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The New Method for Ranking Grouped Credit Customer Based on DEA Method

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Abstract

Data Envelopment Analysis (DEA) is a widely used non-parametric method for ranking by Decision-Making Units (DMU). Despite the fact that DEA method does not require numerous preconditions, the necessity of the DMUs to be homogeneous is one of the most important rules in applying this technique. Moreover, in real world problems, due to the nature of DMUs, the need for ranking the grouped data has gained significant importance. Credit rating of the financial facility applicants is considered by the banks and financial institutions as one of the most important management issues and significant budget is allocated to develop and imply an effective rating system. Since the applicant organizations operate in different businesses and

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industries, and simultaneous rating of these companies using the DEA method leads to violation of homogeneity rule, thus, application of this powerful tool is restricted. The purpose of this paper is to resolve this key weakness in such a way that makes it possible to simultaneously consider the heterogeneous companies. The results of the proposed method have shown an enhanced capability for rating the decision-making units.

***Keywords**: Modified Data Envelopment Analysis, Grouped data, Credit rating, banking.*

***JEL Classification:** C10, C14, C18, C30, G21*

1. Introduction

The purpose of this paper is to develop a Data Envelopment Analysis (DEA) method for simultaneous rating of the grouped units such as financial facility applicants which operate in different industrial groups. DEA is a non-parametric efficiency evaluation method and has the benefit of not assuming a particular functional form for the production function and deals directly with observable data. The basic idea of the application of non-parametric methods for efficiency measurement were introduced by Farrell (1975) in "Effective productivity measurement" paper which actually led to the development of a novel mathematical method compared with the parametric methods. His theories and ideas led the mathematicians and economists to develop the non-parametric production functions and different efficiency measurements. He laid the foundation of optimization branches in the mathematics science by proposing the most pivotal ideas about the structures of the productivity measurement models and methods and increasing the output and consequently, the productivity without requiring more resources. This was later extended by the work of Charnes, Cooper and Rhodes in 1978 based on the mathematical programming models known as CCR model. In 1984, another model was developed and proposed by Banker, Cooper and Charnes known as BBC. In other words, the basic DEA model is divided into CCR and BCC models. Each model can be investigated from two perspectives: Input-Oriented and Output-Oriented. There are two solutions for each model (CCR and BCC). Thus, eight basic DEA models have been used by some researchers and various models have been developed and extended based on these basic models.

During the last decade, in most of the countries, different applications of the DEA method for performance evaluation have been witnessed. The reason for this widespread acceptance is the possibility of evaluating the complicated and ambiguous relationships among multiple inputs and outputs. This method also provides the ability of benchmarking and identifying inefficient resources. Despite the capabilities of this method, some preconditions especially about the nature of DMUs have restricted the application of this method. One of these preconditions is the homogeneity of the DMUs. The violation of this rule leads to deviations in the problem results. A great deal of rating problems in organizations deal with units that are grouped in completely individual groups and it is necessary to rate them simultaneously. Diversity of the companies and industries adds to the complexity of the credit-based ranking of the financial facility applicants. In other words, one of the most important problems that banks and financial institutions are facing for credit rating of their clients is difference of financial structures and performance of the clients across different groups or industries. This has become a difficult condition for managers and executives in this field. In this paper, DEA method has been extended in order to achieve a comprehensive model for rating the grouped data to be able to perform the rating of different groups of financial facilities applicants at the same time. Then, in section2, literature review of the rating models including the application of DEA method is provided. In section 3, the research methodology is explained in a hierarchical structure. In section 4, the proposed model is explained in greater detail using the data obtained from Tehran Stock Exchange. Section 5 is dedicated to the conclusion. In the final section, limitations and implications for future research are provided.

2. Literature Review

With continuous development of the credit evaluation field, this field plays an important role in the economy of the countries and certification bodies leverage new tools and methods and more advanced technologies in order to extend the credit management process. Credit evaluating is one of the major efforts that have been made in this field. Credit evaluation is defined as the assessment of the client's (credit and financial facility applicants) repayment ability and the probability of the client's failure to repay the debt. The credit evaluation models are divided into two categories: parametric and non-parametric methods. Discriminate Analysis, Linear Probability Model, Logit and Probit models are among the widely used parametric models in various credit researches. The most notable non-parametric models are Analytical Hierarchy Process (AHP), Decision Tree Classification Method, Genetic Algorithm (GA), Expert Systems, Artificial Intelligence, Neural Networks, and Mathematical Planning (Data Envelopment Analysis). The previous researches and studies show that DEA is recognized as one of the most applied rating methods as the mathematical methods subsets. Figure 1 illustrates the steps of this structured process. As it is shown in figure 1, the rating and DEA problems have been investigated in parallel and after the review of the national and international studies, the focus is put on the rating models using DEA method and finally, research innovations are determined through the Gap Analysis.

Result of the Figure 1 has shown that DEA method has been applied mostly for the comparison of the utility of the banks and their branches. The researches made in the field of banking utility (productivity) has led to the publication of special issues in the original operational research journals and has become a specialized field.

Performance measurement of banks at the branch level shows that the number of the studies carried out for credit-based ranking of the clients using DEA method is limited. For instance, ZChe et al., in 2010; Eddie al., in 2007; Emel et al., in 2003 used DEA method for credit rating of clients. One of the major reasons that DEA method has not been applied in credit evaluating field is the heterogeneity of the units. As we mentioned earlier, homogeneity of the DMUs is one of the principal preconditions for the application of DEA method where the financial facility applicants in different industries are not homogenous at the first view. Moreover, necessity for simultaneous rating of these enterprises with respect to the limited resources of the banks for credit allocation and industry prioritization has driven the banks and financial institutes to develop and implement viable and robust system for this purpose. In this paper, besides determining the credit evaluation metrics (criteria), DEA model has been developed in a way that it is applicable for simultaneous rating of applicant companies in different industries. Table 1 provides the summary of the gap analysis results that define the innovation of this research.

Figure1: Schematic view of the literature review process.

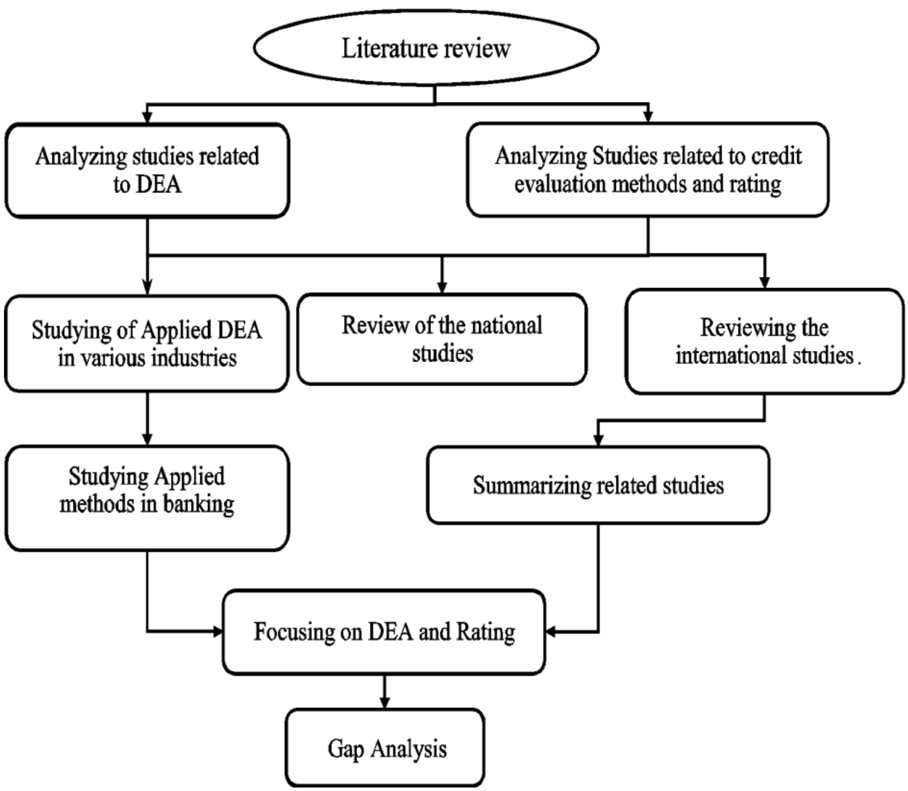


Table 1: The gap analysis results

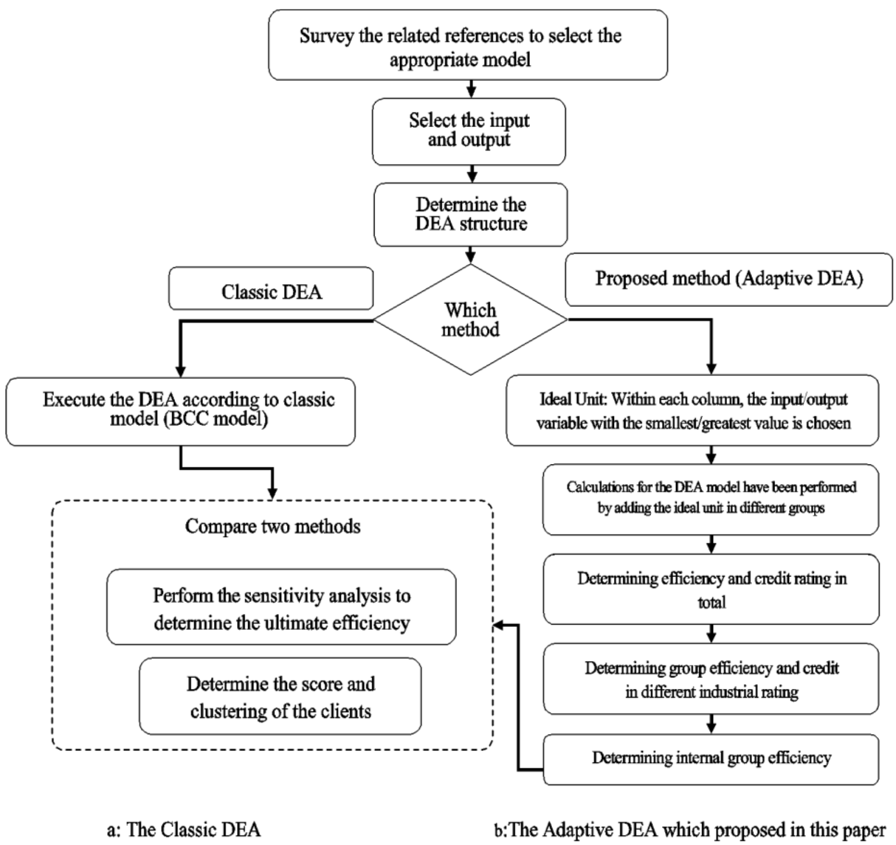
Authors	Year	Evaluation Criteria Determination	Criteria Prioritization	Rating/Scoring	Group- based Rating	Efficient Units Rating	Designing the Credit Evaluation Structure	Model Comparison	Sensitivity Analysis
Emel et al.,	2003	✓	✓	✓				✓	✓
Grunertet et al.,	2005	✓	✓	✓					
Lee and Chen	2005	✓	✓	✓				✓	
Jankowitschet et al.,	2007	✓	✓						✓
Huang et al.,	2007	✓	✓	✓				✓	
Eddie	2007	✓		✓					✓
Abdou et al.,	2008			✓				✓	
Stefanescu et al.,	2009			✓					
Abdou	2009	✓	✓	✓				✓	✓
Tsai and Chen	2010	✓		✓				✓	✓
ZChe et al.,	2010	✓	✓	✓					✓
Yap et al.,	2011	✓		✓				✓	
Malik M., Thomas	2012	✓		✓					✓
Chi and Hs	2012	✓	✓	✓				✓	✓
Hens and Tiwar	2012			✓				✓	
Bijak and Thomas	2012	✓		✓				✓	
This study	**-**	✓	✓	✓	✓	✓	✓	**-**	✓

3. Models and Methodology

3.1. Using the DEA method for ranking grouped data

In this study the overall implementation steps of proposed model for credit evaluating of grouped data are as follows:

Figure 2: The implementation steps of proposed model (Adaptive DEA) for client credit clustering



1- Identify and categorize model's input and output and normalize the applicants' information.
2- Execute DEA model in the existing and proposed method which is called Adaptive DEA.
3- Perform the sensitivity analysis to determine the ultimate efficiency.
4- Compare the obtained results from two DEA methods and determine the efficiency and accuracy of the proposed model.
5- Determine the score and clustering of the clients.

In this study, the adaptive DEA method has been used to identify the credit criteria for the bank’s facilities applicants and then an efficient method has been proposed for credit clustering of the bank’s facility applicants. The applied DEA model in this study is described as follows:

Model Parameters and variables
i = 1, 2, …, n Number of input variables
J = 1, 2, …, m Number of output variables
K = 1, 2, …, k Number of the industry
R = 1, 2, …, r Number of industrial clusters
θ = efficiency

S_{iR}^{-} :Input slack of i^{th} variable in R^{th} cluster

$$S_R^- = \sum_{i=1}^{n} S_{iR}^-$$

S_{jR}^{+} :Output slack of j^{th} variable in R^{th} cluster

$$S_R^+ = \sum_{j=1}^{m} S_{jR}^+$$

λ_{KR} : Shadow price of K^{th} industry in R^{th} cluster

λ_R : Shadow price of R^{th} cluster

$$\lambda_R = \sum_{K=1}^{k} \frac{\lambda_{KR}}{K}$$

$$\sum_{R=1}^{k} \lambda_R = 1$$

γ_K : Shadow price of K^{th} industry

$$\gamma_K = \lambda_R \times \lambda_{KR}$$

X_{iKR} :i^{th} Input variable vector for K^{th} industry in R^{th} cluster

Y_{JKR} :J^{th} output variable vector for K^{th} industry in R^{th} cluster

X_{iR} :i^{th} Input variable vector for R^{th} cluster

$$X_{iR} = \sum_{K=1}^{k} \frac{X_{iKR}}{K}$$

Y_{JR} :J^{th} Output variable vector for R^{th} cluster

$$Y_{JR} = \sum_{K=1}^{k} \frac{Y_{JKR}}{K}$$

X_R : Input variable vector for R^{th} cluster

$$X_R = \sum_{i=1}^{n} \frac{X_{iR}}{n}$$

Y_{JR} :Output variable vector for R^{th} cluster

$$Y_R = \sum_{j=1}^{m} \frac{Y_{JR}}{m}$$

X_{oR} : The input variable value of the ideal unit between R^{th} clusters

Y_{oR} : The output variable value of the ideal unit between R^{th} clusters

X_{oKR} : The input variable value of the ideal unit between all units

Y_{oKR} : The output variable value of the ideal unit between all units

Mathematical Model:
Objective function

$$Min = \theta - \varepsilon\left(\sum_{i=1}^{n}\sum_{r=1}^{r} S_{iR}^{-} + \sum_{j=1}^{m}\sum_{r=1}^{r} S_{jR}^{+}\right)$$

The Objective function is defined in order to maximize the efficiency and minimize distance from efficiency frontier.

Constraints:

$$\sum_{R=1}^{r} \lambda_R \times Y_{JR} - S_R^{+} = Y_R \qquad \text{j:1,2,….,m}$$

$$\sum_{R=1}^{r} \lambda_R \times X_{iR} + S_R^{-} = \theta X_R \qquad \text{i:1,2,….,n}$$

$$\sum_{K=1}^{k} \sum_{R=1}^{r} \lambda_{KR} \times Y_{JKR} - S_{JR}^{+} = Y_{JR} \qquad \text{j:1,2,….,m}$$

$$\sum_{K=1}^{k} \sum_{R=1}^{r} \lambda_{KR} \times X_{iKR} + S_{iR}^{-} = \theta X_{iR} \qquad \text{i:1,2,….,n}$$

$$\sum_{R=1}^{r} \sum_{k=1}^{k} \lambda_R \times \lambda_{KR} = \sum_{K=1}^{k} \gamma_K = 1$$

$$\sum_{R=1}^{r} \lambda_R = 1$$

$$X_{oR} = Min\{X_{1R}, X_{2R}, ..., X_{nR}\}$$

$$Y_{oR} = Max\{Y_{1R}, Y_{2R}, ..., Y_{mR}\}$$

$$X_{oKR} = Min\{X_{111}, X_{112}, ..., X_{nkR}\}$$

$$Y_{oKR} = Max\{Y_{111}, Y_{112}, ..., Y_{mKR}\}$$

$$X_R^{*} = Min\{X_1, X_2, ..., X_R\}$$

$$Y_R^{*} = Max\{Y_1, Y_2, ..., Y_m\}$$

$X_{iR}, Y_{JR}, \; X_R, Y_R \geq \varepsilon$ i = 1, 2, …, n, J = 1, 2, …, m, R = 1, 2, …, r

$\lambda_{KR}, \lambda_R, S_{iR}^-, S_{jR}^+, S_R^-, S_R^+ \geq 0$

θ free

3.2. The influential factors on customer credit rating

For determining the criteria affecting the client's credit rating, in the first step, the criteria have been identified and categorized through the literature review. Then, these criteria and the related clusters have been improved through several interviews with senior experts from different bank branches and banking facility applicants. The summary of the final criteria and their clustering is provided in table 2.

Table 2: Comparative Studies and Input and Output Variables

Variable	Factor		Authors
Input	In(1)	Capital	Cummins et al.(2002) , Feroz et al., 2(2003)
	In(2)	Retained Profit	Aitman (1998), Feroz et al., 2(2003), Cheng et al. (2007)
	In(3)	Current Liability	Liang et al.(2006)
	In(4)	Long-term Liabilities	Omero et al.(2005), Molhotra et al.(2008)
	In(5)	Legal reserves	-
Output	Out(1)	Interest Coverage Rate	Liang et al.(2006), Cheng et al.(2007), Molhotra et al.(2008), Margaritis et al.(2009)
	Out(2)	Asset Return Ratio	Brid (2001), Capobianco et al.(2004), Duzakin et al.(2007), Molhotra et al.(2008)
	Out(3)	Quick Ratio	Duzakin et al.(2007)
	Out(4)	Average Collection Period	Feroz (2003)
	Out(5)	**Return on Shareholder's equity**	Brid (2001), Margaritis et al.(2009), Liang et al.(2006)

For determining the validity level of the criteria, the opinions of the banking credit experts, financial management professors and credit applicant experts have been taken into account. Stability of these criteria has been calculated through the Cronbach's Alpha method and has been verified by 86%.

Static population in this study has been drawn based on the investigation and consultation with filed senior experts and as a result, 35 companies that have received the bank financial facilities from 2009 to 2010 and were listed in the Tehran Stock Exchange have been selected. These information and financial ratios have been completed with respect to the Stock Exchange rules and regulations and are homogenous and highly accurate. Also, access to the financial information of the selected companies is easier in this way.

4. The Proposed DEA Model (Grouped DEA)

In this study, a dummy unit has been considered as an “ideal” unit and is named as "Ideal unit". The output and input variables in the ideal unit are determined as follows (the schematic is shown in figure 2):

1- Within each column, the input variable with the smallest value is chosen.

2- Within each column, the output variable with the greatest value is chosen.

3-The minimum value of every input variable is considered as the input variable value of the ideal unit.

4- The maximum value of every output variable is considered as the output variable value of the ideal unit.

5- Calculations for the DEA model have been performed by adding the ideal unit as a new unit.

6- Determining efficiency and credit rating in total

7- Determining group efficiency and credit rating in different industries

8- Determining internal group efficiency

In the Adaptive DEA, the ideal unit has to be defined whenever the model is executed. Use of the ideal unit in DEA model reduces the company prioritizing steps based on the efficiency level, reduces the decision-making and calculation time, eliminates the efficiency of 100% and above 100%, optimizes the number of the target companies, and finally, encourages the efficient companies to achieve the ideal condition. This model proposes a direct, shortcut and dynamic path for efficient and inefficient companies to achieve a higher level of efficiency.

4.1. Information analysis of the understudied companies

Debt collection constitutes a considerable amount of financial resources required for banking operations. For banks that have been unsuccessful at collecting debts, it means the loss of a considerable part of assets and financial resources. Therefore, banks try to properly evaluate the credit applicants more efficiently by using different methods for reducing the credit and facilities' non-pay off risk. The companies for the statistical sample have been chosen from 10 different industries including: food, pharmaceutical, electrical devices, automotive, basic metals, cement and plaster, manufacturing equipment and machinery, telecommunications, glass and crystal, and mineral industry.

When model input and output are defined, it is necessary to normalize the information due to industry variety and statistically heterogeneous companies. The normalized information is provided in table 3.

Using the normalized information and GAMS software, efficiency for each unit is calculated. The obtained results from the DEA method for companies (relative and final efficiency) are provided in table 4.

Table 3: Input and output values for the studied companies

DMU	group	Inputs					Outputs				
type		In(1)	In(2)	In(3)	In(4)	In(5)	Out(1)	Out(2)	Out(3)	Out(4)	Out(5)
DMU 1	1	0.457	0.133	0.075	0.174	0.382	0.135	0.982	0.18	0.257	0.317
DMU 2		0.186	0.327	0.054	0.251	0.527	0.282	0.917	0.245	0.118	0.397
DMU 3		0.172	0.088	0.012	0.171	0.394	0.197	0.575	0.207	0.158	0.286
DMU 4		0.328	0.214	0.015	0.165	0.277	0.125	0.411	0.135	0.752	0.294
DMU 5		0.248	0.165	0.021	0.121	0.391	0.148	0.725	0.822	0.695	0.268
DMU 6		0.368	0.018	0.015	0.115	0.094	0.032	0.516	0.502	0.827	0.721
DMU 7	2	0.185	0.055	0.029	0.118	0.411	0.128	0.726	0.197	0.531	0.427
DMU 8		0.224	0.782	0.341	0.275	0.274	0.099	0.769	0.165	0.127	0.315
DMU 9	3	0.161	0.981	0.189	0.492	0.412	0.087	0.918	0.809	0.172	0.712
DMU 10		0.167	0.063	0.012	0.151	0.392	0.257	0.896	0.159	0.217	0.349
DMU 11		0.148	0.529	0.275	0.316	0.545	0.179	0.942	0.951	0.111	0.712
DMU 12		0.183	0.225	0.027	0.251	0.297	0.112	0.812	0.407	0.769	0.727
DMU 13		0.028	0.975	0.016	0.216	0.592	0.192	0.851	0.291	0.912	0.127
DMU 14	4	0.199	0.352	0.173	0.115	0.274	0.118	0.168	0.392	0.891	0.429
DMU 15		0.617	0.369	0.096	0.116	0.276	0.112	0.818	0.418	0.413	0.642
DMU 16	5	0.218	0.276	0.015	0.127	0.527	0.122	0.728	0.389	0.695	0.518
DMU 17		0.128	0.242	0.026	0.119	0.112	0.105	0.175	0.197	0.517	0.812
DMU 18		0.094	0.179	0.431	0.475	0.048	0.167	0.284	0.415	0.375	0.915
DMU 19	6	0.419	0.098	0.25	0.341	0.327	0.027	0.725	0.147	0.192	0.175
DMU 20		0.124	0.126	0.013	0.121	0.142	0.042	0.395	0.871	0.527	0.287
DMU 21		0.056	0.829	0.012	0.181	0.121	0.165	0.452	0.325	0.361	0.296
DMU 22		0.253	0.147	0.011	0.162	0.872	0.014	0.222	0.498	0.397	0.452
DMU 23	7	0.068	0.196	0.282	0.277	0.505	0.182	0.241	0.272	0.539	0.481
DMU 24		0.217	0.141	0.015	0.117	0.285	0.125	0.892	0.189	0.894	0.586

DMU	group	Inputs					Outputs				
DMU 25	8	0.328	0.137	0.014	0.252	0.219	0.096	0.945	0.197	0.367	0.421
DMU 26		0.242	0.415	0.011	0.211	0.417	0.027	0.127	0.212	0.285	0.297
DMU 27		0.018	0.745	0.021	0.117	0.128	0.172	0.922	0.842	0.471	0.342
DMU 28	9	0.621	0.248	0.051	0.282	0.351	0.225	0.968	0.158	0.542	0.571
DMU 29		0.317	0.156	0.016	0.151	0.342	0.117	0.722	0.751	0.821	0.428
DMU 30		0.286	0.541	0.025	0.174	0.351	0.115	0.741	0.925	0.274	0.272
DMU 31		0.321	0.722	0.042	0.124	0.512	0.217	0.269	0.261	0.295	0.568
DMU 32		0.045	0.641	0.121	0.212	0.115	0.486	0.516	0.927	0.116	0.821
DMU 33	10	0.441	0.025	0.168	0.274	0.012	0.227	0.249	0.822	0.271	0.572
DMU 34		0.352	0.049	0.257	0.215	0.541	0.411	0.275	0.711	0.561	0.625
DMU 35		0.412	0.117	0.618	0.718	0.217	0.126	0.212	0.768	0.549	0.276
Ideal DMU		0.018	0.018	0.011	0.115	0.012	0.486	0.982	0.951	0.912	0.821

Table 4: Calculated efficiency

Type	Efficiency	Credit rating	Group efficiency	Group credit rating	Internal group efficiency	Internal group credit rating
DMU (0)	1	1	1	1	1	1
DMU 1	0.976	2	0.797	3	0.987	2
DMU 2	0.961	3			0.973	3
DMU 3	0.497	24			0.503	5
DMU 4	0.467	26			0.473	7
DMU 5	0.482	25			0.488	6
DMU 6	0.949	4			0.960	4
DMU 7	0.521	22	0.718	5	0.544	3
DMU 8	0.915	5			0.956	2
DMU 9	0.901	6	0.876	2	0.948	2
DMU 10	0.853	8			0.897	3
DMU 11	0.508	23			0.534	6
DMU 12	0.841	9			0.885	4

Type	Efficiency	Credit rating	Group efficiency	Group credit rating	Internal group efficiency	Internal group credit rating
DMU 13	0.828	10			0.871	5
DMU 14	0.371	33	0.581	7	0.414	3
DMU 15	0.791	12			0.883	2
DMU 16	0.768	13	0.731	4	0.868	2
DMU 17	0.744	14			0.842	3
DMU 18	0.682	16			0.771	4
DMU 19	0.659	17	0.544	9	0.795	2
DMU 20	0.452	27			0.545	4
DMU 21	0.439	28			0.529	5
DMU 22	0.628	18			0.757	3
DMU 23	0.597	19	0.572	8	0.749	2
DMU 24	0.548	20			0.689	3
DMU 25	0.422	29	0.437	11	0.550	3
DMU 26	0.532	21			0.696	2
DMU 27	0.357	35			0.466	4
DMU 28	0.342	36	0.479	10	0.361	6
DMU 29	0.385	32			0.408	4
DMU 30	0.417	31			0.448	3
DMU 31	0.886	7			0.943	2
DMU 32	0.367	34			0.383	5
DMU 33	0.812	11	0.614	6	0.896	2
DMU 34	0.425	30			0.469	4
DMU 35	0.705	15			0.778	3

4.2. Sensitivity analysis

For analyzing the results, the process is repeated by eliminating an input or an output factor from all of the DMUs based on stepwise method. This may cause an increase, decrease or no change in DMU's efficiency. If elimination of an input factor leads to the unit's efficiency increase, then that input variable is a surplus and has a significant effect on the efficiency of that unit. However, if the efficiency of that unit is reduced, that means the unit has accurately and carefully utilized the input variable and has a significant impact on unit's efficiency. Also, this analysis can be performed by eliminating the output variables. For example, if elimination of an output leads to the increase of unit's efficiency, then that unit has not been successful in achieving the desired output and should pay more attention to increase its output and that output has a considerable impact on DMU's efficiency. On the contrary, if the efficiency of that unit is reduced, that means the DMU has been successful in achieving the desired output and has a significant impact on DMU's efficiency.

Accordingly, the changes of DMU's efficiency are provided in table 5.

Table 5: Efficiency reduction in case of input or output variable elimination

Efficiency reduction value in case of input elimination							Efficiency reduction value in case of output elimination				
Group	**Efficiency**	**In(1)**	**In(2)**	**In(3)**	**In(4)**	**In(5)**	**Out(1)**	**Out(2)**	**Out(3)**	**Out(4)**	**Out(5)**
1	0.797	0.036	0.360	0.013	0.016	0.096	0.241	0.000	0.049	0.042	0.019
2	0.718	0.076	0.203	0.125	0.129	0.357	0.011	0.214	0.000	0.141	0.191
3	0.876	0.786	0.108	0.179	0.134	0.140	0.232	0.062	0.091	0.001	0.109
4	0.581	0.074	0.093	0.108	0.108	0.382	0.000	0.304	0.000	0.354	0.151
5	0.731	0.000	0.055	0.122	0.130	0.284	0.000	0.000	0.000	0.286	0.000
6	0.544	0.000	0.132	0.000	0.004	0.159	0.105	0.018	0.064	0.094	0.062
7	0.572	0.148	0.000	0.000	0.248	0.000	0.008	0.011	0.098	0.000	0.008
8	0.437	0.120	0.000	0.077	0.084	0.067	0.067	0.034	0.082	0.038	0.039
9	0.479	0.016	0.126	0.082	0.094	0.084	0.074	0.017	0.085	0.108	0.003
10	0.614	0.322	0.173	0.161	0.173	0.356	0.040	0.004	0.065	0.062	0.005

In order to determine the importance of each input and output variable globally, it is necessary to calculate the average efficiency reduction. Accordingly, based on the average efficiency reduction, it is possible to provide an overall analysis on each input and output variable's importance (priority) among the facility applicants.

Accordingly, inputs and outputs have been eliminated for each industry and the respective efficiency has been calculated. The importance of the inputs and outputs for each industry are provided in table 6.

Table 5: Efficiency reduction in case of input or output variable elimination

Efficiency reduction value in case of input elimination							Efficiency reduction value in case of output elimination				
Group	**Efficiency**	**In(1)**	**In(2)**	**In(3)**	**In(4)**	**In(5)**	**Out(1)**	**Out(2)**	**Out(3)**	**Out(4)**	**Out(5)**
1	0.797	0.036	0.360	0.013	0.016	0.096	0.241	0.000	0.049	0.042	0.019
2	0.718	0.076	0.203	0.125	0.129	0.357	0.011	0.214	0.000	0.141	0.191
3	0.876	0.786	0.108	0.179	0.134	0.140	0.232	0.062	0.091	0.001	0.109
4	0.581	0.074	0.093	0.108	0.108	0.382	0.000	0.304	0.000	0.354	0.151
5	0.731	0.000	0.055	0.122	0.130	0.284	0.000	0.000	0.000	0.286	0.000
6	0.544	0.000	0.132	0.000	0.004	0.159	0.105	0.018	0.064	0.094	0.062
7	0.572	0.148	0.000	0.000	0.248	0.000	0.008	0.011	0.098	0.000	0.008
8	0.437	0.120	0.000	0.077	0.084	0.067	0.067	0.034	0.082	0.038	0.039
9	0.479	0.016	0.126	0.082	0.094	0.084	0.074	0.017	0.085	0.108	0.003
10	0.614	0.322	0.173	0.161	0.173	0.356	0.040	0.004	0.065	0.062	0.005

Table 6: Input and output variables priority rating by industry

Efficiency reduction value in case of input elimination						Efficiency reduction value in case of output elimination				
Group	**In(1)**	**In(2)**	**In(3)**	**In(4)**	**In(5)**	**Out(1)**	**Out(2)**	**Out(3)**	**Out(4)**	**Out(5)**
1	3	1	5	4	2	1	5	2	3	4
2	5	2	4	3	1	4	1	5	3	2
3	1	5	2	4	3	1	4	3	5	2
4	5	4	2	3	1	5	2	4	1	3
5	5	4	3	2	1	5	4	3	1	2
6	5	2	4	3	1	1	5	3	2	4
7	2	5	4	1	3	3	2	1	5	4
8	1	5	3	2	4	2	5	1	4	3
9	5	1	4	2	3	3	4	2	1	5
10	2	4	5	3	1	3	5	1	2	4

5.2. Conclusion and Suggestions for Future Research

The purpose of this paper is to resolve this key weakness in such a way which makes it possible to simultaneously consider the heterogeneous companies (DMUs). The results of the proposed method have shown an enhanced capability for rating the decision-making units. In this study, these financial ratios have been considered as the DEA model input and output variables. In this research, the efficiency has been calculated using the existing and the Adaptive DEA model which demonstrates identical results. Then, the effect of each input and output variable on the efficiency value has been determined using the sensitivity analysis. Finally, the companies were rated by industry and results show the influence of the industry type on the input and output ratings. The proposed model defining an ideal unit results in the reduction of prioritizing steps, calculation and decision-making time, and reduction of the number of target companies to achieve the ideal situation. Furthermore, the new proposed DEA model provides a straightforward, shortcut and dynamic path to obtain a greater efficiency for both efficient and inefficient companies and it is used for simultaneous rating of the grouped units such as financial facility applicants that operate in different industrial clusters and groups.

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