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RESEARCH PAPER

An Integrated Neural Networks and MCMC Model to Predicting Bank's Efficiency

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Abstract

In the banking industry, there is intense competition between banks to attract resources and facilities. With the development of new services, bank managers try to improve their services and attract more customer deposits by differentiating between competitors' services. This research uses a two-stage TOPSIS method with the combination of neural network model and Monte Carlo simulation trading method to analyze and compare bank productivity forecasts with the 4 efficiency criteria of the banking industry. TOPSIS was first used in two steps to rate the efficiency of banks and then a model was created for banking performance with clear forecasting ability. Secondly, an MCMC sampling method and ANN training were presented. Integrated neural networks and MCMCs were used which are consistent with TOPSIS results. The simulation effect of the selected variables was predicted and their effect on performance was observed. The proposed method was used successfully for predicting performance and ranking banks based on the relative importance of performance criteria expressed by considering the performance levels in the TOPSIS method. Then, the artificial neural network was modeled using the results obtained from the TOPSIS method, an effective model for appropriate prediction of bank performance. Based on the results of the proposed model and the level of importance of performance measures, cost and revenue structure were considered to be the main causes of inefficiency.

Keywords:
Forecast;
TOPSIS;
Neural networks;
Monte Carlo;
Efficiency

Introduction

For economic growth, the availability of financial and banking institutions with good performance is very important. The use of ranking methods in the comparative assessment of banks has increased dramatically [1]. One of the most effective methods in the field of financial evaluations is multi-criteria decision-making methods [2]. [3] explore the performance of Islamic banks in the Middle East, North Africa, and Asian countries by using data envelopment analysis and inefficient banking resource management.

This research has been designed to predict and evaluate the efficiency of banks by applying a two-step topical method and a combination of Neural Networks and Monte Carlo Markov Chain Simulation. The main objective of this research is to rank the banks based on their performance.

This research continues, in the second part, the review of literature in the third section of the research background regarding the methods used in the financial evaluations. In the fourth part

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of the research methodology, and in the fifth section, the results are analyzed using the data derived from the performance of the banks, and Section 4 presents the results.

Theoretical foundations and research background

One of the applications of real-life modeling is to predict the future status of the system. A forecast is a statement about an uncertain event that is often, but not always, based on experience or knowledge. The prediction is the process of estimating unknown positions. A forecast provides a prediction about future events and can transform past experiences into predictions of future events.

Although accurate information does not guarantee future incidents, in many cases, predictions might be helpful in planning possible developments. In many applications, such as time series analysis, models might be estimated using the observed observations [4]. One of the simulations in this field is the analysis of time series using interconnected methods such as Artificial Neural Networks. Artificial Neural Networks are new systems and computing methods for machine learning, knowledge representation, and finally, applying knowledge to predict outcomes from complex systems.

Banks play an important role in economic development, and as a result, the measurement of the performance of banks has attracted widespread attention. Performance evaluation with the aim of rating units can be evaluated in two parametric and non-parametric approaches [5]. A parametric method is an approach for the assessment of hypotheses with quantitative variables using the statistical and boundary principles (SFA). In non-parametric mode, methods with no previous default including DEA are used.

Maghyereh and [6] evaluated various banking departments and [7] evaluated financial segments using data envelopment analysis. In the evaluation analysis, regression models were used to model the performance of banks. [8] considered regression to explain banks' performance.

Recently, researchers have proposed predictive models for evaluating performance in financial institutions. Predictive models propose processes for examining the causes of inefficiencies and solutions for the future and is a process in which one tries to provide the best prediction of the probabilities presented. [9] و [10] used artificial neural network models in prediction-based evaluations. An artificial neural network uses a nonlinear regression technique for modeling processes. In this method, each neuron creates a linear combination of inputs to feed other neurons [11]. In particular, the combination of modeling and predictive techniques can have a significant effect on the performance of the proposed model [12].

[13] conducted an assessment of the efficiency of Islamic banks in Malaysia using TOPSIS and neural networks. In the present research, an artificial neural network and a two-step approach were used to assess the efficiency of banks in Iran.

Research model and estimation method

Feasible, quantitative and non-quantitative criteria are involved in assessing the performance of banks. The study examines three examples of the current performance index at the international and international financial institutions and the Banking Supervision Committee of Bazil, the International Settlements Bank (BIS). Then using [14] method, these criteria are used as the variables in the two-step stepwise method and they are used to rank the banks accordingly. Finally, by using the [15] and the neural network method and the Monte Carlo method, predictions of the bank's future status are carried out using the sensitivity analysis of the validity of the results.

TOPSIS method

TOPSIS is a multi-criteria decision analysis method, In this method, m is evaluated by the n criterion and the ranking of units is minimized by distance to positive ideal points and maximization of distance from the ideal negative points. In other words, in ranking options in the method, TOPSIS earns the highest-likelihood options with an ideal solution.

To use the TOPSIS method, the following steps should be taken:

Step 1: Create Decision Matrix

Each option is given a score based on each criterion. These privileges can be based on quantitative or qualitative values. In either case, a decision matrix m * n must be formed.

Step 2: Normalize the decision matrix

At this point, the decision matrix should be normal. Normalizing the values is used by the vector method. To normalize the decision table values, the vector method is used.

$$r_{ij} = x_{ij} / \sqrt{\sum_{i=1}^{m} x_{ij}^2}, \quad i = 1, 2, ...m \quad and \quad j = 1, 2, ..., n \tag{1}$$

The numeric value of the obtained i option is normalized based on the j criterion and the decision matrix layers

Step 3: Generate a Normalized Decision Matrix

The normalized matrix is based on the weight of the criteria. AHP hierarchical analysis or Shannon entropy can be used to calculate the weights of the criteria. The harmonic matrix is obtained according to Eq. 2 and by weight multiplication of each criterion in the layers associated with the normal matrix of each criterion.

$$W = (w_{ij})_{m\times n} = (w_j r_{ij})_{m\times n} \tag{2}$$

Where, w_{ij} gives the weight of each evaluator.

Step 4: Calculate the positive and negative idealities

The calculation of the ideal positive and negative ideal point is the next step. In this step, for each indicator, a positive ideal (A_a) and a negative ideal (A_b) are calculated according to (3) and (4).

For the criteria that have a positive impact, the ideal is the highest of those criteria. For the criteria that have a positive impact, the negative ideal is the smallest value of that criterion. For the criteria that have a negative impact, the positive ideal is the smallest value of that criterion. For negative measures, the negative ideal is the largest criterion.

$$A_a = \{\left\langle \min(w_{ij} \left| i = 1, 2, ..., m) \right| j \in J_+ \right\rangle, \left\langle \max(w_{ij} \left| i = 1, 2, ..., m) \right| j \in J_- \right\rangle\} = \left\{\alpha_{aj} \,|\, j = 1, 2, ..., n\right\} \tag{3}$$

$$A_b = \{\left\langle \max(w_{ij} \left| i = 1, 2, ..., m) \right| j \in J_+ \right\rangle, \left\langle \min(w_{ij} \left| i = 1, 2, ..., m) \right| j \in J_- \right\rangle\} = \left\{\alpha_{bj} \,|\, j = 1, 2, ..., n\right\} \tag{4}$$

Step 5: Distance from the positive and negative ideals and calculating the ideal solution

In this step, the relative closeness of each option becomes an ideal solution. Euclidean distance of each option is calculated from the positive and negative ideal using Eqs. 5 and 6.

$$d_{ia} = \sqrt{\sum_{j=1}^{n} (w_{ij} - \alpha_{aj})^2}, \quad i = 1, 2, ..., m \tag{5}$$

$$d_{ib} = \sqrt{\sum_{j=1}^{n}(w_{ij} - \alpha_{bj})^2}, \quad i = 1, 2, ..., m \tag{6}$$

Step 6: In this step, the relative closeness of each option is considered to be an ideal solution. For this, the Eq. 7 is used.

$$CL_i^* = \frac{d_i^-}{d_i^- + d_i^+} \tag{7}$$

The value of CL is a number between zero and one. The closer it gets to the one, the solution is closer to the ideal solution and the better solution.

Artificial Neural Networks

Artificial Neural Networks (ANNs) are computational methods for machine learning, displaying knowledge and applying knowledge to predict outcomes from complex systems. The main idea behind these networks is inspired by the way the biological nervous system works for data processing and learning. The key element of this idea is to create new structures for the information processing system. The system consists of a large number of super-interconnected processing elements called neurons that are synchronized to solve a problem and transmit information through synapses. These networks are able to learn. Learning in these systems is adaptive; in neural networks, the weight of the synapse changes in such a way that if new inputs are received, the system produces the correct response. Artificial neural networks are one of the learning models to be used for prediction [11].

The predictive model is a process in which a technique is used to select the best possible forecast for outputs. Leading multilayer networks are the most successful applications of the neural network, which includes the input layer, the intermediate hidden layers, and the output layer. In this model, the input value is transmitted through the transfer function to the output layer and finally, a pattern of information is constructed. By adding hidden layers of the network, the ability to analyze more complexity and activation functions are selected according to the user's needs. Neural networks are one of the most famous models used in prediction to discover the relationship between hidden layers in variables [16].

Bayesian models

The Bayesian model, a method for categorizing phenomena, is based on the probability of occurrence or occurrence of a phenomenon. If for a given specimen space a partition that reduces the important part of anxiety by knowing which of the disrupted events has occurred can be selected, this is useful as it calculates the probability of an event by conditioning the occurrence or non-occurrence of another event. Using this case and probing the desired event in relation to the other event, the probability can be calculated. Bias Theory is a framework for formulating statistical inferential problems which is an opposite method and uses mathematical transformation and the allocation of various coefficients to data. Achieving common causes requires repetition of repeated experiments [17].

There are three stages in the Bishop approach: firstly, the researcher should express their belief in reality and pass it through the statistical filter of the expected mean, variance, and the power of belief in the original belief. These three criteria can be based on past experience, past research, or a combination of both. The second step is to collect the results of experiments or observations. This step can be carried out by summarizing statistics similar to those predefined.

The third stage also consists of combining the correct expression and the early beliefs and shaping the later information. Later information can be new and more informative than basic information. The combination of later information with other research provides a new formulation [18].

Sampling can continue until it covers the whole community or until the last contradictions are justified. This method is flexible in using different coefficients and mathematical transformations. The Bayesian theory is as sensitive as the sample (n). This method is based on the estimation of a random variable based on input signal observations, the philosophy of business based on combining the input signal observations with the probability distribution of the process. Bias theory is expressed in (8).

$$P(m \backslash O) = \frac{P(O \backslash m)P(m)}{\int_M P(O \backslash m)P(m)d_m} \tag{8}$$

where in $P(o \backslash m)$ the probability of sampling o is significant m. In $p(m)$, the amount of marginal distribution is in m. As soon as a subsequent distribution of a parameter is obtained, it is used to estimate or express probabilistic expressions about the parameter [17]. Eq. 8 is the White House law. The main point in the law is to connect a probability condition to its reverse probability. Eq. 8 is normalized by Eq. 9.

$$P(m \backslash O) = Zp(O \backslash m)\,p(m) \tag{9}$$

Given the possible values of the variables, the objective function of the observations is sampled and the simulated data are obtained according to (8) and the value of the objective function according to the parameters defined in Table 1 from (11).

$$P(O \backslash m) = \exp(-OF) \tag{10}$$

$$OF = w_j \sum_{j=1}^{ND} \sum_{i=1}^{N_{obs}} w_i \frac{(O_i - S_i)^2}{(\sigma_i)^2} \tag{11}$$

Nervous networks are now widely used as flexible models for regression and categorization issues. However, the main question is if there is a limitation in the training of the data, how trustworthy this method is. Behavioral training for neural networks shows that this method is used for complex natural models without fear of controlling data exodus during training. Therefore, Bayesian complex models can be used to examine the probability function of using the Monte Carlo Markov chain method in theoretical and computational aspects.

Table 1. Parameters defined in Bayesian equations, MCMC and ANN

A(X)	Public function	OF	objective function
ANN	Artificial neural network	P(m)	Initial probability distribution
MCMC	Monte Carlo Markov Chain		
MSE	Mean squared error		
M_{NN}	The number of models selected from the ANN chain	w	Weighting factor
M_w	Non-homogeneity	B_p	Cumulative Bank Data
N_{iter}	The number of repetitions proposed in the model	Z	Normalization function
ND	Number of data	α	Probability of acceptance of the candidate's design
N_{MC}	MCMC sampling length		
N_{obs}	Number of observed data	σ	The standard deviation of observed data error
N_p	Cumulative data	σ_s	Standardized standard deviation
$q\left(m_{k+1}/m_k\right)$	Distribute the proposed scheme	o	Observed data
		s	Simulated data

Models of the Monte Carlo Markov chain

[20] state that the Monte Carlo Markov chain method (MCMC) is a group of algorithms used to sample probability distributions, which is based on the construction of a Markov chain with desirable characteristics. As a sample of the optimal distribution, the chain mode is used for a large number of steps, The MCMC method is to construct a strong framework in realistic statistical modeling. The quality of this sample cause an increasing number of steps. Typically, structure a Markov chain with desirable features is simple. The main problem is the number of steps needed to converge the chain state with an acceptable error to a constant distribution. A good chain is a chain in which, from the beginning of an arbitrary position, we get a very quick distribution.

The MCMC model can be used to estimate the standard deviation of random variables by considering multi-dimensional constraints. This method is a basis for several statistical approaches and nonparametric models, Which is done by methods without boundaries and preset assumptions. Typically, the use of the Markov chain of Monte Carlo is always related to the starting point, so this sampling method only estimates the distribution.

Integrated Artificial Neural Network and Monte Carlo Markov Chain Models

In this study, the hybrid model of the neural network and the Markov chain used in the Mazccio and [15] is used to predict the efficiency of banks. In fact, their proposed model is a repetitive process of using the Bayesian integrated model using the Monte Carlo Markov chain and artificial network.

The proposed model is based on two steps; the first step is the samples obtained from the MCMC and the second step is the ANN neural network. Each step contains the following repetitions:

1. The first step involves sampling for an initial set of points to create an artificial neural network. The prototypes are derived using the LHSM method [21], which creates a dataset for the first set of ANN.

2. Using the MC-MC M-H algorithm, a long chain N_{MC} is created to generate output and compute probabilities.

3. Select the M_{NN} number of models from the previously generated chain that includes the selection of the number of spatial points in the Markov chain. The distance between consecutive points depends on the size of the chain and the number of points to be desired. Selected models are used to calculate output data in order to re-train ANNs.

4. ANN training with new points created in step 3 and topology defined in the first stage of training and doing repetitions.

5. Repeat steps 2, 3, and 4 include a repeat of the procedure until we reach the stopping point (maximum number of repetitions).

6. The latest Markov chain produced in this process is used to measure the results. The models, after passing through the number of repetitions specified, reach a satisfactory answer according to the stop criterion, in constructing a cumulative probability curve according to the values defined for The target function.

Finally, each sample obtained in step 1 produces a simulation model whose comprehensive ANN algorithm is in form (1).

$$n = 0$$

$$for \quad k = 1 : \prod_{i=1}^{P} n_i \quad do$$

$$Builtparametervectorvalues : P_k = \left[v_1, v_2, ..., v_p \right]$$

$$for \quad j = 1; nt \quad do$$

$$n = n + 1$$

$$InitializeANN^{(n)}$$

$$TrainANN^{(n)}$$

$$end \quad SimulateANN^{(n)} with \quad the \quad test \quad data \quad set \quad and \quad compute \quad MSE^{(n)}$$

$$end$$

$$selectANNwith \min MSEfromtheset \left[ANN^1, ANN^2, ..., ANN^n \right]$$

$$n \quad is \quad the \quad total \quad in \quad number \quad of \quad trained \quad ANN, given \quad by \quad n = ntx \prod_{i=1}^{p} n_i$$

Fig. 1. ANN comprehensive algorithm for determining ANN weights

In previous [22], [23], and [24], most performance factors are considered for variables, and there is no predictive analysis in this level. In this research, an artificial neural network, integrated modeling method and the MCMC method have been used to predict actual results. For this purpose, the MATLAB-9.0 model has been used.

Data and experimental results

Using financing methods, tools, products and new financial services may be one of the most important banking developments tools. The assets of Iranian banks are listed in Table 2 from 2011 to 2016. The data shows that the total assets increase in the year 2012 with 41.6 percent, in 2013 with 34.5 percent, in 2014 with 23.8 percent, and in 2015 with 21.3 percent increase. This amount is expected to increase by less than 10% by the end of 2016.

Table 2. Total Assets of Banks from 2011 to 2016 (in Thousand Billion Rials)

banks	2011	2012	2013	2014	2015	2016
Total assets	6700	9490	12770	15820	19200	More than 20000

Classification data are presented in Table 3 with the criteria for the efficiency of banks in the TOPSIS method and the effective functional variables. these criteria contain the volume of transfer deposits, total operating costs, total assets, capital and net income. Also, in this table, four performance variables are among the most important indicator identified in the performance assessment of banks, which are derived from indicators used by the International Banking, Standing Banks, Banking Supervisory Committee (BIS). These criteria are used to assess the differences in the efficiency levels of banks. These indicators have a direct and indirect impact on the main components of the costs and revenues of the bank. These values include the ratio of net income to the average ROA and net income ratio to ROE, the benchmark of cost-to-cost ratios, and, lastly, the criterion of capital adequacy, derived by dividing the base capital into the sum of assets adjusted to the risk factors by percentage it will be counted.

Table 3. Categorized data with TOPSIS criteria and variables that affect the criteria

Variables		**Minimum**	**Maximum**	**Average**	**The standard deviation**
TOPSIS Criteria	Deposits	6741	1057183	300308	309426
	Total operating costs	274	69251	16858	22048
	Net profit	151	19044	3876	5144
	Total assets	6395	1151009	336823	342476
	Fund	4000	99065	2495	26886
	net income	1915	172404	34602	42911
ANN performance metrics					
	Time	1	2	3	4
	ROA	0.001	0.14	0.017	0.020
	ROE	0.005	0.510	0.018	0.015
	cost benefit ratio	0.080	1.462	0.611	0.029
	Capital adequacy	**0.013**	**0.082**	**0.093**	**0.091**

The data includes 60 samples of 20 Iranian banks in 3 years 2012, 2013 and 2014, accounting for 71% of the total number of Iranian banks. By applying the TOPSIS method and taking into account the performance criteria, the proximity to the ideal option is achieved. In Fig. 2, the performance levels are based on the Tapsis method and frequencies obtained a group of classes. The concession levels indicate that the results are roughly Gaussian distribution around the mean, which shows overlapping Gaussian distribution and distribution with an increasing number of data. The results of this research can be broadly extended to the whole society.

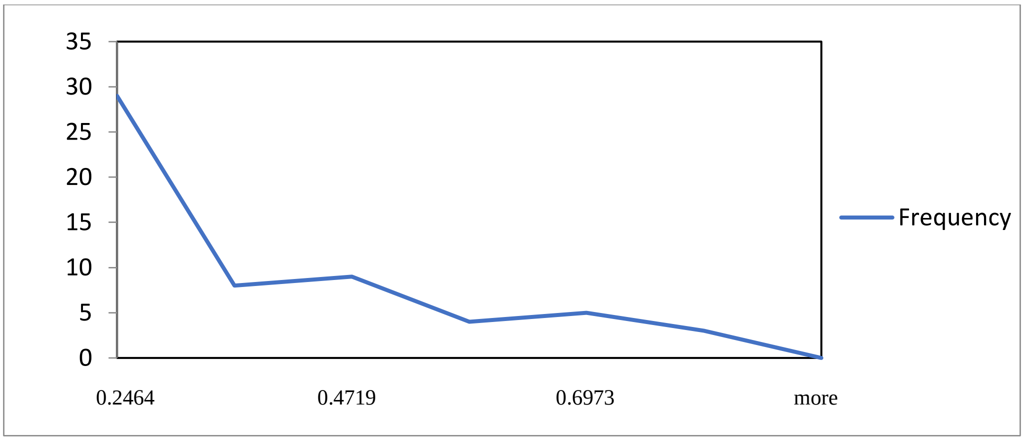

Fig. 2. Frequency levels of TOPSIS rated privileges

Efficiency points obtained by the TOPSIS method in two stages of using this method, are shown for each year as a box diagram in Fig. 3.

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
a	20	33.3%	40	66.7%	60	100.0%
b	20	33.3%	40	66.7%	60	100.0%
c	20	33.3%	40	66.7%	60	100.0%

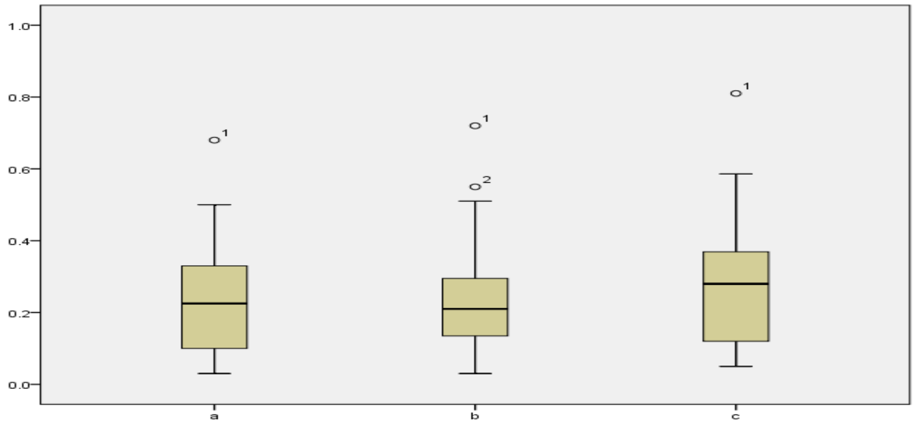

Fig. 3. Boxes of performance levels by the years studied

In Fig. 3, it can be seen that the efficiency average has an approximate stability less than 0.5. This level is about 0.2. However, this low average and high variance in the years studied are due to various factors. At the beginning of the decade, economic downturns, economic hardship, and the bottlenecks of international sanctions have limited economic and national economic activity. Since 2013 by strengthening financial stability in the global economy at the same time as the general orientations of monetary, credit and currency policies, the gradual return and relative equilibrium of inflation and the transition to the conventional process of recession have been taken. Due to actions based on expert and central bank insights, inflation has been steadily decreasing and a slope of negative growth has been observed. Also, it was possible the gradual withdrawal of the economic crisis with the relative relaxation of macroeconomic developments in 2014.

By obtaining the coefficient of the closeness of the TOPSIS method, the banks' ranking is based on the four criteria of ROA, ROE, B / C and capital adequacy in Table 4.

Table 4. Banks ranked by taking into account the four evaluation criteria and the TOPSIS method

ranking	Bank name	year	TOPSIS Score
1	Sarmayeh Bank	2014	0.81
2	Sarmayeh Bank	2013	0.72
3	Sarmayeh Bank	2012	0.68
4	Karafarin Bank	2014	0.58
5	Karafarin Bank	2013	0.55
6	Parsian Bank	2014	0.52
7	Parsian Bank	2013	0.51
8	Parsian Bank	2012	0.50
9	Eghtesad Novin Bank	2014	0.42
10	Eghtesad Novin Bank	2013	0.41
11	Eghtesad Novin Bank	2012	0.39

ranking	Bank name	year	TOPSIS Score
12	Sina Bank	2014	0.36
13	Sina Bank	2013	0.34
14	Sina Bank	2012	0.33
15	Tejarat Bank	2014	0.33
16	Tejarat Bank	2013	0.32
17	Bank Melli	2014	0.31
18	Tejarat Bank	2012	0.29
19	Karafarin Bank	2012	0.28
20	Bank Melli	2013	0.27
21	Bank Mellat	2013	0.26
22	Refah Bank	2014	0.25
23	Bank Melli	2012	0.24
24	Bank Mellat	2013	0.24
25	Refah Bank	2013	0.23
26	EDBI BANK-IBAN	2013	0.23
27	Bank Saderat Iran	2014	0.23
28	Bank Mellat	2012	0.21
29	Bank Pasargad	2014	0.20
30	EDBI BANK-IBAN	2013	0.19
31	Bank Pasargad	2013	0.19
32	Bank of Industry and Mine	2014	0.19
33	Refah Bank	2012	0.18
34	Bank Saderat Iran	2012	0.18
35	Tourism Bank	2013	0.18
36	EDBI BANK-IBAN	2013	0.17
37	Bank Saderat Iran	2013	0.17
38	Bank Pasargad	2012	0.15
39	Tourism Bank	2012	0.15
40	Bank of Industry and Mine	2013	0.14
41	Tourism Bank	2014	0.13
42	Bank of Industry and Mine	2012	0.11
43	Ansar Bank	2014	0.11
44	Ansar Bank	2013	0.10
45	Saman Bank	2014	0.10
46	Middle East Bank	2014	0.09
47	Ansar Bank	2012	0.09
48	Middle East Bank	2013	0.08
49	Saman Bank	2012	0.08
50	Middle East Bank	2012	0.07
51	Saman Bank	2013	0.07
52	Bank Sepah	2014	0.07
53	Iran Zamin Bank	2012	0.05
54	Iran Zamin Bank	2014	0.05
55	Bank Sepah	2013	0.05
56	Iran Zamin Bank	2013	0.05
57	Bank Sepah	2012	0.05
58	Bank Day	2012	0.03
59	Bank Day	2014	0.03
60	Bank Day	2013	0.03

After scoring and performance ranking using the TOPSIS method, the ANN and MCMC compilation models are executed based on the efficiency of the TOPSIS. The functional criteria in Table 3 are used as predictor variables. All steps are based on the research of [15].

To create the first ANN, the TOPSIS privileges are used as the initial set of points. Parameters are defined for the first ANN. The number of these points is 60, in step 3, 42 points for training and 18 points for testing. The number of hidden layers is between 3 and 15 and for each ANN, the training process is repeated 10 times, and finally, the test data is compared with the results from the efficiency of the banks. The structure of the ANN will remain constant until the last repetition. The ANN parameters in Table 5 are in two parts a and b. The best number of neurons in the hidden layers is determined by the form (1).

Table 5. ANN parameters

a

Criterions	Description	Type	Minimum	Maximum
ROA	Income-to-asset ratio	Numerical percent	0.001	0.14
ROE	Ratio of income to equity holders	Numerical percent	0.005	51.0
C/B	cost benefit ratio	Numerical percent	0.008	46.1
Capital adequacy		Numerical percent	0.013	0.13

b

Parameter type	Multi-layer nerve nerve network	Description
Number of layers	3 (input-output and 1 hidden layer)	
The number of neurons in the hidden layer	3-15	
Learning algorithm	Levenberg –Marquardt Back Propagation Error and Bayesian settings	The best mode is obtained from the algorithm of the Fig. 1.
Transfer function	Input layer Hidden layer Output layer	The best mode is obtained from the algorithm of the Fig. 1.
Input data	Tables 3 to 5	
Output data	Revealed information	

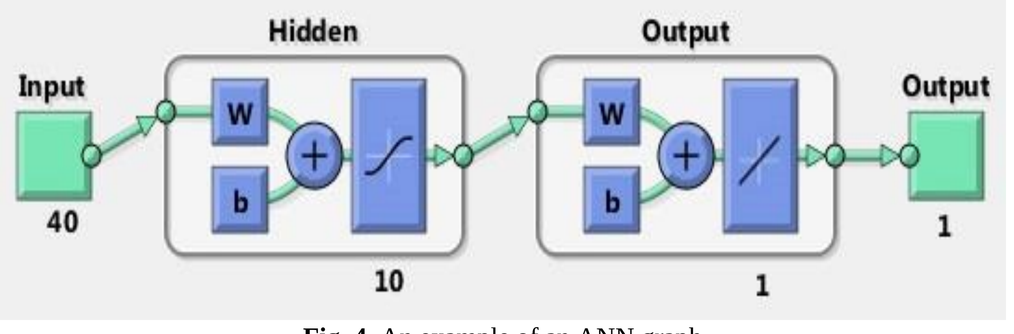

Fig. 4. An example of an ANN graph

Based on the comparison between the outputs, the objective function is formed, so that the network output is adjusted to an acceptable tolerance. The RMSE values in Fig. 5 are specified in each ANN. It can be seen that most of the errors occurred in the initial reps and the results were improved in subsequent reps and the RMSE decreased. However, this decrease with increasing ANN flows is not only declining and it increases with the increasing number of nerve network layers. Among these, a variety of cross-acceptance patterns (n-th) have been used to obtain a smaller RMSE in the training and testing process, and to identify hidden layers. In this test, the best RSME = 0.019 and the 10-fold technique are obtained.

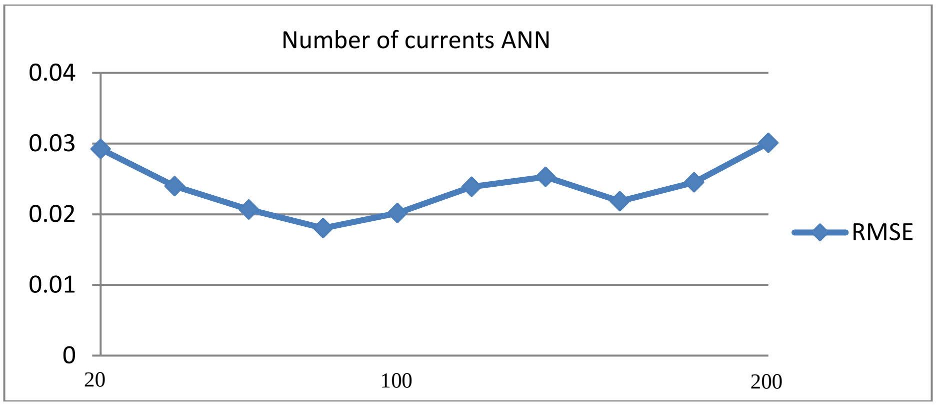

Fig. 5. RMSE variations in different ANN flows

In Fig. 6, the relative importance of performance criteria, which is achieved by taking into account the efficiency levels in the TOPSIS method is expressed. In the next step, the artificial neural network is modeled using the results obtained from the TOPSIS methodology, an effective model for performing a proper forecasting of banks performance. Two criteria of the four predictive and predictive criteria in the artificial neural network are the criteria for the cost-benefit ratio and ROA that are directly related to the cost structure of the banks. Given the relative importance of these two criteria and their specific and negative impact on the performance of banks, based on the results of the proposed model, the major causes of inefficiencies are expected to be the cost and income structure. Cost effects in different cases and inadequate management in economic crises are considered to be important factors in lower efficiency and a learning curve is needed to manage situations for improvement.

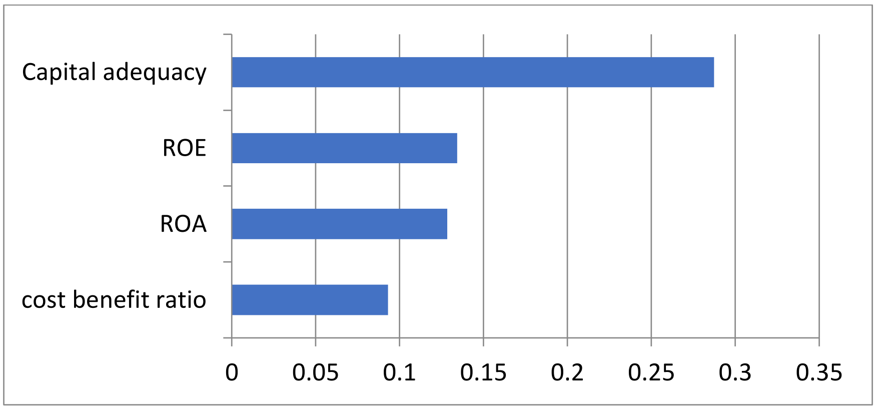

Fig. 6. The importance of performance criteria in rating performance levels

Based on the results of the neural network, the reasons for the inefficiency of the banks can be achieved according to the considered performance criteria. Therefore, the most reasons are based on the cost structure of banks, and the high cost of banks due to considered inefficiencies. By increasing the number of functional criteria, it is possible to discover other causes of inefficiency.

Conclusion

Considering the importance of banks in the country's economic development, a strong competitive environment is formed to gain the best rating and performance evaluation is an important indicator. In this research, the ranking of banks was based on four important indicators at the efficiency levels according to the latest available information from 20 Iranian banks in 2014. The ranking was based on the TOPSIS method. In the following, the correlation between the results of the TOPSIS and the prediction with the status of the banks in the coming years was compared using the combined method of repetition of artificial neural networks and Monte Carlo, and a large dispersion was observed in the performance. The results of the research findings in the course of the study show that different indicators from the point of view of decision-makers, maybe the important criteria in the ranking of banks has an unpredictable effect, but any cases used in this study significantly reduces uncertainty in prediction and consistent framework. In fact, it should be noted that the current ranking may differ from the ranking provided by other researchers, which is due to the importance of the indicators to each other in terms of decision-makers and considering the evaluation of important levels of performance.

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