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The New Method for Credit Customer Selecting by Integration of A^2 and Data Envelopment Analysis (A^2_DEA)

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Abstract

This paper develops a decision support tool using an A^2 method and data envelopment analysis (DEA) approach (A^2-DEA). This new method is applied for the bank credit customer selection problem and credit scoring as a pilot survey at Export Development Bank of Iran. The proposed method has led to fewer calculations, faster and more accurate decision making, less complexity, and ability to analyze many scenarios with only one or a few

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judgments of decision makers while the effect of the subjective opinion of one single decision maker will be avoided. This proposed method is compared with adaptive analytical hierarchy process approach, which is suggested by Lin et al., in 2008, and it is named A^3. An illustrative example demonstrates the implementation of the proposed approach. This example demonstrates how this approach can avoid the main drawback of the current method, and more importantly, can deal with the credit customer selection more convincingly and persuasively. The implementation results show that this method is significantly valid for ranking credit customers. Comparison of methods shows that although A^3 have benefits, it also suffers from limitations, which can be avoided by the A^2-DEA model, also improves the time and cost needed for implementing in comparison.

Keywords: *A^2 method, Data envelopment analysis, Credit customer selection.*

JEL Classification: *C21, C22, C51, G21, G23*

Motivation and Significance

There have been several selecting and scoring methods reported in the literature. However, each of these methodologies has its strength and weakness. This study proposes an integrated algorithm for ranking and selecting credit customer based on A^2method and data envelopment analysis (DEA) which is named A^2-DEA model. The proposed algorithm is capable to rank and select credit customer based on a set of input–output data. The results of this study provide policy makers with an appropriate tool to make more accurate selecting of customers for issuing loans. This is because the proposed approach is capable of handling non-linearity, complexity as well as uncertainty that may exist in actual data sets.

1. Introduction

Credit scoring models are widely used by financial institutions, especially banks, to assign credit to good applicants and to differentiate between good and bad credit. Using credit scoring can reduce the cost of the credit process and the expected risk of being a bad loan, enhancing the credit decision, and saving time and effort. Particularly, with the fast growth in the credit industry and the huge loan portfolio management, credit scoring is regarded as the most important technique in banks and has become a very critical tool during recent decades. For banking institutions, loans are often the primary source of credit risk. Traditional lending practice has been to grant loans that have a positive net present value (NPV) and to deny those that do not. Recently, the use of various models has been increased significantly. To assess the risk of these loans, banks use credit scoring models and credit ratings to estimate default risk on a single obligor basis.

Credit scoring is a basic binary classification task in finance. Many studies have contributed to increasing the accuracy of the classification model with various kinds of statistical tools. With the rapid growth in the credit, credit-scoring models with low discriminatory power can lead to under-pricing of bad and overpricing of good loans. Therefore, credit scoring needs high accuracy to avoid bad debts. The objective of the Credit scoring 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 risk of facilities repayment. Until now, various methods such as Data Envelopment Analysis, Linear Regression and Logistics, Genetic Algorithm, Data mining and Neural Networks, 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 applicant's evaluation criteria, compare and credit assessment of the results obtained from the improved DEA and finally, classify the facility applicants.

In other words, this article presents the development of a conceptual framework which aims to ranking the different industry sections for issuing loan based on multiple factors. The proposed conceptual framework combines the A^2 method which is suggested by Hosseini Nasab et al., in 2012 with the non-parametric technique known as DEA. This approach uses the result of AHP and DEA as input values of the Artificial Neural Network (ANN) model for developing and improving the A^2 method, with a little change based on the experience of experts in the field. We have named this method A^2-DEA. For comparing this new method, we have used the A^3 methodology (which was presented by Lin et al., in 2008) to determine the priority of different industries for issuing loan. In other words, in this paper we have proposed a new method named A^2-DEA and have compared it with the A^3 method. In spite of A^2 having advantages, there are also some limitations which include the lack of ability in having objective decision while it is based on subjective decision. We have omitted these limitations by proposing the A^2-DEA method. Increased speed of implementation, decreased cost, ability of both subjective and objective decision, ability of analyzing several scenarios in short time and low cost, are some of the A^2-DEA advantages. In this study, we have followed these questions: 1- How can we assess the ranking of industries for issuing a financial institution special bank by the A^2-DEA and A^3 methods? 2- What are the advantages of the A^2-DEA method to the A^3 method? How can we analysis several scenarios by the A^2-DEA method?

The remainder of this paper is organized as follows, Section 1.1 briefly presents the well-known A^3 method presented by Lin et al. and section 1.2 is devoted to introducing the AHP approach introduced by Herrera-Viedma (2004) and artificial neural networks data envelopment analysis (DEA). The details of the research methodology are illustrated in section 2. Then in section 3, the model development and experimental details of this study are presented. Section 4 discusses the results and scenarios, and Section 5 presents the concluding remarks of this study. In section, the limitations and future research are explained.

1.1. Adaptive AHP Approach (A^3)

In 2008 Lin et al., proposed the A^3 method, which used a soft computing scheme, Genetic Algorithm (GA), to recover the real number weightings of the various criteria in AHP and provided a function for automatically improving the consistency ratio of pairwise comparisons.

Saaty proposed a method of measuring Consistency Ratio (CR) (see Saaty, 1980). If CR exceeds 0.10, the pairwise comparison needs to be reassessed. The reassessment process is boring and does not guarantee the consistency of pairwise comparisons. Thus, another reassessment is necessary if the resulting CR remains unsatisfactory. Reassessment is simply too expensive for sorting out inconsistencies. In the investigation of Lin et al., the A^3 method using GA is developed to recover the continuous relative importance weights of the various criteria based on two objective values: (1): CR, and (2): the difference of the derived pairwise weighting matrix (PWM) from the initial PWM. In this method, the search process of GA is guided by minimizing CR; it results in an adapted PWM with lower CR, which is acceptable in terms of the consistency requirements of AHP. The search process is also guided by minimizing the difference from the initial PWM. Thus, the resulting PWM reserves the original beliefs of the decision maker (DM) regarding the relative importance relationship among the criteria. The proposed A^3 also provides an automatic mechanism for improving CR, and thus eliminates the reassessment process of AHP. In section 3, this method is explained by means of an empirical case for comparing with the A2 method, which we have proposed in this study, and we have also discussed the advantages and limitations of both methods.

1.2. A^2 Method and Data Envelopment Analysis (A^2-DEA)

1.2.1. Analytical hierarchy process (AHP)

The AHP is based on pairwise comparison judgments and can provide a flexible and powerful tool for handling both qualitative and quantitative multi-criteria problems, which is developed by Saaty (1980). Its main distinction is that AHP has been applied to a wide variety of decisions. AHP provides an estimate of additive utility weight that best matches the initial information provided by the decision-maker and it provides a meaningful way to measure and combine tangible and intangible criteria in any decision. This can also be used with other techniques. For instance, Wanichpongpan et al. (2007), Hermann et al. (2007) and Kim et al. (2009) used AHP and Life Cycle Assessment (LCA) as decision support tool or multi-criteria analysis tool in fields of assessing environmental performance or assessing the recycling potential of materials. In this paper, we integrate AHP and ANN to consider not only qualitative and quantitative factors but also having many scenarios in short time and low cost.

The traditional AHP uses n×(n-1)/2 judgments in a preference matrix with n alternatives. Because of that, it takes a long time to collect judgments and to do calculations. In this study, rather than using conventional AHP، the pairwise comparison approach is based on the model which Herrera-Viedma proposed in 2004. This method considers only n-1 judgments and enables decision makers to express their preferences over a set of alternatives with the fewest judgments, it also avoids checking the consistency in the decision-making process. In section 4, this method is explained by means of an empirical case.

1.2.2. Artificial neural network (ANN)

A neural network is a simplified model of the way the human brain processes information. ANNs mimic the ability of the biological neural systems in a computerized way by resorting to the learning mechanism as the basis of human behavior (Cui and Han, 2008). ANNs are a class of flexible non-linear models that can find patterns adaptively from the data. Theoretically, it has been demonstrated that given an appropriate number of non-linear processing units, ANNs can learn from experience and estimate any complex functional relationship with high accuracy. Their approximating power comes from the parallel processing of the information from the given data. ANNs have been broadly applied to many estimating problems. For instance Kuo et al., have integrated ANN and two multi-attribute decision analysis methods to develop a green supplier selection model. The main reason for their success is that they are capable of discovering the hidden relationship (mapping) in data. ANNs have a lot of application in recent years. In 2012, Liao presented a general methodology for developing environmental emergency decision support systems (EEDSS) based on ANN.

The ANN `learns' the governing relationships in the input and output data sets by modifying the weights between its nodes. In essence, a trained

ANN model can be viewed as a function that maps input vectors to output vectors. Single hidden layer network based on Back Propagation (BP) learning is the most widely used model form for estimating. BP learning is a kind of supervised learning introduced by Werbos (1974) and later developed by Rumelhart & McClelland (1986).

At the beginning of the learning stage all weights in the network are initialized to small random values. The algorithm uses a learning set, which consists of input – desired output pattern pairs. Each input – output pair is obtained by the offline processing of historical data. These pairs are used to adjust the weights in the network to minimize the Sum Squared Error (SSE). This error function measures the difference between the real and the desired values overall output neurons and all learning patterns. After computing SSE, the back propagation step computes the corrections to be applied to the weights.

The architecture of ANN model usually consists of three parts: an input layer, the hidden layers and an output layer. The information contained in the input layer is mapped to the output layer through the hidden layers. Each neuron can receive its input only from the lower layer and sends its output to the neurons only on the higher layer.

To find out the most reliable model, several performance indicators can be used. The performance of the ANN models based on their reliability is evaluated by a regression analysis between the predicted values by the ANN models and the actual values. The indicators used with aim of performance evaluation for both training and test data sets are the root mean square error (RMSE) and correlation coefficient. The root mean square error is calculated by:

$$RMSE = \sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - \hat{y}_i)^2} \tag{1}$$

where $\hat{y}_i$ is the predicted value by the ANN model, y_i is actual value and m is the number of points in the data set. The absolute fraction of variance, a statistical criterion that can be applied to multiple regression analysis, is calculated by:

$$R^2 = 1 - \left(\frac{\sum_{i=1}^{m}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2}\right) \tag{2}$$

The absolute fraction of variance ranges between zero and one. Ideally, R^2 should be close to one, whereas a poor fit results in a value near zero.

1.2.3. Data envelopment analysis (DEA)

DEA is a methodology based on applications of linear programming. It has been successfully employed for assessing the relative performance of a set of firms, usually called decision making units (DMU), which uses a variety of identical inputs to produce a variety of identical outputs. The basic ideas behind DEA date back to Farrel, but the recent series of discussions started with the article by Chames et al. (1985). We give very briefly the salient features of DEA, more detailed information can be obtained elsewere in (Jamas and Pollitt, 2003; Jamas et al., 2004; Giannakis et al., 2005).

Assume that there are n DMUs which convert I input to J outputs. In particular, the m^{th} DMU produces outputs y_{jm} using x_{im} inputs. To measure the efficiency of this conversion process by a DMU, a fractional mathematical programming model, denoted by model (1) is proposed. The objective function of the model maximizes the ratio of weighted outputs to weighted inputs for the DMU under consideration subject to the condition that the similar ratios for all DMUs are less than or equal to 1. Hence, we have:

$$Max\,Ej = \frac{\sum_{j=1}^{Jj} y_{jm} v_{jm}}{\sum_{i=1}^{I} u_{im} I_{im}}$$

$$S.t:$$

Model (1): $$0 \leq \frac{\sum_{j=1}^{Jj} y_{jm} v_{jm}}{\sum_{i=1}^{I} u_{im} I_{im}} \leq 1 \quad (n = 1,2,3,.., N) \qquad (3)$$

$$v_{jm}, I_{im} \geq \varepsilon \qquad (i = 1,2,3,.., I) \;\; (j = 1,2,3,.., J)$$

where subscripts *i, j* and *n* stand for inputs, outputs, and DMUs, respectively. The variables y_{jm} and u_{im} are the weights to be determined by the above mathematical program. The term ε is an arbitrarily small positive number introduced to ensure that all of the known inputs and outputs have positive weight values. The n^{th} DMU is the base DMU in the above model. The optimal value of the objective function of model (1) is the DEA efficiency score assigned to the m^{th} DMU. If the efficiency score is 1 (or 100%), the m^{th} DMU satisfies the necessary condition as DEA efficient. Otherwise, it is considered as DEA inefficient. Note that the inefficiency is relative to the performance of other DMUs under consideration.

It is difficult to solve the above model because of its fractional objective function. However, if either the denominator or numerator of the ratio is forced to be unity, then the objective function will become linear, and a linear programming problem can be obtained. By setting the denominator of the ratio equal to unity, we can obtain the following output maximization linear programming problem, denoted as model . Therefore, it is possible to produce the input minimization linear programming problem.

Model (2):

$$
\begin{aligned}
&Max\,Ej = \sum_{j=1}^{J} y_{jm} v_{jm} \\
&S.t: \\
&\sum_{j=1}^{Jj} y_{jm} v_{jm} - \sum_{i=1}^{I} u_{im} I_{im} \le 0 \ \ (n = 1,2,3,..,N) \\
&v_{jm}, I_{im} \ge \varepsilon \qquad (i = 1,2,3,..,I) \qquad (j = 1,2,3,..,J)
\end{aligned}
\tag{4}
$$

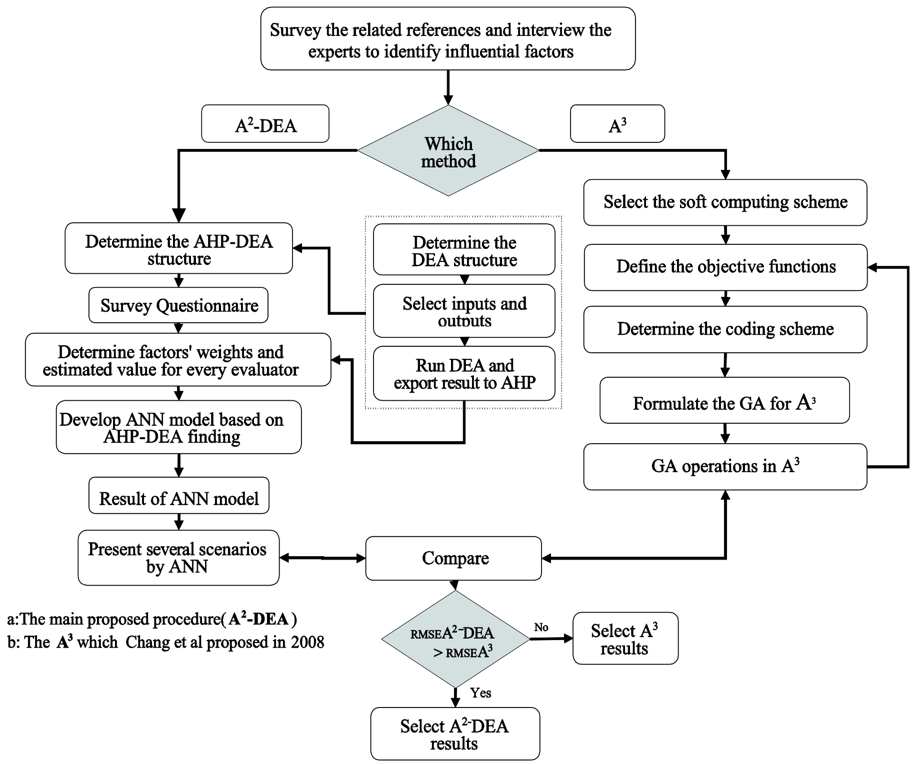
A complete DEA exercise involves solution of *N* such models, each for a base DMU (*m=1,2,.., N*), yielding *N* different set of weights (v_{jm}, u_{im}). In each model, the constraints are the same while the ratio to be maximized is changed. DEA literature uses more advanced concepts such as the dual of the previous model [model (2)], and incorporation of returns to scale. There are also many extensions to the basic models described here (Jamas et al., 2004). Charnes et al., have provided detailed accounts of the important developments in the history of DEA. Thus, DEA has the ability to give a single index of performance, usually called the efficiency score, synthesizing diverse characteristics of different DMUs. Because of this ability, DEA has received numerous applications over the past two decades.

2. Methodological Approach

Saaty (1980) developed the AHP method to solve the problems of multi criteria decision-making (MCDM) for determining the rank or preferences of decision alternatives. According to the previous explanation (section 1.2.1) for using the AHP model, groups of expert opinion of decision makers are needed, which it is time consuming and costly. Therefore, we cannot use AHP easily for introducing several scenarios. To remove these shortcomings, Hosseininasab et al., had proposed the integration of the AHP and ANN (for more explanation refer to 1.2.2) models, which called A^2 in 2012. Because this method has many benefits, we integrate this method as subjective tool with DEA as objective tool (for more explanation refer to 1.2.3). One of the important benefits of using ANN is the ability of generalizing variables, which are gained from a real world problem. It is also useful for presenting several scenarios as an accurate, fast running, and inexpensive method for decision makers. In the proposed model, when AHP-DEA and ANN models are set up, measuring the priority of industries for issuing loan when the budget is limited, can be made easy by the opinions of a few decision makers, thus the calculation of the geometric mean of answers that are obtained from many experts will be unnecessary. Additionally, with ANN, we can analyze many scenarios with the change of any criteria of AHP-DEA in a short time. In the next step, we have compared the proposed model with the A^3 model. We have used this model for comparing, because the aim of the A^3 model is to avoid reassessment while decreasing cost.

In the proposed model, the major criteria of the assessment process were identified with the help of literature review, and experience of experts in the field. In this model, an AHP-DEA structure was proposed in which the criteria's weights were determined for every decision maker. An ANN model was implemented and trained by using AHP-DEA results in order to avoid using the AHP-DEA model. It causes decreased execution time and increased efficiency of result. The details of ANN procedure have been shown in Fig. 1 (section a), and are explained briefly in section 2.2. The priority of industries, which is determined in ten sections (I1-I10) by experts, is achieved from running the ANN model. Although using ANN helps avoid aggregation of decision makers' judgments by an average method, the most important contribution of this study is that it provides decision makers with useful scenarios about influential criteria to make decisions concerning which industries would be better to be selected to issue loan in two subjective and objective perspectives. For comparing and surveying benefits and limitations of the proposed model, we apply the A^3 model, which is explained briefly in section 1.2 [see Fig. 1 (section b)].

Figure 1: The procedure of measuring the priority of industries for issuing loan (A^2-DEA and A^3)



2.1. The selection criteria and building of the AHP-DEA model

The first step in developing the AHP-DEA model is building a hierarchical structure of the problem. The goal and all the decision criteria are classified into three major levels. In the first step of the application of the AHP-DEA model, the decision hierarchy of the AHP model is constructed to rank credit customers in different industries. The goal of the AHP-DEA model is placed at the first level of the hierarchy. For selecting the factor of second level, we surveyed the literature (see Table1). In order to obtain further information to identify and categorize the criteria affecting the clients credit rating applying for banking facilities, as the most important 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 Table1.

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 bank financial facilities from 2010 to 2011 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. In addition, access to the financial information of the selected companies is easier in this way.

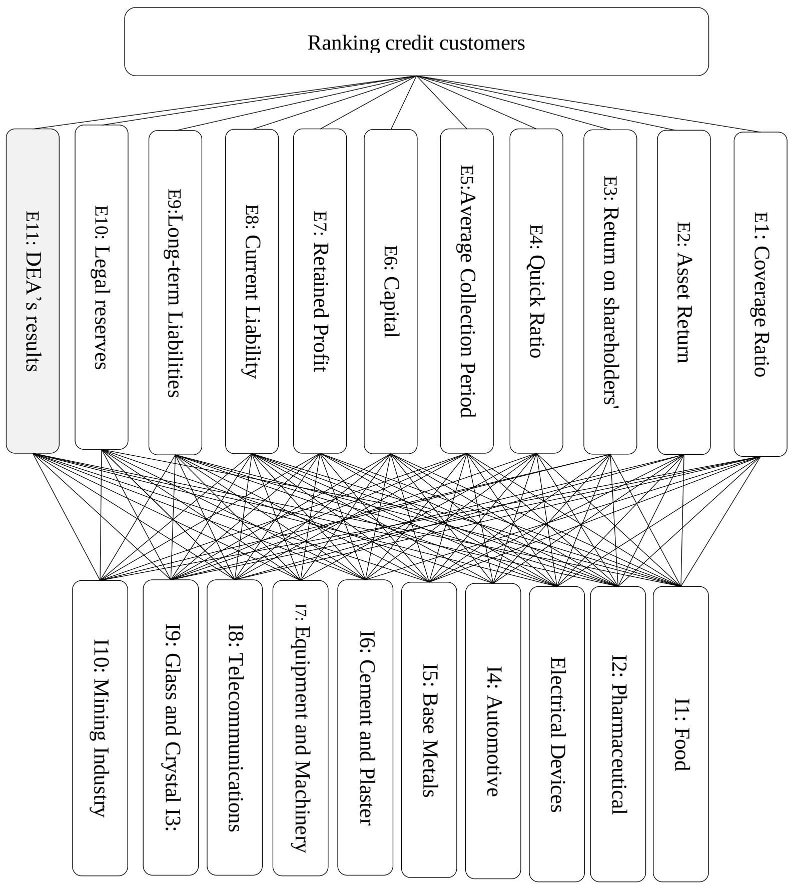
These ten factors plus last factor, which is related to result of DEA, are placed at the second level of the hierarchy. In other words, according to Fig 2, the eleventh factor is related to DEA’s results. In fact, the efficiency scores measured by DEA are placed in AHP. Determining of inputs and outputs is one of the most important steps of DEA method. Table 1 shows the structure of DEA based on literature review.

Table 1: Comparative studies for selecting factors of second level of AHP-DEA

DEA Info		AHP_DEA Info	Factors	Authors
Variable	**IN/OUT**	**labels'**		
Input	In(1)	E1	Capital	Cummins et al. (2002) , Feroz et al. 2(2003)
	In(2)	E2	Retained Profit	Aitman (1998), Feroz et al. 2(2003), Cheng et al.(2007)
	In(3)	E3	Current Liability	Liang et al.(2006)
	In(4)	E4	Long-term Liabilities	Omero et al.(2005), Molhotra et al.(2008)
	In(5)	E5	Legal reserves	-
Output	Out(1)	E6	Interest Coverage Rate	Liang et al.(2006), Cheng et al.(2007), Molhotra et al. (2008), Margaritis et al.(2009)
	Out(2)	E7	Asset Return Ratio	Brid(2001), capobianco et al.(2004), Duzakin et al. (2007), Molhotra et al.(2008)
	Out(3)	E8	Quick Ratio	Duzakin et al. (2007)
	Out(4)	E9	Average Collection Period	Feroz (2003)
	Out(5)	E10	Return on Shareholder's equity	Margaritis et al. (2009), Brid (2001), Liang et al.(2006)

For determining the third level of AHP structure, we used the company's classification. Debt collection constitutes a considerable amount of financial resources required for banking operations. For banks that have been unsuccessful at collecting debts, 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 statistical sample of companies 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. Fig. 2 describes the hierarchy of the AHP-DEA model.

Figure 2: The hierarchy framework for ranking credit customers



2.2. The building of the A^2-DEA model

The steps of ANN modeling are according to the integrated AHP-ANN (A^2)–DEA approach. The proposed hybrid A^2–DEA model has the following basic steps:

Step 1: Determining the input and outputs variables: This decision addresses the definition of the input variables (e.g., rate of any criteria) and the output variables (e.g., section of industries) in order to assign them to the network of each model as inputs and outputs, respectively. In addition, the way of presenting data to the network have to be determined. One way to do this is to present all available process variables as network inputs, and then let the network modify itself during training so that the connection of any insignificant variables becomes weak. Another approach is to be more selective, and introduce as inputs only those variables that are surely affecting the process of outputs. The first approach is called the ‘‘global network’’ while the second is termed the ‘‘focused network’’.

Step 2: Selecting and preparing the train, validation and test data set: In the data selection step, it is necessary to ensure the sufficiency and integrity of the data used to train and test the network, whereas the network performance can be directly influenced by the presented data. It is not simply possible to say how many data sets are required, because this depends on the nature of the process modeling problem and the cost of providing data.

The prepared data set is categorized randomly into three sets: Train, validation, and testing data sets. Generally, the training data should cover the whole of data variation range. The validation data set is used to ensure that there is no over-fitting in the final result. In order to validate the models, a data set is selected randomly from training data. When a significant over-fitting has occurred, the error of validation data starts to increase and the training process is stopped.

In order to enhance the model fitness, several tasks for preparing data may be performed such as: (1) data integrity check, (2) extreme data removal, (3) data scaling, and (4) data coding. Scaling of the data is automatically carried out during the training phase of the ANN. Data are preprocessed (scaled to [0, 1]) through dividing each dataset by its norm. Finally, our outputs are post-processed and returned to their original scale.

Step 3: Tune and run all plausible networks for proposed ANN model**:** Developing an ANN model includes determining the number of layers, the number of neurons in each layer, each layer's transfer function, and how the layers are connected to each other. The performance of an ANN model depends on the fitness of the network features. For instance, too few neurons may result in under-fitting, but too many neurons may yield over-fitting, which means that all the training data fit well, but ANN model performance for test data is low.

The optimal configuration of each model is selected according to the training process results. Therefore, various architectures for each network are proposed with diverse features. During the training process, representative examples of inputs and their corresponding outputs are presented to the models. Each ANN model that its network trained and learned the governing relationships in the data set by modifying its weights and biases, called the fitted model. Ultimately, the optimal configuration for each network based on the user-specified error function is chosen by trial and error.

There are various training algorithms to fit ANN models. The most popular algorithm in optimization and estimation applications is the standard back propagation (BP) (Nascimento, 2000). This algorithm is a widely used iterative optimization technique that locates the minimum of a function expressed as equation 5.

$$E = \frac{1}{2}\sum_{m}\left(y_{dm} - y_m\right)^2 \tag{5}$$

where, y_{dm} is the target value of the output layer, and y_m is the ratiocinated value of the output layer. Based on BP algorithm, during the training process, the deviation between the network output and the desired output at each presentation is computed as an error. This error, in the quadratic form, was then fed back (back propagated) to the network and used for modifying the weights.

The training process carries on while one of three user-specified conditions is met at least. These conditions consist of (1) exceeding the maximum number of epochs, (2) meeting the performance goal, and (3) decreasing of the gradient descent rate to the less than the allowable limit.

Step 4: Select the best network configuration for ANN model based on error function: The optimal configuration of each model is selected according to the training process results. Therefore, various architectures for each network are proposed with various features. During the training process, representative examples of inputs and their corresponding outputs are presented to the models. Each ANN model that its network trained and learned the governing relationships in the data set by modifying its weights and biases, called the fitted model. Ultimately, the optimal configuration for each network based on the user-specified error function is chosen by trial and error.

2.3. The building of the A^3 model

The A^3 model was proposed in 2008 to improve the traditional AHP method of solving MCDM problems from three perspectives: (1) cost effectiveness (2) timeliness and (3) improved decision quality. According to Fig. 1, five main steps are needed for applying A^3, which are briefly discussed here.

Step 1: Select the soft computing

Technique selection depends on the characteristics of the problem field. Lin et al. used genetic algorithm (GA) as the best choice for this method. The GAs, first proposed by Holland (1976), are algorithms based on the observation of the natural selection in the evolution of natural lives. The basic GA mechanism consists of three basic operations: (1) reproduction; (2) crossover; and (3) mutation. For detailed description of GA operations, please refer to Goldberg (1989).

Step 2: Define the objective

Two objective functions are proposed in this method, which are the consistency ratio (CR) and a difference measurement between the adapted PWM and the original PWM. CR is definitely a primary objective value to be minimized and the other objective is required to guide the search toward the direction that reserves the DM's original belief in the relative importance of the various criteria. The difference measurement between the adapted PWM and the original PWM is considered as the second objective.

Step 3: Determine the coding scheme

In A^3, the gray code (GC) scheme is adopted. Because by using GC, three important concerns are considered: (1) the coding scheme should guarantee global search; (2) the coding should be compact; and (3) similar numbers should be coded similarly.

Step 4: Formulate the GA for A^3

Since the goal is to determine the values of elements in PWM so that the eigenvector (the final weights for the various criteria) of the matrix can be found, the considered parameters include all the elements of PWM. The PWM is a positive reciprocal matrix. Thus, only the elements in the upper triangular of PWM are required. The elements on the reciprocal positions can be obtained by $a_{ji}=1/a_{ij}$ where a_{ij} is the element of row i and column j in PWM. Therefore, only $(n^2\text{-}n)/2$ elements are required for constructing PWM. Thus, we can consider the $(n^2\text{-}n)/2$ elements as the parameters in GA.

Then, an individual gene called genotype in GA for A^3 is built. Each parameter is a chromosome on the genotype. The values of the $(n^2\text{-}n)/2$ elements in PWM are coded into GCs. Each digit in GC is either 0 or 1. In addition to the digits for the $(n^2\text{-}n)/2$ elements in PWM, three real number parameters should be recorded on each genotype: (1) the maximum eigenvalue of the relative importance weight matrix, (2) the difference index (DI) between the original genotype and the derived genotype, (3) the overall index (OI) combining the performance of CR and DI. Since the lower eigenvalue achieves the lower CR, the maximum eigenvalue represents the first objective (i.e., consistency). The DI represents the second objective (i.e., the difference from the original genotype). There are many ways to measure DI, such as the Hamming distance between the two genotypes or the summation of square differences of all elements between the two genotypes. In the proposed $A^{3,}$ the DI is defined As $[(|G./G^*|+|G./G^*|)/(n^2-n)]$. Where G and G^* are row vectors of the original and derived genotypes in the real number format. In this equation, "./" means element-to-element division. That is, the division is performed for each pair of elements at the same position in the two genotypes. The last parameter in the genotype is an overall evaluation of the two objectives. It is obvious that the goal of A^3 should be to reduce the values of both of DI and OI. The lower value of the first objective means the better consistency. The lower value of the second objective means better conformity between the derived PWM and DM's original belief. Thus, a straightforward definition for OI is simply the summation of λ_{max} and DI. Since the lowest value of λ_{max} is n (number of criteria) and the lowest value of DI is unit (when two genotypes are identical), it is intuitive to define OI as shown OI= $(\lambda_{max}-n)+(DI-1)$. In the data structure of a genotype, there are totally $[((n^2-n)/2)+3]$ elements. The first $(n^2-n/2)$ elements are in GC format (i.e., 0 or 1). The last three elements are real numbers (Lin et al., 2008).

Step 5: GA operations in A^3

A primary genotype is created from the upper-right triangle of the initial PWM. In this paper, we use the GA operations proposed by Lin et al. According to Lin et al. the primary genotype should reproduce 20 times to generate 20 identical genotypes. Next, mutation should be applied to all genotypes except 1. This mutation results in an initial population with only 1 genotype that is identical to the original genotype; the other 19 genotypes are slightly different from the original genotype. During the second step, the initial population should cross over with itself to generate 400 (20×20) off-springs. Only 1 outcome g is the identical to the original genotype and 399 new genotypes are produced. All 400 genotypes are evaluated, and the best 20 genotypes are selected for further evolution. The evolution process stops when all genotypes are the same or the objective performances do not improve any more. Then, the genotype with the best objective performance is selected as the final genotype. The PWM is then constructed based on the final genotype, and the eigenvector of the PWM is found to be the final weights for the various criteria.

3. Model development and experimental details

A real world decision-making problem in ranking of credit customer for a case project (Export Development Bank of Iran) is adopted as a case study. In this problem, both the A^3 approach and the proposed A^2-DEA are applied for ranking of credit customers.

3.1. Experimental details of proposed model (A^2–DEA model)

Step 1: Collecting data and calculating the weights of the criteria

Collecting the expert judgment for running AHP-DEA model is very important and because of the large number of decision makers, it is a challenging work. The model which Herrera-Viedma proposed in 2004 helps the decision maker to express his or her opinion easily in a short time. A special questionnaire for AHP which Wang et al., (2007) has proposed was used to complete a pairwise comparison matrix.

For applying the A^2-DEA model, a team of decision makers has completed the questionnaire according to current organization strategy. The team consists of 85 experts, including managers and experts from six departments of the bank. For instance, 5 judgments of decision makers for a set of eleven adjoining factors {E1.E2, E2.E3, E3.E4, E4.E5, E5.E6, E6.E7, E7.E8, E8.E9, E9.E10 and E10.E11} are listed as follows (Table 2):

Table 2: The judgment scores for ten criteria evaluated by 5 decision makers

	DM1	DM2	DM3	DM4	DM5	
E1	4:1	3:1	1:1	6:1	7:1	E2
E2	1:5	1:2	1:1	1:8	1:3	E3
E3	1:7	1:9	1:5	1:6	1:9	E4
E4	2:1	3:1	6:1	1:1	4:1	E5
E5	1:9	1:5	1:6	1:2	1:8	E6
E6	2:1	2:1	4:1	4:1	1:2	E7
E7	1:4	1:4	2:1	1:5	1:8	E8
E8	6:1	8:1	6:1	5:1	5:1	E9
E9	9:1	8:1	4:1	3:1	3:1	E10
E10	1:9	1:3	5:1	4:1	1:2	E11

Note: DM= Decision maker

According to Table 2, every DM must fill only 10 cells. The DM must compare 2 factors with each other. In this stage, the DM should ask himself/herself this question and answer it by 9 scales: which factor (for example E1 and E2) is more important in respect to every section of industries and how much does it rate.

The following is the steps for calculating factors' weight based on Herrera-Viedma' model (2004) after collecting the opinions. To illustrate these steps, the assessment of decision maker 1 is selected as an example here.

1-Table is the pairwise comparison matrix of decision maker 1 which shows the importance of each two adjoining factor for a set of n - 1 preference values.

Table 3: First step of pairwise comparison matrix of decision maker 1

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	E11
E1	1	4.00	x	x	x	x	x	x	x	x	x
E2	x	1	0.20	x	x	x	x	x	x	x	x
E3	x	x	1	0.14	x	x	x	x	x	x	x
E4	x	x	x	1	2.00	x	x	x	x	x	x
E5	x	x	x	x	1	0.11	x	x	x	x	x
E6	x	x	x	x	x	1	2.00	x	x	x	x
E7	x	x	x	x	x	x	1	0.25	x	x	x
E8	x	x	x	x	x	x	x	1	6.0	x	x
E9	x	x	x	x	x	x	x	x	1	9	x
E10	x	x	x	x	x	x	x	x	X	1	0.11
E11	x	x	x	x	x	x	x	x	X	x	1

2- In this step, the elements are transformed into an interval [0, 1] by equation 5 in which $a_{ij} \in [1:9,9]$ and $W_{ij} \in [0,1]$.

$$W_{ij} = (1/2)(1+\log_9 a_{ij}) \tag{5}$$

where W_{ij} indicates the lack of indifference between factors i and j, $W_{ij} = 1$ suggests that factor i is absolutely more important than the factor j, $W_{ij} = 0$ denotes that factor i is absolutely less important than the factor j, and $W_{ij} > \frac{1}{2}$ reveals that the factor i is preferred to factor j.

3- To calculate the remaining elements, equation's 6 and 7 are used.

$$W_{ij} + W_{ji} = 1 \qquad \forall\, \mathrm{i, j} \in \{1,...,9\} \tag{6}$$

$$W_{ji} = ((j-i+1)/2) - W_{i(i+1)} - W_{(i+1)(i+2)} - W_{(i+2)(i+3)} - .... - W_{(j-1)j} \tag{7}$$

4- If this preference matrix contains any values that are not included in the interval [0, 1], but in an interval [-a, 1 + a], then a transformation function is required to preserve the reciprocity and additive transitivity. The transformation function is given by equation 8 where indicates the absolute value of the minimum in this preference matrix.

$$f(W_{ij}) = w_{ij} = (W_{ij} + a)/(1+2a) \tag{8}$$

5- Final weight is achieved by using the average of the normalized matrix row. The normalized matrix and final priority of influential factors for decision maker 1 are shown in Table 4.

Table 4: Normalized weight matrix and priority of influential factors

	E1	**E2**	**E3**	**E4**	**E5**	**E6**	**E7**	**E8**	**E9**	**E10**	**E11**	**Priority**	**Rank**
E1	0.070	0.073	0.069	0.061	0.065	0.050	0.056	0.040	0.059	0.069	0.059	0.061	10
E2	0.053	0.059	0.052	0.038	0.044	0.017	0.028	0.000	0.033	0.051	0.033	0.037	11
E3	0.073	0.075	0.072	0.065	0.068	0.055	0.060	0.047	0.063	0.072	0.063	0.065	9
E4	0.096	0.095	0.096	0.098	0.098	0.101	0.100	0.104	0.099	0.097	0.099	0.099	6
E5	0.088	0.088	0.088	0.087	0.087	0.085	0.086	0.084	0.086	0.088	0.086	0.087	7
E6	0.115	0.111	0.115	0.124	0.120	0.137	0.130	0.148	0.127	0.116	0.127	0.125	2
E7	0.106	0.104	0.107	0.112	0.110	0.121	0.116	0.127	0.114	0.107	0.114	0.113	3
E8	0.123	0.118	0.124	0.136	0.131	0.154	0.144	0.168	0.140	0.125	0.140	0.137	1
E9	0.101	0.100	0.101	0.105	0.104	0.111	0.108	0.116	0.107	0.102	0.107	0.106	4
E10	0.074	0.077	0.074	0.068	0.070	0.059	0.064	0.051	0.066	0.074	0.066	0.068	8
E11	0.101	0.100	0.101	0.105	0.104	0.111	0.108	0.116	0.107	0.102	0.107	0.106	5

6- The above stage is applied for calculating other decision makers' matrix too.

Step 2: Calculating the weight of section of industries.

Using ten options as AHP outcome (I1 to I10) causes, the calculation of final priority gets easy. Table 5 is the list of five numbers of the pairwise comparison matrices for a set of ten possible outcomes as an example.

Table 5: The judgment scores given to the priority of section of industries

Factors	Industry sections	DM1	DM2	DM3	DM4	DM5	Industry sections
	I1	1:3	1:2	3:1	2:1	1:2	**I2**
E1	**I2**	4:1	1:1	2:1	3:1	2:1	**I3**
	I3	1:1	1:2	1:3	2:1	1:3	**I4**
	I4	1:4	1:2	1:4	1:5	1:2	**I5**
	I5	1:1	2:1	2:1	2:1	1:2	**I6**
	I6	2:1	4:1	3:1	3:1	2:1	**I7**
	I7	1:4	1:2	1:4	1:4	1:1	**I8**
	I8	1:3	2:1	1:2	3:1	3:1	**I9**
	I9	5:1	5:1	4:1	3:1	4:1	**I10**
.	.						.
.	.						.
.	.						.
E9							
**E10	**I1**	1:3	1:1	1:5	1:2	1:4	**I2**
	I2	2:1	1:1	3:1	2:1	3:1	**I3**
	I3	1:2	1:4	1:1	1:2	2:1	**I4**
	I4	1:4	1:3	1:2	1:4	1:3	**I5**
	I5	2:1	3:1	5:1	4:1	4:1	**I6**
	I6	3:1	3:1	3:1	2:1	4:1	**I7**
	I7	3:1	3:1	4:1	4:1	2:1	**I8**
	I8	2:1	1:1	1:2	2:1	4:1	**I9**
	I9	4:1	5:1	3:1	4:1	4:1	**I10**

**** E1-E10 is related to factors of second level and E11 is related to result of DEA and it is not necessary the judgment scores.

All the stages described in the previous section, are applied for calculating the priority of outcomes for any decision maker (note that to transform the values and the scale [1: 5, 5] into [0, 1], the function $p_{ij} = (1/2)(1 + \log_5 a_{ij})$ is used instead of equation 5.

According to Fig 2, the eleventh factor is named DEA's results. In step 2 for calculating the weight of section of industries we need the result of running DEA which calculated by the GAMS software and shows in Table 4.

At the end of this section, to obtain the priority of any section of industries we use equation 9 and the result is shown in Table 6:

$$ES = \sum_{i=1}^{9} p_i w_i \tag{9}$$

where w_i denotes the estimated weight of i criteria. i, and p_i represents the weight of the possible outcome, concerning influential criteria i.

Table 6: Priority of every section of industries by decision maker 5

	E1	E2	E3	E4	E5	E6	E7	E8	E9	E10	*E11	Priority	Rank
	0.061	0.037	0.065	0.099	0.087	0.125	0.113	0.137	0.106	0.068	0.106		
I1	0.059	0.060	0.141	0.133	0.101	0.095	0.069	0.069	0.093	0.081	0.073	0.089	10
I2	0.03	0.101	0.109	0.117	0.079	0.081	0.171	0.142	0.102	0.110	0.058	0.104	3
I3	0.062	0.081	0.171	0.064	0.158	0.123	0.035	0.139	0.060	0.077	0.092	0.098	5
I4	0.16	0.161	0.137	0.118	0.079	0.155	0.069	0.110	0.118	0.145	0.115	0.120	1
I5	0.092	0.181	0.084	0.070	0.118	0.045	0.103	0.069	0.088	0.110	0.149	0.094	8
I6	0.166	0.151	0.107	0.094	0.060	0.115	0.137	0.109	0.086	0.080	0.143	0.112	2
I7	0.121	0.085	0.066	0.167	0.080	0.078	0.109	0.076	0.131	0.104	0.092	0.101	4
I8	0.061	0.063	0.082	0.064	0.155	0.077	0.070	0.069	0.123	0.141	0.120	0.094	9
I9	0.149	0.077	0.064	0.061	0.064	0.077	0.119	0.110	0.110	0.112	0.093	0.095	7
I10	0.101	0.040	0.038	0.114	0.105	0.153	0.116	0.109	0.088	0.041	0.066	0.097	6

* The result obtained by DEA

Now we have 85 comparison matrices with final results. In traditional AHP model, some methods such as the average value are used for the integration of the judgment values of the decision makers. In this study, to avoid using averages and to have a capability of different scenarios about influential factors, the ANN model was used as follows.

Step 3: Ranking of credit customer by ANN

Adopting a global approach in presenting the data to the network, the ANN model for the measuring the rank of credit customer in different industries sections was trained by BP algorithm based on Levenberg - Marquart rule. This ANN model includes eleven inputs that consist of the weight of "E1" to "E11" obtained from AHP model while it has ten outputs, which are the priority of "I1" to "I10". The obtained data form AHP results are divided into 85% as the train data and the rest (15%) as the test data.

To choose the optimal network of the ANN, a number of different network configurations, including one hidden layer and different numbers of neurons in hidden layers with various transfer functions were provided. However, in this network, selection of more than one layer leads to a decrease in the network training performance. The training process was run in the MATLAB so a minimum of the user-specification error function: i.e., RMSE was reached while the number of epochs is fewer than 3000.

The optimal network for the ANN model was selected based on training and test RMSE of networks. When the number of neurons in the hidden layer was equal to 20, it was the least training RMSE of network. The ANN model results are shown in Table 7.

Table 7: The weight and priority of industries sections that obtain from ANN model

	I1	I2	I3	I4	I5	I6	I7	I8	I9	I10
Weight	0.065	0.0981	0.089	0.153	0.098	0.147	0.099	0.079	0.075	0.089
Priority	10	3	6	1	4	2	5	8	9	7

3.2. Experimental details of A^3 model

In AHP weightings, the relative importance among criteria at the same level is compared to obtain PWMs using the discrete 9-value scale of Saaty. Five managements of five important departments joined in assessing AHP weightings in the case study. Each member was required to complete eleven relative importance assessment tables, and thus generated eleven PWMs, including one level-one PWM, ten level- two PWMs.

In the first level, DMs must compare every ten factors (E1 to E10) with each other and rate them by 9-value scale which it makes one PWM. For example, When DM1 compares the two first factors (E1: Coverage Ratio, E2: Asset Return) and gets the 3:1, It means that according to DM' belief, Coverage Ratio is 3 times more important than Asset Return in respect to credit rating. In the second level, DMs must complete 10 PWMs. They compare 10 industry sections (I1 to I10) in respect to every 10 factor of first level. For example, DM compares two first industry sections (Food, Pharmaceutical) and gets the 1:5. It means that according to DM' belief, pharmaceutical industry is more important than food industry in respect to strategy of bank. Totally, 55=5×(1+10×1) PWMs were obtained. Among the 55 PWMs, only 20 PWMs were acceptable (i.e., CRb0.10) at the first assessment; the rest 33 PWMs required reassessment. In the A^3 weightings, the primitive PWMs obtained from the first assessment of the AHP weightings is automatically reassessed when CR exceeds 0.10. In the case study, 33 (out of 55) PWMs were unacceptable (that is, CRs N0.10). Thus, the A^3 is applied to adjust the relative importance values of the criteria in the unacceptable PWMs to meet the consistency requirement. A prototype computer program was designed with the MATLAB language for implementing the proposed A^3. Table displays the average criteria weightings, and the shows the average CR, DI and OI values using the A^3.

Table 8: The average of weightings, CR, DI and OI values obtained using A^3 approaches

Criteria	Average weightings of criteria	
	Level one	Level two
E1	0.100	
E2	0.044	
E3	0.076	
E4	0.102	
E5	0.082	
E6	0.110	
E7	0.112	
E8	0.137	
E9	0.162	
E10	0.079	
I1	-	
I2		0.080
I3		0.092
I4		0.098
I5		0.171
I6		0.079
I7		0.131
I8		0.092
I9		0.092
I10		0.092
Weighting approach	0.100	
Assessment cycle	Primitive	Final
No. of PWM	55	33
Average CR	1.85	0.075
Average DI	1	1.15
Average OI	0.79	0.65

4. Discussion and Scenarios

Table shows the result of A^3 method and the proposed method. According to this result, there is no significant difference between the results. However, by comparing the process of these two methods, we can sort benefits of A^2– DEA and limitations of A^3 as follows:

1. The most important ability of proposed method (A^2– DEA) is related to objective and subjective view in decision-making process, while in A^3 method only subjective view is noticed.
2. While in proposed method the number of DMs is more than A^3 method, time of filling questioner in A^2– DEA method is so easy, and it doesn't take long time. Because in A^3 every DM has to fill n(n-1)/2 cell while in A^2 there are only n-1 cell for filling.
3. The aim of A^3 model is to decrease the time of collection and calculation by using GA. In this method, we have to calculate CR while in A^2– DEA, it is possible to avoid checking CR. Therefore, it causes to consume less time and less cost.
4. Another benefit of A^2– DEA is the ability to design several scenarios and analyses in short time. In this section, we show an example of one scenario.

The proposed model was applied to the current situation of the bank and decision makers filled the questionnaires based on the current situation. For designing a scenario, we assume that the current situation can be changed. In this study, when strategy changes, we don't need to have all of evaluator's opinions for solving the model by A^2- DEA. we need to fill only one questionnaire by a decision maker. In this case, one specialist as an evaluator with respect to the assumption will complete the questionnaire. The required input data for ANN could be obtained based on the evaluator opinions. The A^2 – DEA result shows that the new weight of every industry sections in the new assumed scenario is: 0.069, 0.087, 0.071, 0.108, 0.143, 0.162, 0.045, 0.023, 0.163, and 0.128 . Thus, it can be concluded that such a proposed action can cause the increase obtaining of better industry section. Similarly, different scenarios can be presented in order to determine the priority of industry sections according to any strategy status while it is impossible to have several scenarios in short time by other methods.

Table 9: The result of A^2-DEA and A^3 approaches

Criteria	Average of weightings of criteria			
Weighting approach	A^2-DEA method		A^3method	
	Level one	Level two	Level one	Level two
E1	0.068		0.100	
E2	0.042		0.044	
E3	0.072		0.076	
E4	0.082		0.102	
E5	0.068		0.082	
E6	0.132		0.110	
E7	0.118		0.112	
E8	0.151		0.137	
E9	0.102		0.162	
E10	0.072		0.079	
E11	0.101		-	
I1		0.065		0.080
I2		0.0981		0.092
I3		0.089		0.098
I4		0.153		0.171
I5		0.098		0.079
I6		0.147		0.131
I7		0.099		0.092
I8		0.079		0.092
I9		0.075		0.092
I10		0.089		0.070

Therefore, by having different scenarios in short time and low cost, the bank can analyze the most appropriate industry section.

5. Conclusion

This paper presented an integrated algorithm based on A^2 and DEA to rank industry section. To show the applicability and superiority of the proposed framework, actual data are used. The proposed algorithm may be used to rank industry section in the future by optimizing parameter values. The proposed algorithm first uses AHP structure proposed by Herrera-Viedma and DEA to generate weights of factors for each industry sections. It then run ANN for building expert tools to have ability of analyzing a lot of scenarios in short time and low cost. The outputs of the AHP-DEA are used for ANN model. This paper presented a highly unique flexible A^2-DEA algorithm to rank credit clients in different industry section. Fig.1 represents this algorithm. The A^2-DEA approach considered new indicators in addition to conventional approach. Because of non-linearity of the ANN in addition to its universal approximations of functions and its derivate that makes the algorithms highly flexible.

Results showed A^2-DEA provides results that are more accurate. The proposed approach is also compared with A^3 in ranking of bank credit customers. Its features are compared with previous models to show its advantages over previous models. The A^2-DEA is capable of dealing both data complexity and ambiguity due to ANN mechanisms.

The proposed model, consists of three capabilities which are explained in previous sections(3.2 and 4). First, by implementing the proposed model we can have different scenarios in a short time and minimum cost for analyzing various strategies in ranking of industry sections. Secondly, in A^2-DEA we have objective and subjective view. In the proposed model, when AHP and ANN models are setup, a priority of sections can be easily made by the opinion of one single expert. In this study, using the AHP model proposed by Herrera-Viedma, it is possible to avoid checking consistency and collecting the experts' opinions in less time, so that the number of pairwise comparison judgments is declined to n-1 whereas the traditional analytic hierarchy approach uses n(n-1)/2 judgments in a preference matrix with n attributes. Therefore, we can see that the proposed model is time consuming.

Most importantly, the integration of AHP,DEA and ANNs improves the ranking of the credit customers in various industry section. The top management can design scenarios to choose the best decision or actions to select the best company by analyzing different scenarios. Thirdly, by this method management can determine the priority in every short period while the time and cost of estimation is decreased.

6. Limitations and Future Research

Despite, several benefit of A^2 -DEA in measuring the priority of credit industry sections, there are limitations, which should be removed, and it can be considered by other researches. One of the limitations is that the A^2 -DEA adapt PWMs based on a primitive assessment. The other limitation is that both of models are limited to crisp evaluation, and fuzzy approaches or integrating A^3 and A^2-DEA can be explored in future investigations. Selection of input and output is one of the other important stages of proposed model. Therefore, others can focus this item for future research.

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