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Adaptive DEA for clustering of credit clients

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A R T I C L E I N F O

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A B S T R A C T

Competition among the industrial and service organizations to provide their clients with financial and credit requirements through the banking facilities has considerably increased. On the other hand, the challenge facing these financial and credit resources is that they are limited. Therefore, the optimal allocation of these limited financial resources with the aim of maximizing the investment value is of a great priority for banks and other financial institutes. In this study, first the credit criteria for the applicants for bank facilities have been identified and then based on the improved Data Envelopment Analysis (DEA) technique, an effective method has been proposed for the client clustering. The improved DEA method which is called Golden DEA reduces the calculation time and increases the decision-making operations that ultimately lead to the improvement of the existing method. Also, the improved DEA model provides a short, dynamic and straight path in order to achieve greater efficiency for every institution. The priority provided by the improved DEA method has been compatible with the priority given by the existing DEA method for all of the understudied cases.

1. Introduction

One of the most common activities of the banks, and financial and credit institutions is to provide financial and credit facilities to their clients. Due to the limited financial resources, banks always strive to improve the client evaluation and loaning process using decision-making tools and techniques. Client rating models provide a large and considerable amount of the information required by the banks for the effective management of the credits. The objective of the client rating models is to predict the risk of the repayment by the clients and classifying the credit applicants. The advantages of these methods include time saving, cost saving, eliminating the personal judgments, increasing the applicant evaluation accuracy and reducing the facilities repayment risk. Until now, various methods such as Data Envelopment Analysis [1], Linear Regression and Logistics [2], Genetic Algorithm [3,4], Data mining[5]and Neural Networks[6], have been proposed for the client rating. One of the major causes of bankruptcy for banks and financial institutions is their inability to collect the debts. Therefore, nowadays, client rating is considered as one of the most critical subjects in the financial management context. The objective of this paper is to identify and classify the facility applicants evaluation criteria, compare and credit assessment of the results obtained from the improved DEA and the existing DEA methods and finally, classify the facility applicants.

The structure of this paper is as follows: in section2, the related literature review is presented. Section 3 deals with the application of the DEA method in the client classification context. In section 4, the influential factors on the customer credit rating have been identified and clustered. In section 5, the improved DEA model (Golden DEA) is described, and the sampled companies have been analyzed in section 6. Section 7 is dedicated to the sensitivity analysis and the industry level analysis results are provided is section8.Finally, the conclusion and areas for future research are provided in section 9.

2. Research background

2.1. Literature Review

Facilities provided by banks play a significant role in country's economy, since the increase in the investments leads to the development of the country's economic pillars [7]. On the other hand, provision of these facilities exposes the banks to customer credit risks-Customer credit risk is the probability of the debt (loan) not being paid off by the facility applicants (clients). There are several ways to manage and control the customer credit risk. One way is the use of the customer credit classification based on their behavior forecast [8] .The assessment and classification of the customer credits incorporate a great deal of complexities due to various qualitative and quantitative factors such as financial, economic and cultural. On the other hand, the thorough assessment of customer credit imposes the cost increase and operations delay. This time constraint and necessity of accurate assessment add up to its complexity [9,10]. Levy et al.(1991) has used five factors which are Credit, Capacity, Capital, Collateral, and Character for the assessment of the applicant's specifications[11]. According to Basel Committee on Banking Supervision (BCBS), banking operations are exposed to several risks such as Credit Risk, Market Risk, Liquidity Risk, Operating Risk, Legal Risk, Human Risk, Interest Rate Risk and Price Fluctuations Risk[12]. The lack of effective and efficient decision-making for the customer credit assessment and measurement in banks leads to undesirable outcomes and risks in the financial mechanisms [13]. The most common application of customer credit rating is to estimate the probability of debt (loan) payoff [14]. The most common models for customer credit rating are Logit and Probit model, Linear Discriminate Analysis, The Closest Neighborhood, Neural Network and Genetic Algorithm models [15].

Credit rating utilizes methods which help the financial institutes in decision-making as to whether to accept or reject the facility applicants. This decision-making is considered as one of the most important credit processes [16]. The credit rating for each customer is, in fact, a number that represents the credit status of the facility applicant at a specific time. It is a valid method for credit background evaluation and it is a simple and quantitative method for debt payoff (payment) risk assessment and a tool for balancing the investment portfolio, decision-making transparency, customer credit risk assessment and finally, for predicting and resolving the crisis[17](Dellin et al, 2005). Additionally, this process quantitatively categorizes the effects of different variables [18] (Cooper, 1999). This method is one of the fundamental and effective tools available in the investment markets and risk management [19] and helps to reduce the assessment time, decrease the assessment costs, make the acceptance process target-based and increase the validity of the credit decisions [20].

Data envelopment analysis is a fractional mathematical programming technique that has been developed by Charnes, Cooper, and Rhodes (1978) [21]. The DEA methodology is a non-parametric approach which is used to define the efficiency frontiers and calculate the relative efficiency for each of the observations based on the level of deviation from the most efficient observation. One of the strengths of the DEA is to measure and calculate the relative efficiency without determining the input and output data weights with use of less data. DEA method is suitable for selecting the best location for a shop, best candidate for a job, best plan, best contractor and etc. There are two DEA models: Input-oriented model (CCR) and Output-oriented model (BCC). CCR model is designed with assumption of constant returns to scale while BCC model is referred to Variable Return to Scale.

In DEA model, efficiency rating is performed based on three criteria: how many times a function or department has been chosen as the benchmark, the weighted sum of the times a function or department has been chosen as the benchmark and Peterson-Anderson model. Banks decide to accept or reject the credit or loan applicant and decide the proper loan pay-off period by analyzing their financial ratios. These analyses are done based on the balance sheet, profit and loss statement, and liquidity flow information. The use of financial ratios is the most common method for analyzing the financial data and for that purpose, banks and financial institutions are clustered based on the financial status, credit rating and credit risk. Financial ratios are divided to five groups of Liquidity, Activity, Leverage, Profitability and Stock Market. Emel et al (2003) upgraded the quantitative analysis used in the financial performance modules of state-of-the-art credit scoring methodologies [22]. The DEA-based methodology was applied to data for 82 industrial/manufacturing firms comprising the credit portfolio of one of Turkey's largest commercial banks. Jiao (2007) proposed a validity evaluation model for using the fuzzy logic [23]. Kim and Ahn (2012) tried to propose a convenient model for client credit rating by developing a hybrid model in the banking industry using the Artificial Intelligence [24]. Oreski et al. (2012) proposed a feature selection technique for finding an optimum feature subset that enhances the classification accuracy of neural network classifiers [25].

Maher et al (1997) used neural network and logistic regression techniques in order to improve the forecasting accuracy of the client credit rating models [26]. Yardakall et al.(2004) [27]used the Analytical Hierarchy Process (AHP) for client credit rating in Turkish banks. Biener et al (2012) employed cross-frontier analysis, an innovative tool based on data envelopment analysis, to provide new insight into the relationship between organization and efficiency in international insurance market [28]. Halkos et al (2004) conducted a study with the aim of evaluating the performance of 50 commercial banks in Greece using the DEA technique [29]. Mok et al. (2007), in a research using the DEA technique, determined the efficiency of the Chinese toy making companies [30]. In this study, financial ratios of the companies have been used for the analysis. Tsolas (2004) in his research titled as "Modeling bank branch profitability and effectiveness by means of DEA" proposed a general performance assessment framework in terms of efficiency and effectiveness [8]. Sufian et al (2010) evaluated the efficiency of the Taiwan banking industry between 1999 and 2008 using the DEA method [31]. Client Credit Rating using the financial ratios has been addressed by Brid (2001), Cummins et al. (2002), France et al. (2003), capobianco and Fernandes (2004), Omero et al. (2005), Liang et al. (2006), Duzakin et al. (2007) and Margaritis et al. (2009) , Siriopoulos et al(2010) [9,32-39]; whereas some other researchers, among whom are Liang et al. (2006), Cheng et al. (2007), who performed client credit rating using DEA [36,40].

In this research, the rating of the clients applying for financial facilities has been carried out using the financial ratios and DEA method. For this purpose, the existing and the improved DEA methods were used and the validity of the improved DEA model has been proven by comparing the results. The improved DEA method reduces the calculation and decision-making time, the zigzag and spiral directions, while delivering the same results as the existing DEA method.

3. Using the DEA method for clustering the credit applicants

Client credit rating is a complicated and professional context that requires different solution methods based on the environmental complexity and dynamics. Thus, the first step is to determine the suitable method and to execute it. Credit rating methods are divided into two groups of quantitative and qualitative methods. The qualitative methods depend on the experience and ability of the persons in charge of credit offering but quantitative methods depend on the model and conversion functions. Quantitative models are divided into two groups of parametric and non-parametric methods. Non-parametric methods include AHP, DEA, Expert Systems, Neural Networks, Genetic Algorithm and etc. Parametric methods include Audit Analysis Model, Logit and Probit Models and etc.

Data Envelope Analysis (DEA) technique is a mathematical programming approach to assess the Decision-Making Units (DMU) which use several inputs to generate several outputs. CCR models try to reduce the input while the output is fixed and analyze the effect of each input on the efficiency [41].Therefore, CCR models are mostly suitable for cases where the unit's performance is at the optimum scale while factors such as competition, financial constraints, poor management performance and etc. impede the units from performing at their optimum scale. In this case, in order to assess the effects of the structural changes and encourage the manager to obtain the higher levels of efficiency, BCC model is used. In this study the overall implementation steps of DEA for client credit clustering are as follows:

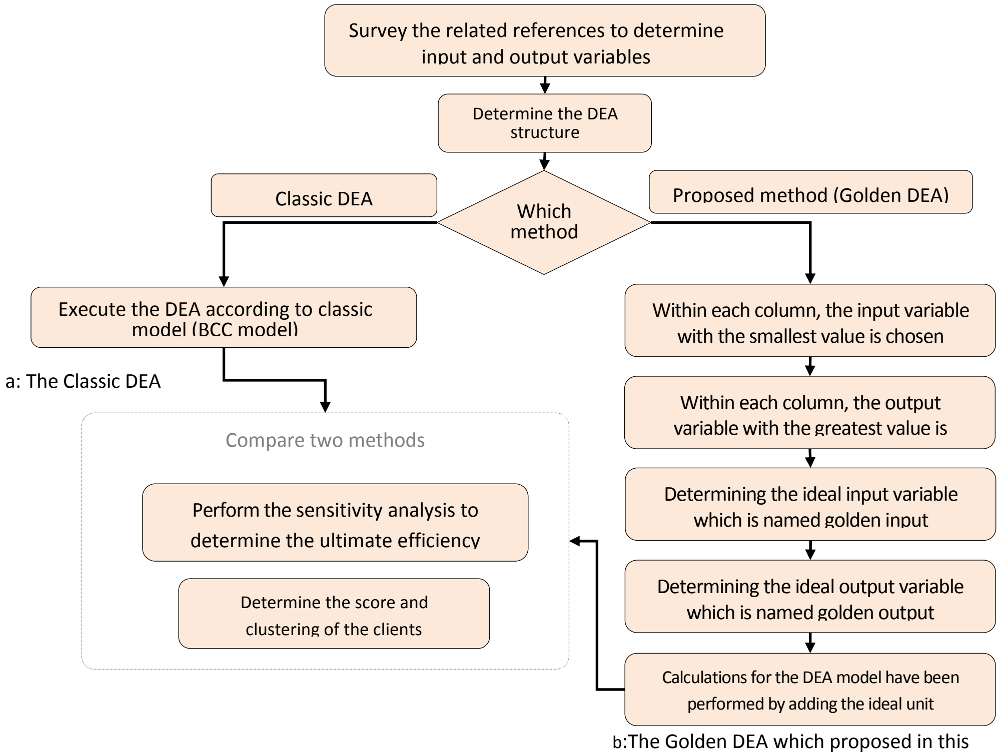

Fig 1 The implementation steps of proposed model (Golden DEA) for client credit clustering

1. Identify and categorize model's input and output and normalize the applicants' information.
2. Execute Data Envelope Analysis model in the existing and the improved model (proposed method which is called Golden DEA and it is explained in section 5.
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 improved model.
5. Determine the score and clustering of the clients.

In Data Envelope model, there's no need to weigh the input and output data since in this method, weights are determined automatically. In this model, several units are chosen as reference units. This reference set represents a linear combination of efficient units and form the efficiency frontiers [41].DEA method calculates the input and output weights through the sensitivity analysis on inputs, outputs and the efficiency difference between units. DEA is a non-parametric mathematical programming model and since there's no need to estimate the form/shape of the conversion function and predetermined assumptions, it's been more practical. DEA requires less information compared to other multi-factor decision-making methods such as AHP [41].Therefore, in this study, the improved DEA method has been used to identify the credit criteria for the banks facilities applicants and then an efficient method has been proposed for credit clustering of the banks facility applicants. The applied DEA model in this study is described as follows:

Model Parameters and variables

$r = 1, 2, \ldots, z$ Number of output variables

$i = 1, 2, \ldots, m$ Number of input variables

$j = 1, 2, \ldots, n$ Number of the examined banks

θ = efficiency

S_r^+ : output slack variable r

S_r^+ : input slack variable i

λ_j : Shadow price for bank j

Y_r : Output-oriented variable vector for all banks

X_i :Input-oriented variable vector for all banks

ε : A non-zero number smaller than any positive real number

x_{ij} : Input variable i for bank j

y_{rj} : Output variable r for bank j

Mathematical Model:

$$\text{Max } y_0 = \theta - \varepsilon\left(\sum_{r=1}^{z} S_r^+ + \sum_{i=1}^{m} S_i^-\right) \tag{1}$$

$$\text{S.t.} \quad \sum_{j=1}^{n} \lambda_j . y_{rj} - S_r^+ = \theta . Y_r \qquad r = 1, 2, \ldots, z \tag{2}$$

$$\sum_{j=1}^{n} \lambda_j . x_{ij} + S_i^+ = \theta . X_i \qquad i = 1, 2, \ldots, m \tag{3}$$

$$\sum_{j=1}^{n} \lambda_j = 1 \qquad j = 1, 2, \ldots, n \tag{4}$$

$$(\lambda_j, S_r^+, S_i^-) \geq 0, \ \theta : \text{free} \tag{5}$$

$$(X_i, Y_r) \geq \varepsilon, \qquad \varepsilon \succ 0 \tag{6}$$

4. Identification and rating of the influential factors on customer credit rating

In order to obtain further information to identify and categorize the criteria affecting the clients credit rating applying for banking facilities, as the first step, these 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 1.

In order to determine 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 large 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.

Table 1 Comparative Studies and Input and Output Variables

Variable	Factor		Authors	Ref
Input	In (1)	Capital	Cummins et al (2002), Feroz et al 2 (2003)	[33],[7]
	In (2)	Retained Profit	Aitman (1998), Feroz et al 2 (2003), Cheng et al (2007)	[14],[7],[41]
	In (3)	Current Liability	Liang et al (2006)	[36]
	In (4)	Long-term Liabilities	Omero et al (2005), Molhotra et al (2008)	[35],[42]
	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)	[36],[40],[42],[38]
	Out (2)	Asset Return Ratio	Brid (2001), capobianco et al (2004), Duzakin et al(2007), Molhotra et al (2008)	[32],[33],[37],[42]
	Out (3)	Quick Ratio	Duzakin et al (2007)	[37]
	Out (4)	Average Collection Period	Feroz (2003)	[7]
	Out (5)	Return on Shareholder's equity	Brid(2001), Margaritis et al(2009), Liang et al (2006)	[32],[38], [36]

5. The proposed DEA model (Golden DEA)

DEA is a mathematical and non-parametric programming method that has been extensively applied due to the absence of the need for the numerous a priori assumptions, needlessness of the estimation of the shape/form of the conversion function and need for less information in comparison with other multi-factor decision-making approaches such as AHP and also for the non-requirement of weighted input and output data [41]. This model seeks to calculate the relative efficiency of the units against each other and when a new unit is added, the efficiency score for all units will change.

In this study, a dummy unit has been considered as an “ideal” unit which named as "golden unit". The output and input variables in the ideal unit (golden unit) are determined as follows (the schematic is shown in Fig (1):

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.

In the improved DEA model (Golden DEA), the ideal unit has to be defined whenever the model is executed. Accordingly, the ideal unit is not a fixed unit and at each execution, it is improved. 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, reduces the zigzag and spiral movements 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.

6. 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 for banks. Therefore, banks try to properly evaluate the credit applicants more efficiently using different methods in order to reduce 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. The most notable companies among these industries include Iran Khodro, SAIPA, Shahab Khodro, Loghman Pharmaceutics, Azadeghan Cement, Khoozestan Steel, Esfahan's Mobarakeh Steel and Machine Sazi Arak Co.

When model input and output are defined, it's necessary to normalize the information due to industry variety and statistically heterogeneous companies. Accordingly, input and output data are divided by total assets value for each company, so different companies of different sizes become homogenous and comparable. The normalized information is provided in Table 2.

Using the normalized information and DEAOS software, efficiency for each unit is calculated for two cases: one case with and one without the ideal unit. The obtained results from the DEA method for companies (relative and final efficiency) are provided in Table 3. The final efficiency is determined by Anderson and Peterson's model for rating the efficient units. As it is shown in Table 3, the efficiency sequence results for DEA (1) and the improved DEA (2) are the same. But, efficiency values for two methods are different, however proportional.

Table 2 Input and Output values for the studied companies

DMU			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	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	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	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	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	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	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	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 25	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	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	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
Golden DMU	0.018	0.018	0.011	0.115	0.012	0.486	0.982	0.951	0.912	0.821

Table 3 Calculated Efficiency

DMU	**DEA (1)**			**Golden DEA (2)**	
Type	Efficiency	Final Efficiency	Credit Rating	Efficiency	Credit Rating
DMU 0	-	-	-	1	1
DMU 1	1	3.697	1	0.976	2
DMU 2	1	3.156	2	0.961	3
DMU 3	0.846	0.846	23	0.497	24
DMU 4	0.805	0.805	25	0.467	26
DMU 5	0.812	0.812	24	0.482	25
DMU 6	1	2.657	3	0.949	4
DMU 7	0.975	0.975	21	0.521	22
DMU 8	1	2.648	4	0.915	5
DMU 9	1	2.237	5	0.901	6
DMU 10	1	2.131	7	0.853	8
DMU 11	0.872	0.872	22	0.508	23
DMU 12	1	1.985	8	0.841	9
DMU 13	1	1.967	9	0.828	10
DMU 14	0.577	0.577	32	0.371	33
DMU 15	1	1.484	11	0.791	12
DMU 16	1	1.536	12	0.768	13
DMU 17	1	1.521	13	0.744	14
DMU 18	1	1.251	15	0.682	16
DMU 19	1	1.237	16	0.659	17
DMU 20	0.781	0.781	26	0.452	27
DMU 21	0.761	0.761	27	0.439	28
DMU 22	1	1.185	17	0.628	18
DMU 23	1	1.172	18	0.597	19
DMU 24	1	1.129	19	0.548	20
DMU 25	0.751	0.751	28	0.422	29
DMU 26	1	1.027	20	0.532	21
DMU 27	0.467	0.467	34	0.357	35
DMU 28	0.452	0.452	35	0.342	36
DMU 29	0.578	0.578	31	0.385	32
DMU 30	0.622	0.622	30	0.417	31
DMU 31	1	2.215	6	0.886	7
DMU 32	0.516	0.516	33	0.367	34
DMU 33	1	1.852	10	0.812	11
DMU 34	0.742	0.742	29	0.425	30
DMU 35	1	1.257	14	0.705	15

7. Sensitivity Analysis

For the purpose of results analysis, the process is repeated by eliminating an input or an output factor from all of the DMUs. 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 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 efficiency values for DMU's before and after the elimination of the input and output variables and amount of increase and decrease in relation to each eliminated input and output variable are provided in Table 4. Further analysis of the results can be expressed as follows: each eliminated input or output variable that reduces DMU's efficiency the most holds the highest rating and this procedure is applied until all the input and output variables have been ranked. For example, long term receivable facilities for DMU (24) have the greatest importance (priority) because elimination of this input variable reduces the efficiency of DMU (24) the most with regard to other DMUs. Results are presented in Table 4 which has been calculated for DEA (1) and DEA (2) which show no significant difference.

Table 4 Efficiency reduction in case of input or output variable elimination

DMU	Efficiency	Efficiency Reduction value in case of input elimination					Efficiency Reduction value in case of output elimination				
Type		In(1)	In(2)	In(3)	In(4)	In(5)	Out(1)	Out(2)	Out(3)	Out(4)	Out(5)
DMU 1	0.976	0.085	0.425	0	0	0.025	0.145	0	0.191	0	0.021
DMU 2	0.961	0.105	0.41	0	0	0.027	0.318	0	0	0.019	0
DMU 3	0.497	0	0.315	0.039	0.049	0	0.405	0	0	0	0
DMU 4	0.467	0	0.427	0.04	0.045	0.438	0.341	0	0.017	0.159	0.015
DMU 5	0.482	0.025	0.285	0	0	0.085	0.235	0	0.088	0.073	0.075
DMU 6	0.949	0	0.296	0	0	0	0	0	0	0	0
DMU 7	0.521	0.151	0.405	0	0	0.286	0.021	0.035	0	0.282	0
DMU 8	0.915	0	0	0.25	0.257	0.427	0	0.392	0	0	0.381
DMU 9	0.901	0.045	0.465	0	0	0.642	0	0	0	0.222	0
DMU 10	0.853	0	0.255	0.082	182	0	0	0.123	0	0	0.092
DMU 11	0.508	0.342	0.176	0.471	0.392	0.428	0.311	0.151	0	0.241	0.127
DMU 12	0.841	0.154	0	0.115	0.125	0.091	0	0	0.003	0.082	0
DMU 13	0.828	0	0	0	0	0	0	0.182	0	0	0.156
DMU 14	0.371	0.147	0	0.215	0.216	0.212	0	0	0	0.176	0
DMU 15	0.791	0	0.186	0	0	0.551	0	0.608	0	0.531	0.302
DMU 16	0.768	0	0	0	0	0	0	0	0	0	0
DMU 17	0.744	0	0.024	0	0	0.375	0	0	0	0.375	0
DMU 18	0.682	0	0.142	0.367	0.391	0.476	0	0	0	0.482	0
DMU 19	0.659	0	0.528	0	0	0.581	0	0.071	0	0	0.057

Table 4 Efficiency reduction in case of input or output variable elimination

DMU 20	0.452	0	0	0	0	0.012	0.419	0	0	0.071	0
DMU 21	0.439	0	0	0	0	0.041	0	0	0.057	0.305	0
DMU 22	0.628	0	0	0	0.017	0	0	0	0.198	0	0.192
DMU 23	0.597	0	0	0	0	0	0	0	0	0	0
DMU 24	0.548	0.295	0	0	0.496	0	0.016	0.021	0.195	0	0.015
DMU 25	0.422	0.361	0	0.231	0.251	0.071	0	0	0.245	0	0.011
DMU 26	0.532	0	0	0	0	0	0.032	0	0	0.113	0
DMU 27	0.357	0	0	0	0	0.13	0.169	0.101	0	0	0.105
DMU 28	0.342	0	0.135	0	0	0.056	0.037	0.021	0.15	0	0.017
DMU 29	0.385	0.035	0	0.085	0.102	0.012	0.113	0	0.275	0.065	0
DMU 30	0.417	0.015	0.305	0	0	0.21	0.037	0	0	0.005	0
DMU 31	0.886	0.012	0.015	0.152	0.171	0.012	0.169	0.065	0	0.142	0
DMU 32	0.367	0.017	0.176	0.171	0.198	0.131	0.012	0	0	0.328	0
DMU 33	0.812	0.272	0.251	0.367	0.397	0.571	0.102	0	0.169	0	0
DMU 34	0.425	0.168	0.192	0.115	0.121	0.412	0	0	0.027	0	1015
DMU 35	0.705	0.527	0.076	0	0	0.085	0.017	0.011	0	0.186	0

Table 5 Importance of input and output variables for the studied companies

Average	Output Variable	Average	Input Variable	Rating
0.194	Interest Coverage Ratio	0.241	Capital	1
0.081	Asset Return	0.175	Retained Profit	2
0.068	Return on shareholders' equity	0.048	Current Liability	3
0.052	Quick Ratio	0.031	Long-term Liabilities	4
0.043	Average Collection Period	0.014	Legal reserves	5

In order to globally determine the importance of each input and output variable, it's necessary to calculate the average efficiency reduction by eliminating each input and output variable. Accordingly, based on the average efficiency reduction, it's possible to provide an overall analysis on each input and output variable's importance (priority) among the facility applicants. The average efficiency reduction along with the related ratings is provided in Table 5.

8. Industry level analysis

In this section, customer credit rating has been performed using DEA for 10 different industries. The purpose of this analysis is to determine the importance of the inputs and outputs at each industry.

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. Based on the results, the most important input and output variables for the food industry are respectively the retained profit and interest coverage ratio. The most important input and output variables for the pharmaceutical industry are respectively the long term facility and assets expected return. Therefore, the industry type has a significant role in determining the input and output variables priority and must be considered in evaluating different company credit levels.

Table 6 Input and output variables priority rating by industry

Industry	Inputs					Outputs				
type	In(1)	In(2)	In(3)	In(4)	In(5)	Out(1)	Out(2)	Out(3)	Out(4)	Out(5)
Food	2	1	4	3	5	1	2	5	3	4
Pharmaceutical	5	3	2	1	4	5	1	3	2	4
Electrical Devices	1	2	5	4	3	2	4	5	1	3
Automotive	3	2	1	4	5	5	2	3	4	1
Base Metals	2	1	3	5	4	2	5	3	5	1
Cement and Plaster	1	2	3	4	5	2	4	3	5	1
Equipment and Machinery	3	1	5	4	2	3	2	5	1	4
Telecommunications	2	3	5	1	4	1	2	4	3	5
Glass and Crystal	3	2	4	1	5	2	1	3	4	5
Mining Industry	1	2	5	3	4	3	1	5	2	4

9. Conclusions

Delayed debts are considered as one of the challenges of country's banking system. One of the fundamental initiatives to resolve this dilemma is the establishment of a credit assessment and client credit rating system for bank clients. The financial ratios extracted from financial statements of the companies have proven to be an effective tool for evaluating the companies. 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 improved 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, elimination of efficiency of 100% and above 100%, reduction of the number of target companies, reduction of the zigzag and spiral directions and encouragement of the efficient companies to achieve the ideal situation. Furthermore, the improved DEA model provides a straightforward, shortcut and dynamic path to obtain a greater efficiency for both the efficient and inefficient companies. Expansion of the DEA model in a way that makes it possible to compare the rated (ranked) companies and to calculate the relative and overall efficiency within each industry group is proposed for the future research.

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