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Optimal credit risk model based on metaheuristic particle swarm algorithm and multilayer perceptron neural network

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Abstract

The present study aims to develop a credit portfolio optimization model in the banking industry using a multilayer perceptron artificial neural network with a metaheuristic particle swarm algorithm. Risk, having its own complexity, is a basic concept in financial markets. Since there is no clear picture of risk realization, financial markets are in need of risk control and management approaches. With regard to data collection, this is a descriptive study and regarding the nature and purpose of the research, it is a developmental-applied one. The statistical population of the research includes all facility files of the last 10 years and the financial statements of a commercial bank, selected by census method. The risk criteria used in the models include fuzzy Value-at-Risk (VaR), fuzzy conditional Value-at-Risk (CVAR), fuzzy average Value-at-Risk(AVaR), fuzzy lower absolute deviation(LAD), fuzzy Semi-Kurtosis, and fuzzy Semi-Entropy. The research models were implemented using a three-layer perceptron artificial neural network. MATLAB software was used to conduct the research. The results indicate that the performance of the fuzzy average Value-at-Risk model is better than other models in evaluating optimal portfolios due to the lower mean squared error rate in generating more revenue. Therefore, it is recommended that the above model be used to optimize the credit portfolio.

Keywords: Portfolio Optimization, Perceptron Artificial Neural Network, Credit Risk, Particle Swarm Optimization Algorithm.

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1. Introduction

Commercial banks and financial and credit institutions attract people's surplus funds as deposits and according to the type of absorbed deposit, they pay bonuses or interim interest. They also provide some of these deposits to individuals or legal entities based on the facility granting process. Accordingly, while formulating and communicating facility credit policies in the form of credit policy package, the bank should consider a principal program for granting facilities as well as allocating credit facilities and finally the method of managing the facility portfolio. Moreover, the bank's policies in the management of facility portfolio have a significant impact on credit risk. Commercial banks and financial and credit institutions can manage the facility portfolio at the time of formulating annual credit policies, and consequently divide the facilities among different sectors and industries, as well as among small, medium and large customers and hence, reduce credit risk. Currently, credit risk is the leading factor in the bankruptcy of banks. If the customers do not repay their obligations on time, these facilities will lead to the bankruptcy of banks, which will disrupt the distribution of bank credits and, hence, disrupt the country's economy [1]. Financial and credit institutions must take into account the credit risk of customers to meet their requirements based on obtaining facilities. Because so far, the problems of facility portfolio management have been the major reason for bankruptcy or loss of banks and financial and credit institutions [2]. Harry Markowitz was the founder of the famous structure in modern portfolio theory. The most important function of the theory has been to create a portfolio risk-return framework for investors to make decisions. By providing a quantitative definition for investment risk, Markowitz presented a mathematical approach to investors in selecting assets and managing portfolios [3]. Markowitz quantitatively showed that the diversification of asset portfolios (bank credits) reduces portfolio risk. Markowitz model is used to determine an efficient portfolio collection and to select among an efficient collection. In fact, risk and return are the basic factors and components of a portfolio management system. Therefore, this concept can be applied directly to the management of loans and facilities in terms of the above-mentioned factors. The management of the facility portfolio is a continuous process of evaluating and taking advantage of various lending opportunities to achieve maximum return within the framework of macro-management goals with a minimum risk. Therefore, the most important components of a model for facility portfolio management will be return and risk of various lending opportunities in different economic sectors [4]. Therefore, in the last three decades, various credit risk assessment models have been used and different estimation methods have been employed to solve this problem. However, each of these studies has some advantages and disadvantages. Hence, in this study, a credit risk assessment model has been developed by using the metaheuristic technique of multilayer perceptron neural network with particle swarm optimization (PSO) algorithm, trying to optimize the credit portfolio using the metaheuristic multilayer perceptron neural network with particle swarm optimization (PSO) algorithm based on credit risk criteria. It should be noted that in developing this model, the parameters in this study have been taken into account, which are as follows:
Facility rate of return, identified credit risks based on the theory of triangular fuzzy credit, as well as the limits of the minimum degree of diversity of the facility portfolio, minimum and maximum asset utilization in the type of paid facilities, considering the costs of creating and maintaining assets in the form of general and specific costs, as well as allocating part of the resources to risk-free assets are considered. Finally, the designed model was examined using MATLAB software version 2016b.

2. Theoretical foundations and Literature review

There have been a lot of arguments about the differences between and characteristics of risk and uncertainty. These two concepts are interrelated but do not overlap. Many monetary and financial institutions try to identify sources of risk so as to control and manage it. If these institutions can properly measure the asset portfolio risk, they will be able to identify the assets that have increased the risk and re-allocate the assets to minimize the portfolio risk. In this section, the keywords and research variables will be explained to give a clear picture of the subject.

The concept of credit risk

Credit risk can be defined as the possibility of delaying, suspecting the receipt, or non-receipt of facilities provided to customers in such a way that the borrower be in default on the main loan and the interest thereof according to the terms of the contract, which may cause problems in the bank's cash flow [5]. As the definition implies, this risk may be manifested in one of the following ways:

1. The probability of decreased ability of the customer to repay the facility received and the interest thereof.

2. The probability of default on the main facility received by the customer and the interest thereof.

Since the banks' capital is small, relative to the total value of their assets, even if a small percentage of the loans are uncollectible, the bank will run the risk of bankruptcy. Types of credit risk include:

- Specific credit risk, including the probability of default due to special circumstances of the borrower who fails to meet the debt obligations to the bank.
- Systematic credit risk, including default due to economic conditions such as recession and economic crisis.

The banking system is constantly exposed to risk, a case that is unavoidable but can be managed. Risk management involves processes, methods, and tools for managing risk in organizational activities. Therefore, banks need to create a coordinated and cohesive system so that they can have the necessary efficiency and speed in the current era when the competition of economic systems has intensified, and also to reduce the probability of non-return of the granted facilities and the interest thereof, thus reducing credit risk. Therefore, in order to prevent losses and improve the situation of banks, decisions should be made each of which may have either a positive or a negative impact on the performance of the bank, in terms of risk management [6]. The risks that affect the financial institution can be categorized in three levels:

The first level: the risks that the financial institution has no control over and is only affected by them.

The second level: the risks that the financial institution has impact on them, but this impact is trivial, and the financial institution is affected by the risk rather than affecting it.

The third level: risks that affect the financial institution, but the financial institution can control and manage them by applying proper methods and tools [7].

Among the risks threatening banks and financial institutions, credit risk is the most critical risk due to its centrality, extent of operations and especially its sensitivity, so it is only the third level risks that the financial institution can overcome and control through risk management methods and tools.

The concept of optimization

The purpose of optimization is to find the ideal solution based on the limitations and requirements of the problem. There may be different solutions to a problem, therefore a function called the objective function is defined in order to compare the solutions and choose the optimal answer. Selection of this function depends on the nature of the problem. For example, travel time or cost are common goals in optimizing transportation networks. However, choosing the proper objective function is one of the most important steps in the optimization process. Sometimes in the optimization, several goals are set simultaneously. Such optimization problems, which involve multiple objective functions, are called multi-objective problems. The simplest way to deal with such problems is to form a new objective function in the form of a linear combination of the main objective functions, in which the effectiveness of each function is determined by the weight assigned to it. Each problem in the optimization has a number of independent variables, called design variables, denoted by the n-dimensional vector x. The purpose of optimization is to determine the design variables so that the objective function is minimized or maximized. Different optimization problems are divided into the following two categories:

A) Infinite optimization problems: In these problems, the goal is to maximize or minimize the objective function without any constraints on the design variables.

B) Finite optimization problems: Optimization in most applied problems based on the limitations thereof, i.e. limitations on the behavior and performance of a system. Equations representing these constraints may be equal or unequal, in which case the optimization method will be different. However, the constraints determine the acceptable area in the design. To optimize the portfolio based on Markowitz risk management model, we use nonlinear planning model.

Artificial neural network

One of the computational methods is artificial neural network, which, through the learning process and using simple processors called neurons, tries to provide a mapping between the input space (input layer) and the desired space (output layer) by recognizing the relationships between the data. Artificial neural networks are aimed at designing a structure similar to the biological structure of the human brain and body network, so that it has the power to learn, generalize, and make decisions. The first step in neural network modeling is to determine the input and target data. In this research, the parameters fuzzy Value-at-Risk (VaR), fuzzy conditional Value-at-Risk (CVAR), fuzzy average Value-at-Risk, fuzzy absolute downside deviations, Semi-Kurtosis, and Semi-Entropy are considered as the input of the network and the expected value resulting from the use of assets (payment of facilities) as the target of the network. The weight of each variable was defined in such a way as to establish a significant relationship between the input data vector and the output data vector. The main problem in designing this network is explaining the number of hidden layers and the number of hidden neurons in the intermediate layers. An artificial neural network can have multiple hidden layers. The greater the number of layers, the more complex the system is able to perceive, although too many layers reduce the accuracy of the prediction and may prevent network convergence. Multilayer networks are very powerful. For example, a two-layer neural network with the first Sigmoid layer and the second linear layer can estimate any arbitrary function with a limited number of discontinuities. In a multilayer neural network, each layer has its own weight matrix, bias vector, and outputs, and the output of each intermediate layer is used as input to subsequent layers. Hence, to solve such problems, neural networks that consist of several neurons or several layers and work in parallel are used. Hidden bilayer neural networks with Sigmoid function in the intermediate layer and linear function in the output layer will be able to approximate all the desired functions with any degree of approximation, provided that there are enough neurons in the hidden layer [8]. Accordingly, in the present study, a three-layer perceptron network was considered for the output neurons due to its great ability (modeling complex and nonlinear systems) with five hidden layers with Sigmoid function and purelin linear transfer function.

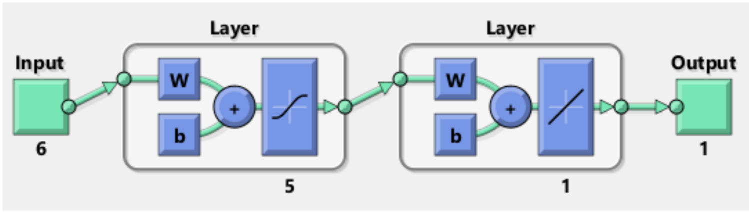

Figure 1: Perceptron neural network model with 6 inputs, 5 hidden layers and one output model

Neural network training

Intermediate layer neurons in the network are used for pattern recognition. Hence, the number of neurons in the hidden layer plays an important role in power of the network. The number of neurons should be chosen in a way that the network have sufficient and not too much power to produce mapping between input and output . In this research, an appropriate number of hidden layer neurons was determined to achieve the most accurate prediction and minimum error in the network based on trial and error method with the Sigmoid layer transfer function. The predictability and performance of the developed neural network were determined using mathematical and statistical methods. To investigate the network performance, mean squared error (MSE) was used as a criterion to measure the accuracy of neural network results.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y-\bar{y})^2 \tag{2.1}$$

In the above relations, n represents the number of observations, y represents the measured values and y represents the predicted value. Multilayer perceptron neural network training means that the free network parameters (weights and biases) are optimized by training algorithms and based on training data (including input and target vectors) so that the amount of error between the network output and the target parameter is minimized. There are generally two types of training: supervised training and unsupervised training. Usually, a function is defined for supervised neural network training, and a set or test data called training data is used to determine the weights of the neural network. In this path, network parameters (weight matrices and bias vectors) are considered constant and fixed. On the return path, the settings of the MLP network parameters is done according to the law of learning to correct the error. The error vector is equal to the difference between the desired response and the actual network response. After calculation error value, it is distributed in the return path from the output layer and through the layers throughout the whole network. To teach the proposed model of the present study, the data are divided into two categories: training data and test data. The total data of the model, related to the optimal Pareto front resulting from credit risk optimization using the metaheuristic multi-objective particle swarm optimization algorithm, include 223 cases, of which 75% (157 cases) were assigned to the training group, 15% (33 cases) to the accreditation group, and finally 15% (33 cases) to the test group (finding errors during training). The training data (including 75% of the total data) were used in the training process to calculate the gradient and optimize the free parameters, and 15% related to the test data of the model and 15% related to the accreditation were randomly assigned. It should be noted that to achieve optimization in the model training process, the particle swarm optimization algorithm has been used.

Particle Swarm Optimization Algorithm (PSO)

Jacqueline Moore and Richard Chapman (1999) introduced the first particle swarm optimization algorithm developed for multi-objective problems. The algorithm proposed by them is based on Pareto, in which, in addition to other vectors, unsuitable answers are defined for each particle vector. Having examined Moore's proposed algorithm, Coello (2008) presented an algorithm in which selecting a solution among the non-dominated solutions was based on the use of the crowding distance method and the niche method, taking into account σ_{share}. Figure 1 shows that using the crowding distance method, a particle is selected as Gbest that has a larger crowding distance. Figure 2 shows that using the niche method, a particle is selected as Gbest that has lower niche count Nci (The amount of crowding around a solution). For each solution, the value of the niche counter is selected and determined.

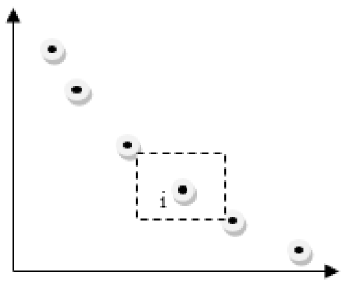

Figure 2: Niche particle method

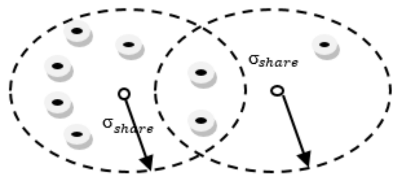

Figure 3: How to estimate the crowding distance of the nearest neighbor

Pseudocode of PSO algorithm

Randomly generate n particles in the dimensions of the solution space of the problem. For all particles, like the i^{st} particle of the current position of the particle, randomly create vi of the particle velocity.
Perform the following steps until the conditions are met for the algorithm to stop:
For each of the particles $i = 1, \cdots, n$ do the following steps:
Calculate the fitnes function.
If the fitness function of the i^{st} particle is better than y_i, then replace the i^{st} particle with y_i and move on to the next step.
Otherwise, go to the next step.
End of loop (per)
Choose the best particle from the members of the current population that has the best fitness function and name it $\hat{y}$.

For each particle $i = 1, \cdots, N$ Do the following steps: Calculate the velocity of each particle based on Equation (2-36) Update the position of each particle based on Equation (2-37). End of loop (per) End the loop (until).

A far as the researchers know, no research has been conducted that directly addresses the issue, and most of the research has been on investment companies and stock exchanges. In fact, employing this method in the bank for the optimization of credit risks is one of the innovations of the present study. However, a few studies related to the subject are introduced:

Metawa (2017) used intelligent techniques such as a kind of genetic algorithm in decision-making in the banking environment such as granting facilities. In this study, using GAMCC, a framework was created to optimize banking financial objectives, including increasing profits and reducing the probability of error, which was obtained by dynamic search of decisions. The results show that in the proposed method, the time of monitoring the facility is reduced from 12% to 50%. Seringnano et al. (2016) introduced a different model to solve the problem of scheduling loan allocation in areas such as home, credit cards, cars, student affairs or business, and used data from financial institutions and fixed interest rate investment to evaluate the proposed algorithm. In this problem, instead of using multidimensional nonlinear programming, which is difficult to calculate, the approximate algorithm method is used.

Malhotra et al. (2015) used neural networks to classify customers of twelve financial institutions in the United States. The model was based on the assumption that the samples be divided into two groups of low-risk and high-risk clients. In other words, customers whose repayment has been defaulted were in the high-risk group and customers who have fulfilled their obligations were in the low-risk group. In this study, the input vector included the following variables: residential home ownership, length of stay at current location, personal credit cards, ratio of total expenses to total income, ratio of total debt to total income and customer credit rating. The results showed the accuracy of predictions at 70 to 77% in in-sample education groups and at 68 to 74% in out-of-sample test groups. In addition, comparison of the results with multivariate audit analysis showed that the prediction accuracy of these models was significantly higher (about 4%).

Abdou (2014) obtained the essential and non-essential components of credit risk prediction from 487 actual loan application data obtained through the Bank of England, where gender and education were non-essential components and net income and employment were considered essential components.

Zare et al. (2020) wrote an article entitled “Credit risk optimization model for crowdfunding process by using Multilayer Perceptron Neural Network”. Based on the simulation results, the proposed model was able to optimize the weights of each of the inputs to the network with lower prediction error and 94.1% efficiency. Moreover, the average error absolute value obtained for training data (0.88), test data (0.94) and evaluation data (0.84) indicating high capability of the proposed model. According to the research results, among the indices, net income with a weight of 0.163, current account with a weight of 0.123 are more important, but “the degree of education” with a weight of 0.053 is less important in the non-defaulted group.

Kiani Ghalehno et al. (2021) wrote an article entitled “A multi-objective formulation for portfolio optimization of credit institutions branches: case study of Keshavarzi bank of Sistan and Baloochestan”. This study aimed to design a multi-objective planning model to maximize returns and minimize risk. The approach to the problem is such that by taking administrative and personnel costs and interest rates on deposits and facilities and rate of the domestic market can offer a variety of portfolios. The branches select the appropriate portfolio as the goal and work plan according to their requirements. Due to the nature of the problem, which has a quadratic objective function, the model will be solved using the NSGAII evolution algorithm. The problem-solving output, which is the Pareto boundary, are performance portfolios, each of which can be selected as an efficient portfolio in proportion to the various returns and risks [9].

Naji Esfahani and Rastegar (2019) published an article entitled Customers' Credit Risk Evaluation Using LINMAP Analysis (A Case Study on an Iranian Commercial Bank). The results indicate the efficiency of the method for forecasting credit behavior of the bank's customers. Considering the method advantages including its independence to the companies' financial background and precision in forecasting relative to prevailing methods, they recommended using this method as input to researches for banks' credit portfolio management [10].

Korde Katooli and Salehi (2018) presented an article entitled "Optimal Feature Selection in order to Bank Customer Credit Risk Determination". In this paper, they present a hybrid Imperialist Competitive optimization algorithm and neural network for increasing classification accuracy in evaluation and measurement credit risk of bank customers. The proposed method identifies the optimistic features, eliminates unnecessary features decreases problem dimension, and increases classification accuracy. To validate this method, it implements on UCI dataset and on a reality dataset of a private Iranian bank. The test results show this method is more satisfactory than other data mining techniques. The neural network error for the test set decreases with selection of effective features and elimination of low-impact features by the Binary Imperialist Competitive Optimization Algorithm. In addition, test data error rate remains at acceptable level for other used classification methods. This article is the first use of algorithms Imperialist Competitive for credit risk assessment of bank customers.

Delvi et al. (2015) conducted a study entitled "The Application of Multi-Purpose Genetic Algorithm in Optimizing Bank's Facilities Portfolio (A Case Study of the Granted Facilities in One of the Commercial Banks of Iran)". The findings show that the resulted optimum facilities portfolio is different from the current portfolio of the bank and can tackle with the different limitations and policies in granting facilities. They also indicate that the effective interest rate and the degree of efficiency of facilities based on the presented model are higher than those of the current facilities portfolio.

3. Research methodology and model presentation

Choosing a research methodology is one of the most important and technical steps that the researcher must follow with special sensitivity based on the purpose of the research. The purpose of this study is to predict and present the bank's credit risk model using multilayer perceptron artificial neural network. The present study is an applied one. Applied research is research that uses the theories, regularities, principles, and techniques developed in fundamental research to solve practical and real problems. In terms of method, the present study is descriptive. Descriptive research can be conducted to understand the current situation or to assist in the decision-making process. The data collection tool in this research is the credit records in one of the commercial banks and the reports taken from the credit dashboard in the bank. The risk criteria used in the models are fuzzy Value-at-Risk, fuzzy absolute downside deviations and semi-entropy. The statistical population of this research includes all facility files of the last 10 years as well as the financial statements of the bank branches that were selected by census method. To achieve the objective of the research the following steps were taken.

1) Identification and selection of factors affecting credit risk.

2) Review of all bank assets during the ten years ending in December 2020 (loans and payment

facilities with current and non-current balance).
3) Neural network training by swarm particle optimization algorithm.
4) Testing predictive power of the neural network. The variables used in this research are presented in the following table.

Table 1: Input, output and hidden layer variables of neural network model

Neural network model input layers	X_1	fuzzy Value-at-Risk
	X_2	fuzzy average Value-at-Risk
	X_3	fuzzy conditional Value-at-Risk (CVAR)
	X_4	Fuzzy Semi-Kurtosis
	X_5	semi-entropy
	X_6	fuzzy absolute downside deviations
	Number of nodes of a (oblique bias node removed)	12
	Scaling method	Standardization
Hidden layer	Number of hidden layers	5
	Number of hidden layer nodes	10
	Animated function	Hyperbolic tangent (tansig)
Output layer	Number of nodes	2
	Animated function	purelin
	Error function	entropy

The expected value of a fuzzy variable
In the literature review, there are different theories for defining the expected value for fuzzy variables, such as Campos and González (1989), Dubois and Prade (1987), Heilpern (1992) and Yager (1981). However, the most general definition of the expected value of a fuzzy variable is provided by Liu and Liu (2008), which has advantages in terms of its applicability for continuous and discrete fuzzy variables. When $\xi = (a.b.c)$ is considered a triangular fuzzy variable such that then $a < b < c$ is obtained by the following equation:

$$E[\tilde{\xi}] = \frac{a + 2b + c}{4} \tag{3.1}$$

Fuzzy Value at Risk
If $\xi = (a.b.c)$ is a fuzzy variable and $\alpha \in (0, 1]$ is the confidence level, then $Var_\alpha(\xi)$ is equal to:

$$Var_\alpha(\xi) = -\inf\{x|Cr(\xi \leq x) \geq \alpha\} \tag{3.2}$$

The above equation shows that the maximum loss of ξ with confidence level α is equal to x (Peng, 2011). Using credibility theory, fuzzy Value at Risk is expressed as follows.

$$Var_\alpha(\xi) = \begin{cases} 2(a-b)\alpha - a & if\ \alpha \leq 0.5, \\ 2(b-c)\alpha + c - 2b, & if\ \alpha > 0.5. \end{cases} \tag{3.3}$$

Fuzzy average Value at Risk
If $A = (a.b.c)$ is a triangular fuzzy number for each confidence level $0 < \alpha \leq 1$, the fuzzy average Value-at-Risk can be expressed using the credibility theory as follows.

$$AVar_\alpha(\xi) = \begin{cases} (a-b)\alpha - a & if\ \alpha \leq 0.5, \\ c - 2b - \frac{1}{4\alpha}(a - 2b + c) + (b-c)\alpha, & if\ \alpha > 0.5. \end{cases} \tag{3.4}$$

Fuzzy Conditional Value at Risk
If $A = (a.b.c)$ is a triangular fuzzy number for any confidence level $0 < \alpha \leq 1$, the fuzzy Conditional Value at Risk can be expressed using the credibility theory as follows.

$$\xi CVar_\alpha(\alpha) = \begin{cases} \alpha a + (1+\alpha)b & if\ \alpha \leq 0.5, \\ (\alpha - 1)b - \alpha c, & if\ \alpha > 0.5. \end{cases} \tag{3.5}$$

Fuzzy lower absolute deviation

Konno et al. (1999) introduced the absolute deviations as a criterion for risk. If $\xi = (a.b.c)$ is considered a triangular fuzzy variable, then the Fuzzy lower absolute deviation is defined as follows:

$$LAD[\xi] = \begin{cases} \frac{(3(b-a)+(c-b))^2}{64(b-a)} & if\ b-a \geq c-b, \\ \frac{((b-a)+3(c-b))^2}{64(c-b)}, & if\ b-a \leq c-b. \end{cases} \tag{3.6}$$

Fuzzy Semi-Kurtosis

If $A = (a.b.c)$ is a triangular fuzzy number for each confidence level $0 < \alpha \leq 1$, the Semi-Kurtosis ξ is defined by the following equation:

$$K_s[\xi] = \frac{1}{10(b-a)}\left[(e-a)^5 + \frac{1}{(b-c)}(b-e)^5 \min(0,(b-e))\right] \tag{3.7}$$

Fuzzy semi-entropy

Zhou et al. (2016) introduced fuzzy semi-entropy and used it as a risk criterion in portfolio optimization. Semi-entropy has also been used as an accepted criterion for measuring the degree of portfolio diversification [11]. If $\xi = (a.b.c)$ is a triangular fuzzy number, the semi-entropy is expressed as follows:

$$E_s(\xi) = \begin{cases} (b-a)\rho - (b-a)\zeta(\rho); & if\ \frac{a+2b+c}{4} \leq b \quad \rho = \frac{2b+c-3a}{8(b-a)} \\ \frac{b-a}{2} + (c-b)\zeta(\tau); & if\ \frac{a+2b+c}{4} > b \end{cases} \tag{3.8}$$

In order to design the neural network model (training and testing), perceptron neural network tools and Matlab software version 2016 were used.

4. Research Findings

After network learning, the process of perceptron artificial neural network with three hidden layers was conducted according to Figure 1. From a total of 223 samples extracted from the Pareto Optimal Metaheuristic Multipurpose Particle Swarm Optimization Algorithm, 157 samples (70%) were included in the training group, 33 samples (15%) in the accreditation group, and 33 samples (15%) were included in the test group. The error of each group (MSE value) related to the declared risks according to Table 2 is as follows:

Table 2: Estimation of mean squared error in three groups of training, testing and accreditation data

Sample		Training	Test	Accreditation
Number		157	33	33
Percent		70%	15%	15%
Value-at-Risk error	MSE-VaR	0.011258	0.010249	0.018235
Conditional Value-at-Risk error	MSE-CVaR	0.002896	0.002743	0.003125
Average Value-at-Risk error	MSE-AVaR	0.000163	0.000294	0.000187
Lower Absolute Deviation	MSE-LAD	0.002451	0.002498	0.003021
Semi-Entropy	MSE-Es	0.023012	0.020145	0.014036
Semi-Kurtosis	MSE-Vs	0..004582	0.004325	0.004536

Table 2 shows the rate of learning error in each of the test, training, and accreditation data groups for research risks. Accordingly, because the values of this index are close to zero, it indicates a low error rate in all three groups. On the other hand, this estimate of the mean squared error in average Value-at-Risk error is lower than other risks and indicates that the fuzzy average Value-at-Risk error model has a role in credit risk optimization compared to other research models. In order to investigate this issue in more detail, the results of linear regression between the test values and the neural network model between the test data are shown in Figure 4.

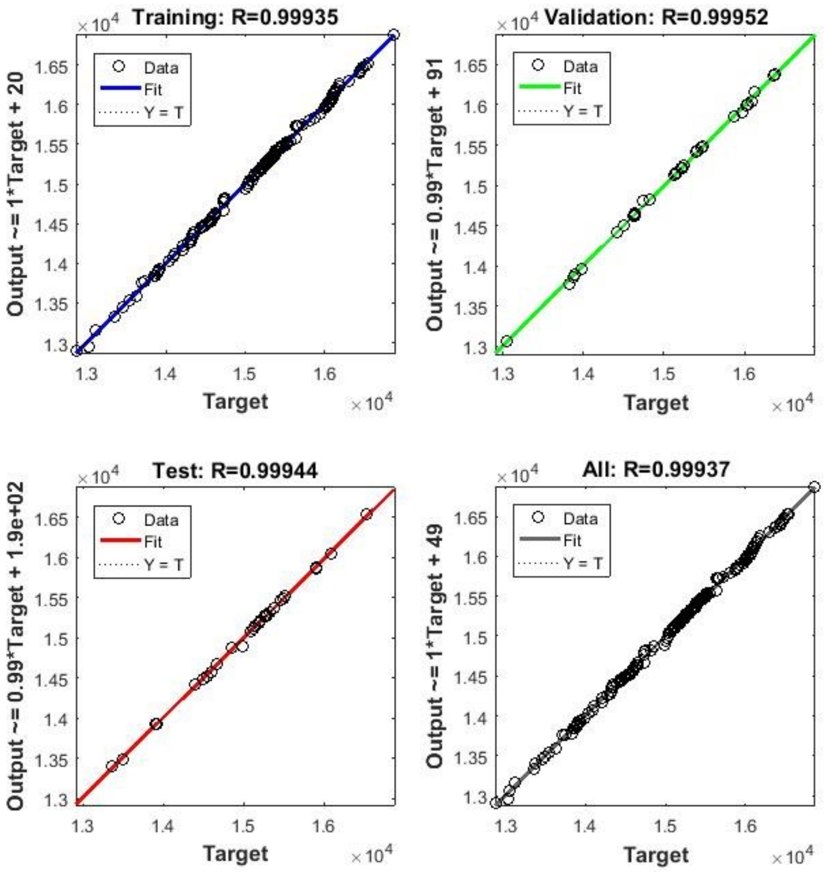

Figure 4: Linear regression between test values and artificial neural network model of mean risk

Figure 4 shows the regression diagram of neural network outputs according to the objectives of training, accreditation, and test sets. Given that most data are located along a 45-degree line, it can be said that there is a perfect fit between the data sets for network learning. It can also be stated that the coefficient of explanation of the perceptron neural network model for training data is equal to 0.99935, for test data is equal to 0.99944, for evaluation data is equal to 0.99952, and finally for the whole data is equal to 0.99937. These values correctly indicate the high fitness ability of the proposed neural network model. The following is an error histogram for the average value at risk model.

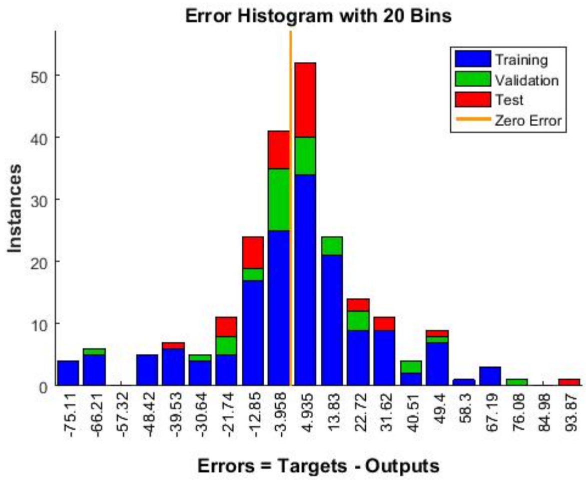

Figure 5: Error histogram diagram

In Figure 5, the blue bars represent the training data, the green bars the accreditation data and the red bars the test data. This histogram shows the distance between data points. Most errors are between $+12$ and -12. Training has stopped when the accreditation error is increased for six repetitions and an error occurs in the 143^{rd} repetition of this histogram. In the following Figure, Figure 6, the optimal model for learning the multilayer perceptron artificial neural network is shown.

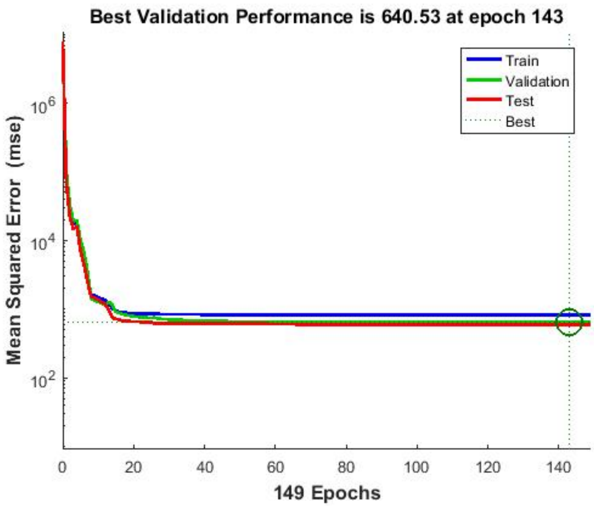

Figure 6: Optimal model of perceptron multilayer artificial neural network learning

As can be seen in Figure 6, the mean square error of the artificial neural network starts at a large value and decreases with subsequent repetitions. This shows that the network learning process is improving. Due to the small amount of the final mean squared errors and also the error of the test set with the error of the evaluation set have similar behaviors and properties, it can be said that the diagram shows the desired situation. In addition, in 143^{rd} repetition, the best performance in the series has occurred and no over-fitness has occurred. Finally, Figure 7 shows fuzzy average Value-at-Risk model, which indicates the final explanation of the model.

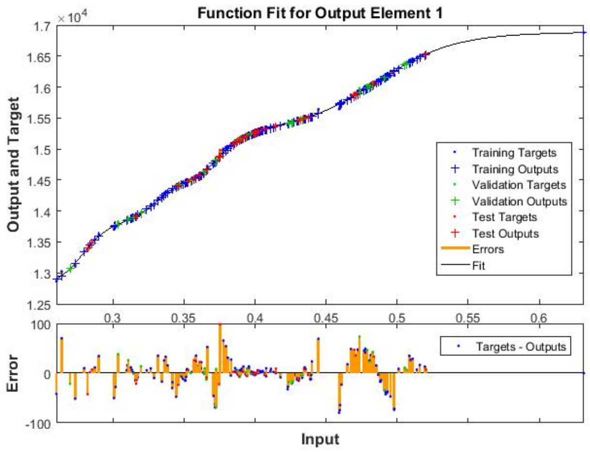

Figure 7: Model performance for output variables and model error diagrams

5. Conclusion and Recommendations

Risk and return are two factors that have always been taken into account in the banking industry. Many financial institutions seek to identify sources of risk and then control and manage it. Hence, in this study, we presented a Three-layer Perceptron Artificial Neural Network using the Particle Swarm Optimization Algorithm. The risk criteria presented in this model are fuzzy Value-at-Risk (VaR), fuzzy conditional Value-at-Risk (CVaR), fuzzy average Value-at-Risk (AVaR), fuzzy semi-Kurtosis, fuzzy lower absolute deviation (LAD), and fuzzy semi-entropy. The proposed model was designed to use entropy as a measure of the degree of diversity. Since diversification is important to reduce risk in a facility portfolio by the manager, the minimum and maximum allocation of resources have been added as two other limitations in existing contracts based on annual credit policies and the number of contracts used in branches through equipping branch resources. Due to the degree of variability that can exist, two other limitations have been added to the model. The results obtained from the implementation of multilayer perceptron artificial neural network model and the results obtained from the comparison of research models according to Table 2 show that the performance of Mean-AVaR model has the ability to explain the model and optimize the amount of credit risk with less error compared to other models in the bank in question. Other future researchers who intend to conduct research in this field are advised to consider other multi-objective optimization algorithms as well as other neural network methods. It is also suggested that the present study be conducted with risks of different dimensions in other banks and the results be compared with each other.

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