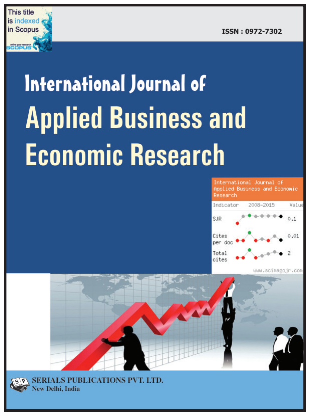

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The Use of GA-Based and PSO-Based Neural Networks for Modeling the Exchange Rate Forecasts in Iran

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ABSTRACT

In recent years, financial and investment markets have experienced an increasing use of artificial intelligence methods in place of conventional quantitative methods, as they have managed to provide a better performance than classical approach. Despite their wide ranging benefits, Artificial Neural Networks (ANNs) are far from flawless. In this study, the artificial intelligence method is combined with two evolutionary algorithms namely Genetic Algorithm (GA) and Particle Swarm Optimization algorithm (PSO) to model the nominal exchange rate daily forecasts or Dollar-Rial exchange rate in Iran over the time period of 21/03/2009 to 22/12/2015. The resulting hybrid models are compared, based on error criteria including MSE, RMSE, MAE and U.Theil, with the ANN which represents the typical artificial intelligence method. The results of this study show the superiority of the PSO-ANN hybrid over other tested models.

JEL Classification: C53, D51

Keywords: Exchange rate, artificial neural network, genetic algorithm, particle swarm optimization algorithm.

1. INTRODUCTION

The ability to forecast the variations of exchange rates is critical for monetary authorities; since it allows them to design an efficient monetary policy geared toward stable prices and increased level of employment. These forecasts are also important for businesses and investors since it allows them to decide how to allocate their assets (Bafande et. al., 2009, p.3). Prediction of exchange rate has long been the center of attention of many policymakers and economic agents and there have been extensive studies on modeling this parameter; as development of models that can determine the future behavior of exchange rate would help policymakers and governments to adopt more efficient decisions. Given the importance of exchange rate in Iranian economy, this study is conducted with the goal of finding a suitable model for forecasting and modeling the exchange rate in Iran. There are generally two approaches to predicting exchange rates. The first approach is the fundamental approach which predicts exchange rate based on other economic variables. The second approach is the univariate approach, also known as technical approach, which predicts the future trend of exchange rate based on its past behavior. Unlike fundamental models which attempt to find relationships between exchange rate and other variables, technical analysis is based on the assumption that the exchange rate is not a random variable, but follows repeating and recognizable patterns (Dargahi & Ansari, 2008). This study is focused on the technical approach. The classic forecast methods, which are usually based on some type of regression model, are simple to implement but can only approximate a forecast in environments that exhibit small variations; however, in cases that environmental conditions are constantly changing, they cannot predict the environmental changes and are thus unable to provide a good forecast. This issue highlights the importance of using modern tools and models to predict this type of data. With the advance of software and hardware in computers, intelligent systems and methods that are mainly based on repetitive algorithms and neural networks have found many applications in various fields of science. For example, non-linear nature of Artificial Neural Networks (ANN) makes them particularly desirable for predicting stock prices. Application of neural networks in economic studies started from the late nineties with the studies of White (1998) on financial markets and predicting the stock price of the IBM Company. In general, the main use of neural networks is in prediction problems (Zhang, 1997). The goal of this study is to design and provide a suitable method for modeling and forecast of exchange rate in Iran and for utilization of evolutionary algorithms in prediction of important economic variables. To achieve this objective, we seek to improve the accuracy of neural network by training it with evolutionary algorithms.

2. THEORETICAL FOUNDATIONS OF NEURAL NETWORK

In the past few decades, artificial neural networks have maintained a successful presence in financial and management problems, and many articles have been presented in this field. The idea of training intelligent networks to solve complex pattern detection problems has turned into an interesting subject of research. Neural networks are valuable tools for a broad range of management applications and crucial components of most data mining systems, and change the way the organization perspective on the relationship between the company's data and strategy (Lisbo, 2000). Research and interest in neural networks began when brain was identified as a dynamic system with parallel processor structure, completely contrary to structure of conventional processors. The modern outlook on function of the brain was formed from the ideas developed in the early twentieth century about the structure of brain as a small community of computational components called neurons. The human brain is made of 10^{11} (one hundred billion) neurons which are believed to have approximately 10^{14} to 10^{15} connections between them, forming a very complex communication network that makes the human brain operate as a parallel processor (Bill & Jackson, 2001).

Neural networks are computational models that are capable of determining the relationship between the inputs and outputs of a physical system through a network of interconnected nodes. The activities of each of these connections is set by historical data (the learning process) enabling the model to discover the relationships between the inputs and outputs. These computational intelligence based systems try to model the neurosynaptic structure of the human brain. Although artificial neural networks are not comparable with the normal nervous system, they do have features that distinguish them in applications such as patter detection, robotics, and control and generally wherever there is a need for learning a linear or non-linear mapping. These features include the trainability, the generalizability and capability of distributed processing.

In the structure of artificial neural network, which is referred to as architecture, neurons (computational units) are connected in groups called layers. Typical architecture of neural networks is composed of three layers: The input layer, which distributes the data on the network, the hidden layer, which processes the data, and the output layer, which extracts the results for specified inputs. One network can be composed of one or several hidden layers. Most studies choose the architecture of artificial neural networks through trial and error, and determine the optimal network by using different numbers of hidden layers and the related neurons and gauging the results. Using a larger number of layers and neurons generally lead to better performance of network in the training phase and worse performance in the test phase, as the network calibrates excessively on data of training phase and loses flexibility for other patterns of data.

The general method of calculations in neural networks is as follows:

Neuron inputs (x_i to x_1) are multiplied by weights (x_i to x_1) and the sum of results obtained from each input goes through a function and forms the neuron output. The corresponding mathematical model is expressed by the following equation:

$$\text{Net } j = \sum_{i=1}^{n} W_{ij} X_j$$

3. RESEARCH LITERATURE

Nelly & Weller (2002) used quarterly data of 1981-2001 to predict US exchange rate fluctuations through genetic algorithm and classic methods. They proved that predictions made by Genetic Algorithm (GA) are better than those made by time-series models. They compared the genetic algorithm model with GARCH and risk matrix models. Tayyebi et. al. (2008) used artificial neural networks for the prediction of annual trend of exchange rate in Iran and compared it with econometric methods (using data of years 1959-2002) to test this theory that artificial neural network has more efficiency in predicting the trend of exchange rate than time series models. In this study, the trend of the exchange rate variable in the mentioned time period was predicted through three methods: regression, ARIMA and Artificial Neural Network (ANN). Evaluation criteria of predicted values of the unified exchange rate's trend were Mean Squared Error (MSE), Root-Mean Squared Error (RMSE) and Theil Inequality coefficient (TIC) which confirmed the fact that neural networks methods are more efficient than their rival methods, because values predicted by the neural network are closer to real values and has less measurement error.

Zera-nejad et. al. (2008) predicted the exchange rate of Iran using time series model and neural networks. This study used daily data during years (2006-2009). The results showed that neural network methods have better performance than the ARIMA method used in that work.

Khodaveysi & Molla-Bahrami (2012) used the stochastic differential equation models of geometric Brownian motion and Merton's jump-diffusion to model and predict the time series trend of exchange rate in the official exchange market of Iran. To evaluate the performance of this model in predicting out-of-sample exchange rate, a comparison was conducted between these models and the ARIMA time series econometric model. Results show that the proposed models have a better performance than the ARIMA model in predicting in-sample and out-of-sample exchange rate based on the RMSE criterion.

4. RESEARCH PROCEDURE AND HYBRID NEURAL NETWORK

Neural networks have a wide range of applications. However, they need rich sources of data and large number of observations to acquire the desired results. When there is no sufficient data for network training, the network cannot exhibit high performance and will have severely restricted applications. To overcome the above problem, in this study, we train the neural network by particle swarm and genetic algorithms and then compare their performance with the neural network to find the best method for predicting the exchange rate. The procedure of this research is shown below.

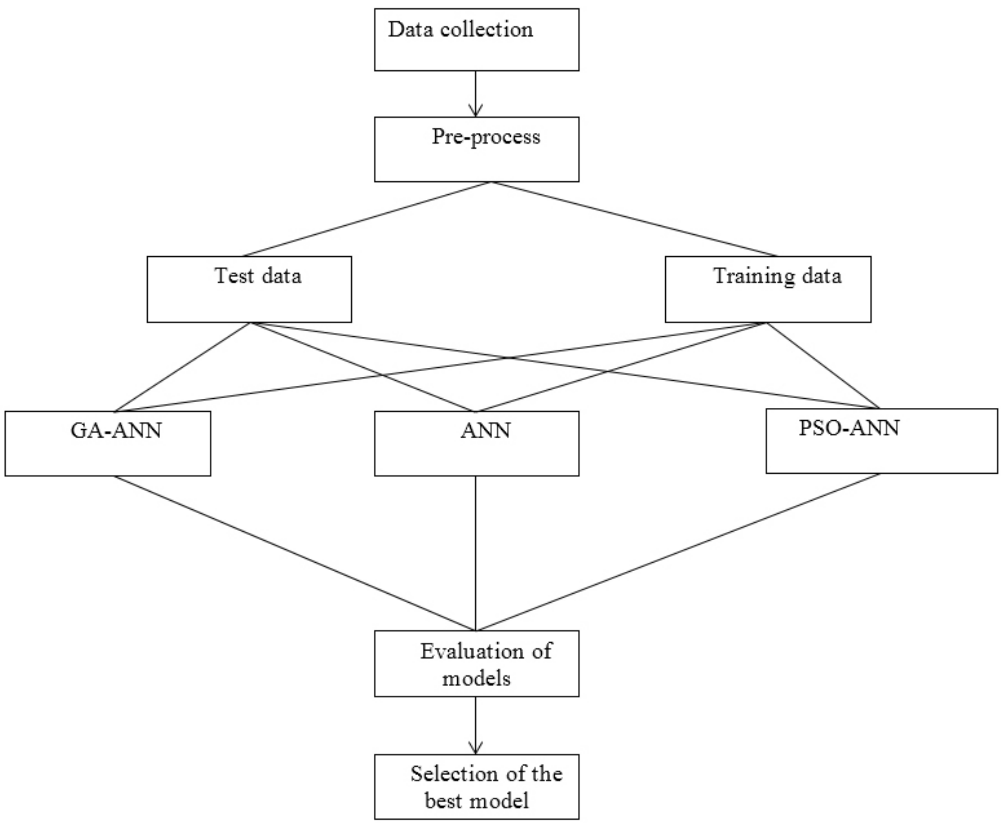


Figure 1: Research procedure

5. DATA COLLECTION

In this study, the data required for comparing the models include daily time series of nominal exchange rates or the exchange rate of Dollar-Rial in the time period of 21/03/2009 to 22/12/2015, which is taken from the website of Iran's central bank and includes a total of 2467 observations. These data are composed of two sections. The first section of the data pertains to time period of 25/03/2014 which is used for training and the second section of the data is related to time period of 26/03/2014 to 19/01/2016, which is used for test and comparison of the following models: feed-forward neural network (FNN) model, GA-ANN hybrid model and PSO-ANN hybrid model.

Table 1
Classification of data into two groups of training and test data

Time series	*Sample size*	*Size of training set*	*Size of test set*
Exchange rate (Dollar-to-Rial)	2467	70%	15%

Source: Research findings

6. RESEARCH RESULTS

One of the main goals of this study is to evaluate the performance of hybrid models in improving the ability of neural network; therefore the structure of the neural network in the three models of artificial neural network and the GA-ANN and PSO-ANN hybrid models will be identical. Different kinds of artificial networks can be to achieve the goals of this study. In this study we used the Multilayered Feedforward Neural Network (MFNN). Table 2 shows how the dollar exchange rate is designed and modeled in the neural network.

Table 2
Design and modeling of the dollar exchange rate in artificial neural network

Neural network type	*Multilayered feed forward*	*Neural network training algorithm*	*Levenberg-Marquardt*
Activation function {Hidden-layer and output layer}	Hyperbolic-linear tangent	Training process stop condition	eav≤1e^{-4}
The number of input neurons {Dollar}	1	Training time period LEVENBERG-MARQUARDT	25/03/2014-24/03/2012
The number of output neurons	1	Training time period LEVENBERG-MARQUARDT	19/03/2016-26/03/2014
Criterion for determining the number of hidden neurons	MSE	Ratio of training and testing data	15% to 70%
The number of hidden layers	1	Learning rate	0.1
The number of hidden neurons	10		

Source: Research findings

In the multilayered feedforward neural network of this study, several neurons and the hyperbolic tangent activation function is used for the hidden layer and the linear activation function[1] is used for the output layer. After determining the number of optimal stopping, different kinds of networks with different number of hidden neurons are designed and trained to determine the number of neurons in the hidden layer of the network. The optimal network is chosen from amongst these networks with respect to the MSE criterion. This means that the network with the minimum MSE that has 10 hidden neurons is used. The training and test periods are composed of 2467 data. 70% of the data is used for training and 15% is used for testing, and network is trained with learning rate of 0.1. We use the early stopping method to stop the training process.

1 In neural network literature, a linear activation function means a linear identity function.

7. EVALUATION OF PREDICTION MODELS

In this stage, we compare the results of GA-ANN and the PSO-ANN hybrid models with the artificial neural network model to evaluate the performance of exchange rate prediction models. To compare the predictive power of artificial neural networks with GA-ANN hybrid model, we use the following criteria: Mean Squared Error (MSE), Root-Mean Squared Error (RMSE), Mean Absolute Error (MAE) and Theil's U Statistic.

Table 3
Comparison between the predictive power of ANN model and the hybrid models

Criterion	*ANN*	*ANN-GA*	*ANN-PSO*
MSE	$10^4 \times 1.32$	$10^4 \times 1.24$	$10^4 \times 1.10$
RMSE	$10^2 \times 1.15$	$10^2 \times 1.11$	$10^2 \times 1.05$
MAE	65.62	62.20	62.50
U.Theil	0.003	0.0029	0.0028

Source: Research findings

As Table 3 shows, the PSO-ANN hybrid model has a significant advantage in all performance evaluation criteria. These results show that the PSO-ANN hybrid model has a lower error, which result in its greater performance in predicting the exchange rate of the following day. To evaluate the accuracy of the models used in this study, we predicted the exchange rate from March 2009 to December 2015. The results are shown below.

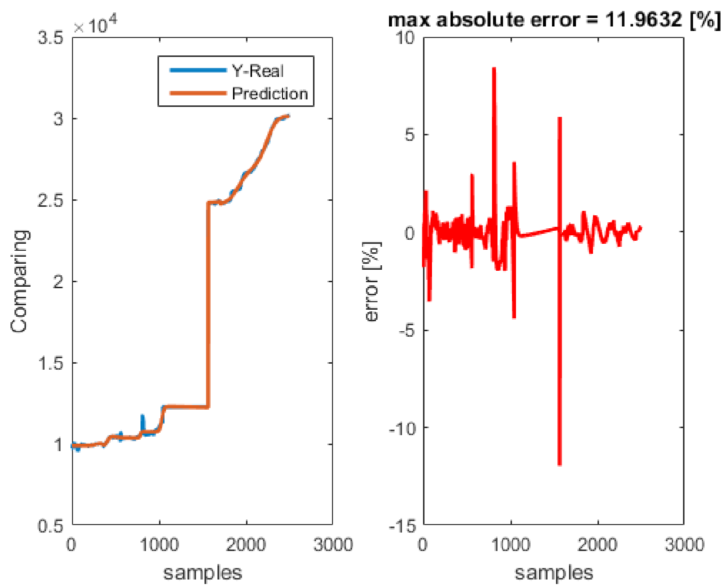


Chart 1: Comparison between the real values and the values predicted by ANN model

According to the above charts, the PSO-ANN hybrid model has 7.305% error which is less than other two models, and this indicates the Superiority of this model in predicting the dollar exchange rate. It can be thus concluded that with the training of data by the particle swarm model allows us to effectively improve the accuracy of the neural network.

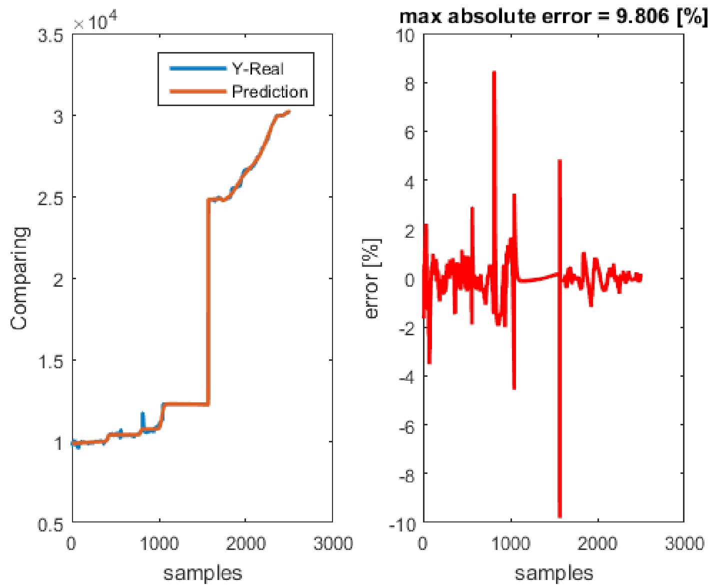


Chart 2: Comparison between the real values and the values predicted by the ANN-GA model

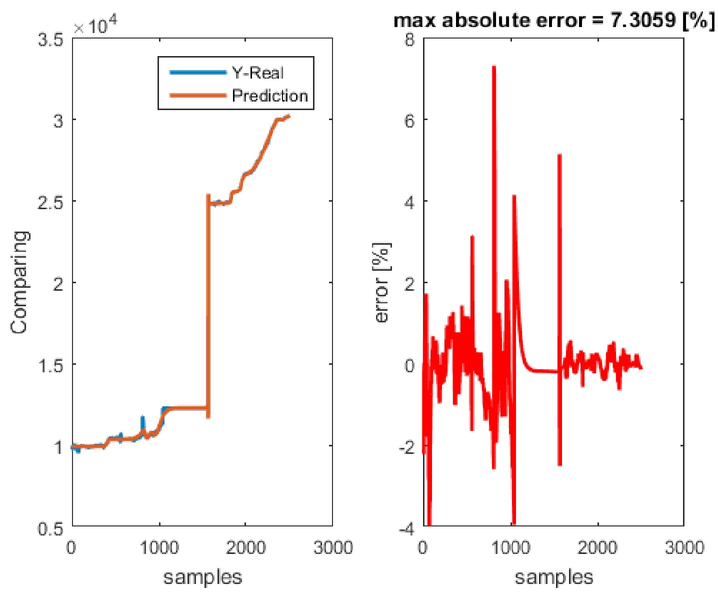


Chart 3: Comparison between the real values and the values predicted by the ANN-PSO model

8. OUT-OF-SAMPLE PREDICTION OF EXCHANGE RATE USING THE PROPOSED MODELS

Predicting 10% of all data (future 240 days) is presented below. As these charts show, the ANN and PSO-ANN models have a more reasonable behavior and prediction than the GA-ANN model. The ANN model predicted an increasing trend with increasing slope for the dollar exchange rate. The PSO-ANN model predicted an increasing trend with decreasing slope for the dollar exchange rate.

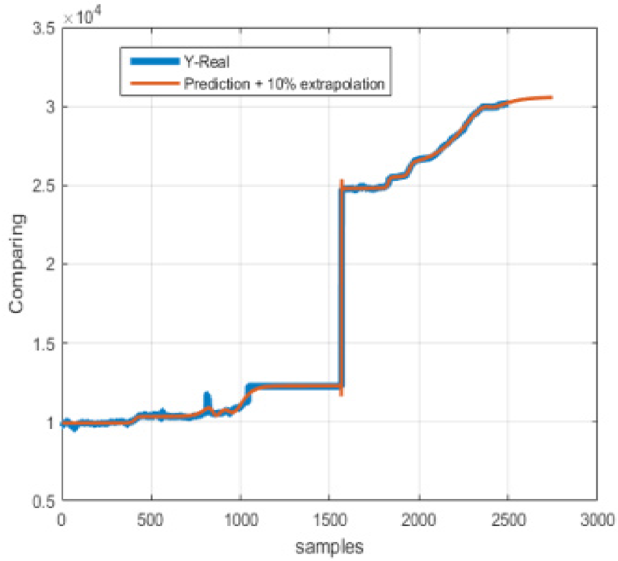
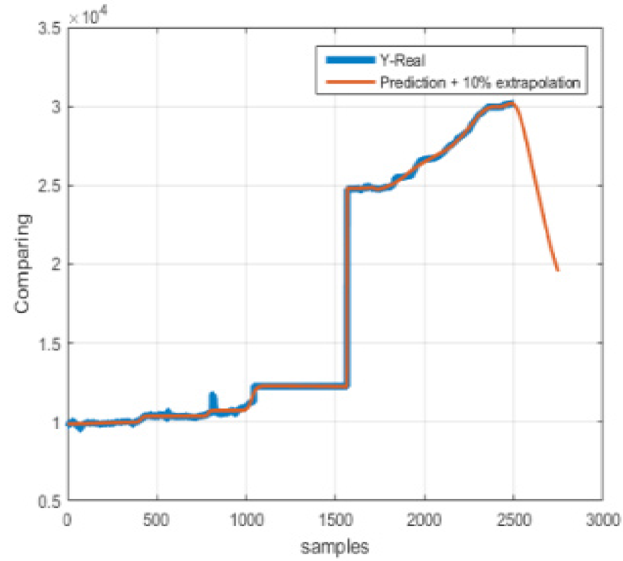


Chart 4: Prediction of ANN model



Char 5: Prediction of GA-ANN model

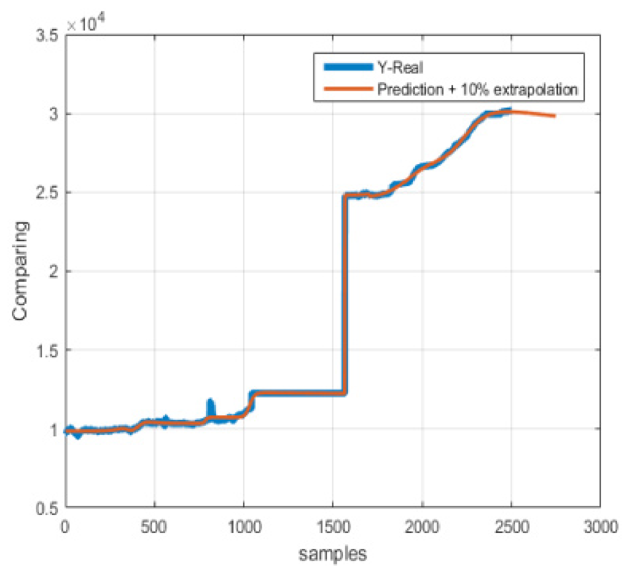


Chart 6: Prediction of PSO-ANN model

9. CONCLUSION

Predicting the trend of economic variables is of significant importance to government and private policy makers for regulating economic relations. There are different methods for short term and long term prediction of economic variables. In recent years, the artificial neural network has emerged as a competitor to traditional statistical methods previously used for this purpose. In this study, we presented two modern ANN hybrid models for predicting the exchange rate in Iran. In the network design, we used multilayered feedforward neural network consisting of several neurons in the input layer, hyperbolic tangent activation function for the hidden layer and linear activation function for the output layer. After determining the number of optimal stops, different kinds of networks with different number of hidden neurons were designed and trained to determine the number of neurons in the hidden layer. The optimal network was chosen amongst these networks with respect to MSE criterion. This means that the network with the minimum MSE which had 10 hidden neurons was chosen. The training and test periods were composed of 2467 data. 70% of the data was used for training with the learning rate of 0.1, and 15% was used for testing. We use the early stopping method to stop the training process. Next, we used the error criteria to compare the studied models. The value of criteria MSE, RMSE, MAE, U. Theil for the PSO-ANN hybrid model were determined to be respectively, 1.10*104, 62.50*102, 1.05 and 0.0028. The PSO-ANN hybrid model showed lower error in predicting exchange rate than the feedforward ANN model, which had previously shown superiority over the linear and conventional econometric methods. According to evaluation results, After the PSO-ANN hybrid model, the GA-ANN showed the next best level of error. In addition, we predicted the trend of exchange rate using the 10% of all data for the following 247 days, and results showed that ANN and PSO-ANN exhibit a more reasonable behavior and prediction than the GA-ANN model. The ANN model predicted an increasing trend with increasing slope for the dollar exchange rate, while The PSO-ANN model predicted an increasing trend with decreasing slope. It can be concluded that proper training of neural network by the particle swarm model can allow us to decrease the error of this network and thus improve the accuracy of forecasts.

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