persons who manage sales persons and staffs in the head office
	number of sales persons (NSP)	The number of persons who do a business with customers directly
	number of branch offices (NBO)	The number of branch offices geographically dispersed
Output	reciprocal of loss rates (LR)	The ratio of premium receipts to claims paid
	working assets (WA)	Sources of property investment (cash, deposit, trust, securities, and real estate)

Because most companies sell various types of life insurance products and their prices are varying among them, the number of insurance contracts can introduce uncertainty in measurement, so I do not include it as an evaluation factor.

4.2 Tier analysis

DMUs are the 29 life insurance companies in Korea. The hybrid DEA system uses the Charnes-Cooper-Rhodes (CCR) ratio model of DEA to evaluate the efficiency of companies. The system divides 29 companies into four different tiers according to their efficiency levels. In the tier analysis, what is important is which tier each company belongs to.

4.2.1 First tier analysis

Table 2 summarizes the result of the first tier analysis.

Table 2. DMUs on the most effective tier 1.

DMUs on tier 1	Reference set
$C_{1}3$	No references
$C_{1}5$	
$C_{1}17$	
$C_{1}25$	

4.2.2 Second tier analysis

After the first tier analysis, the hybrid system applies DEA again only to the inefficient DMUs which are not on tier 1. DMUs whose efficiency scores reach 1 organize tier 2 in the second tier analysis (refer to Table 3). The same procedure is repeated during the number of remaining inefficient DMUs is at least three times multiple of that of inputs plus outputs.

Table 3. DMUs on the second best tier 2 and their references in tier 1.

DMUs on tier 2	References in tier 1			
$C_{2}1$	$C_{1}3$	$C_{1}5$	$C_{1}17$	$C_{1}25$
$C_{2}12$	$C_{1}3$	$C_{1}5$	$C_{1}17$	
$C_{2}13$	$C_{1}3$	$C_{1}17$		
$C_{2}27$	$C_{1}3$	$C_{1}17$	$C_{1}25$	
$C_{2}28$	$C_{1}3$	$C_{1}17$	$C_{1}25$	
$C_{2}29$	$C_{1}5$	$C_{1}25$		

4.2.3 Third tier analysis

Table 4 summarizes the result of the third tier analysis. In this application to 29 life insurance companies, the fourth tier is the last one derived by the tier analysis, as shown in Table 5.

Table 4. DMUs on tier 3 and their references in tier 2.

DMUs on tier 3	References in tier 2		
$C_{3}2$	$C_{2}12$		
$C_{3}4$	$C_{2}12$		
$C_{3}7$	$C_{2}1$	$C_{2}12$	
$C_{3}15$	$C_{2}12$	$C_{2}29$	
$C_{3}16$	$C_{2}12$	$C_{2}29$	
$C_{3}18$	$C_{2}12$	$C_{2}27$	$C_{2}29$
$C_{3}19$	$C_{2}12$	$C_{2}29$	
$C_{3}22$	$C_{2}12$	$C_{2}29$	
$C_{3}24$	$C_{2}12$	$C_{2}13$	$C_{2}27$
$C_{3}26$	$C_{2}12$	$C_{2}27$	$C_{2}29$

Table 5. DMUs on the least effective tier 4 and their references in tier 3.

DMUs on tier 4	References in tier 3			
$C_{4}6$	$C_{3}2$	$C_{3}16$		
$C_{4}8$	$C_{3}2$	$C_{3}16$	$C_{3}24$	
$C_{4}9$	$C_{3}7$			
$C_{4}10$	$C_{3}4$	$C_{3}7$	$C_{3}24$	
$C_{4}11$	$C_{3}4$	$C_{3}18$	$C_{3}22$	$C_{3}26$
$C_{4}14$	$C_{3}16$			
$C_{4}20$	$C_{3}2$	$C_{3}4$	$C_{3}18$	$C_{3}24$
$C_{4}21$	$C_{3}16$	$C_{3}22$	$C_{3}26$	
$C_{4}23$	$C_{3}2$	$C_{3}4$	$C_{3}16$	$C_{3}24$

4.3 Stepwise efficiency improvement path

A SOM, having six input variables and three by three output nodes, is utilized for clustering DMUs. It has 29 DMUs as a training set. Choosing nine output nodes is appropriate since it is manageable to handle with. Training was performed during 20,000 epochs and was terminated when the change of weight was less than a pre-specified threshold, 0.01.

Table 6 shows the results of segmentation and summarizes the characteristics of each segment. Four segments came out. Segment 1 has one member company ($C_{1}3$), segment 2 has seven companies ($C_{3}2$, $C_{3}4$, $C_{4}6$, $C_{4}8$, $C_{4}9$, $C_{2}12$, $C_{4}14$), segment 3 contains 2 companies ($C_{2}1$, $C_{1}5$), and segment 4 contains 19 companies ($C_{3}7$, $C_{4}10$, $C_{4}11$, $C_{2}13$, $C_{3}15$, $C_{3}16$, $C_{1}17$, $C_{3}18$, $C_{3}19$, $C_{4}20$, $C_{4}21$, $C_{3}22$, $C_{4}23$, $C_{3}24$, $C_{1}25$, $C_{3}26$, $C_{2}27$, $C_{2}28$, $C_{2}29$).

Table 6. Characteristics of each DMU segment.

Seg.	NOE (Avg)	NOW (Avg)	NSP (Avg)	NBO (Avg)	LR (Avg)	WA (Avg)
1	1,411,258	7,912	58,415	1,711	1.07	33,016,684
2	113,017	1,554	8,197	374	0.762	1,769,286
3	758,874	6,769	53,760	1,604	1.02	16,180,759
4	28,436	396	1,656	82	1.35	300,244

DMUs on the lower tiers can find a way for improving their efficiency levels by finding and following the reference DMUs on the upper tiers, which reside in the same segment. For example, $C_{3}24$ on the tier 3 has a reference set that consists of $C_{2}12$, $C_{2}13$, and $C_{2}27$ on the upper efficient frontier 2 (tier 2). Among them, the system chooses $C_{2}13$ as a benchmarking target, since it belongs to the same segment with $C_3$24.

Based on the results from the tier analysis and SOM, the hybrid DEA system can at last identify the stepwise improvement path for each DMU on each tier (except tier 1). For example, the system found an improvement path for $C_4$10 like $C_4$10 → $C_3$24 → $C_2$13 → $C_1$17.

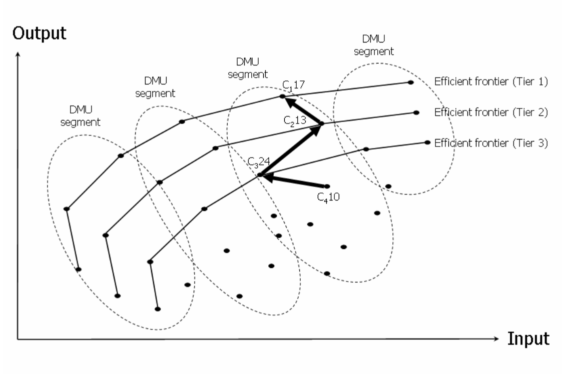

Fig. 3. An improvement path for a DMU $C_4$10 on the tier 4.

As shown in Fig. 3, $C_3$24 is the first benchmarking target on the improvement path toward $C_1$17. Management of $C_4$10 could target the company $C_1$17 from the beginning. However, because there is resource limitation on running business, the strategy pursing a stepwise improvement seems plausible.

According to Table 7, the company, $C_3$24, consumes less net operating expenses (NOE) and operates less number of branch offices (NBO) than $C_4$10. Although $C_2$13, as the second improvement target, spends a similar level of input resources with $C_3$24, the level of working assets (WA) is much higher than that of $C_3$24. At last, $C_1$17 generally spends fewer inputs, especially the number of office workers (NOW), than $C_2$13, but it generates much more outputs, especially in the reciprocal of loss rate (LR). This means that the hybrid DEA system can suggest more important input and output variables to management who considers improving the efficiency of his or her company.

Table 7. Characteristics of the target DMUs on the improvement path for $C_4$10.

Firm	Input factors				Output factors	
	NOE	NOW	NSP	NBO	LR	WA
$C_1$17	26,909	259	1,723	98	0.686	339,621
$C_2$13	26,521	401	1,892	101	0.450	349,576
$C_3$24	25,761	389	1,672	97	0.449	251,910
$C_4$10	32,265	394	1,571	131	0.456	253,137

5 Conclusion and Discussions

In conventional DEA, it simply identifies inefficiencies, identifies comparable efficient units, and locates slack resources. But, the hybrid DEA system I proposed provides more information about discriminant descriptors among input and output variables, which affects the efficiency of DMUs, and about stepwise improvement paths.

The system utilizes a hybrid methodology combining the conventional DEA with the machine learning technology. It was unfolded in two phases. To verify the usefulness of the proposed methodology, the system applied the methodology to evaluating the efficiency of 29 life insurance companies in Korea. The conventional DEA cannot provide any guidelines about efficiency improvement to relatively inefficient companies. The proposed system, however, can choose benchmarking targets for each inefficient company from the reference set. The system can provide information about stepwise improvement path by using SOM as a segmenting tool.

However, the present research has limitations. They can be also the topics for further researches. Environmental factors, including the government policy, may also affect the efficiency of the life insurance companies. Unfortunately, due to the unavailability of data, these variables could not be included in this research. Future system may incorporate exogenous, uncontrollable variables or categorical variables into the production model.

Current practice of management evaluation on life insurance companies in Korea have focused on their capability of growth, productivity, profitability, and soundness and publicity. Therefore a hybrid DEA model including qualitative as well as quantitative data is needed to measure the efficiency of DMUs more accurately.

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