UDC 004.8:336
DOI: 10.20535/SRIT.2308-8893.2024.3.01

IMPROVING THE ACCURACY OF NEURAL NETWORK EXCHANGE RATE FORECASTING USING EVOLUTIONARY MODELING METHODS

S.S. FEDIN

Abstract. A set of models of feedforward neural networks is created to obtain operational forecasts of the time series of the hryvnia/dollar exchange rate. It is shown that using an evolutionary algorithm for the total search of basic characteristics and a genetic algorithm for searching the values of the matrix of neural network weight coefficients allows optimizing the configuration and selecting the best neural network models according to various criteria of their training and testing quality. Based on the verification of forecasting results, it is established that the use of neural network models selected by the evolutionary modelling method increases the accuracy of forecasting the hryvnia/dollar exchange rate compared to neural network models created without the use of a genetic algorithm. The accuracy of the forecasting results is confirmed by the method of inverse verification using data from different retrospective periods of the time series using the criterion of the average absolute percentage error of the forecast.

Keywords: exchange rate, genetic algorithm, evolutionary modeling, neural network, optimization, forecasting, accuracy, time series.

INTRODUCTION

In the foreign and domestic practice of financial analysis and forecasting, artificial intelligence information technologies are widely used, which are currently an integral auxiliary tool in the process of making managerial decisions in the field of economics and finance [1]. The use of these technologies, in particular, contributes to the successful solution of the tasks of forecasting currency and stock exchange rates, assessing the risk of financial and banking operations, analyzing and forecasting market indicators, credit ratings of businesses etc. [1–3].

Management of economic entities, including financial systems, is carried out under conditions of uncertainty, which necessitates the use of methods of obtaining information on economic indicators to make a reasonable judgment about possible future states of the system or alternative ways and timing of their implementation. Future uncertainty cannot be completely eliminated, so the main task of decision-making under uncertainty is to find “good” or “best” decisions from a range of alternatives.

One of the tools in the process of making such decisions is the forecasting methodology [4; 5]. The need to use different forecasting methods is caused by the fact that in the context of nonlinear dynamic processes of financial markets, determining their future states is a difficult task, but obtaining reliable information about the value of financial indicators is a key aspect of supporting decision-making at a certain point in time.

According to the results of independent studies confirms the assumption that the time series of financial indicators, in particular, stock prices and exchange rates, are characterized by nonlinear trends at different periods of retrospection [6–9]. The dynamics of exchange rates is characterized by complex nonlinear dependencies with a high level of noise and veiled periodic components with variable amplitude, which causes the presence of heterogeneous components in the time series and does not allow for the selection of a single model structure for the entire time series data set [10]. Thus, at different periods of retrospection, the structure of the model (the nature of the trend) changes, this increases the degree of information uncertainty and reduces the reliability of forecasting. The solution to this problem requires the use of artificial intelligence methods, including neural networks and evolutionary modeling.

A common characteristic of these non-parametric information processing methods is the ability to recognize patterns — trends based on the generalization of input information [11]. The ability to model nonlinear processes and adaptability allow the use of neural networks and evolutionary algorithms in solving various forecasting problems in the face of noisy input data [12; 13]. In addition, compared to classical analytical models, neural networks allow obtaining reliable forecast estimates for non-stationary and periodic time series of financial indicators [11].

Thus, the use of neural network and evolutionary forecasting methods can be viewed as a generalization of traditional approaches to solving the urgent problem of recognizing trends in the time series of exchange rates and timely management decision-making.

PROBLEM DEFINITION

To build a multilayer feedforward neural network, let us assume that the set of training sample examples is represented by data vectors (X, Y), the structure of which determines the number of inputs N and outputs M of the neural network, where $X=(x_1,x_2,\ldots,x_N)$ is the value of the input vector, and $Y=(y_1,y_2,\ldots,y_M)$ — the desired (actual or reference) values of the output vector.

Then the process of training a neural network as a dynamic system consists in achieving such a state of the network in which the differences between all output Y' and the desired values of the training sample vectors Y do not exceed the value of the error δ, which is determined in advance and calculated in a certain way. In this case, the task of training a neural network is to determine the values of all its characteristics, so that when any vector X from the set of training examples (X,Y) is fed to the input, the neural network output for a given set of weight coefficients W is the vector $Y'(W)=\{y_1'(W),y_2'(W),\ldots,y_M'(W)\}$, which differs from the reference vector Y by no more than value of error δ.

In this case, the objective function (training criterion) will be the error $\delta_{\max}(W)$ — the maximum difference between Y' and Y for all vectors of the training set containing *n* elements. The minimum value of the error δ will allow obtaining the maximum training accuracy of the neural network model.

The objective function is represented as the sum of the squares of deviations of the values Y from the values Y', obtained by the dynamic process of propagation of training sample examples from the inputs to the outputs of the neural network

$$\delta(W) = \frac{1}{2}\left\| Y - Y_i'(W) \right\|^2 = \frac{1}{2}\sum_{k=1}^{M}(Y_k - Y_k'(W))^2 . \qquad (1)$$

Then the iterative process of finding the weights of inter-neuronal connections *W* of the neural network that would satisfy the given value of criterion (1) can be carried out by the gradient descent method based on the dependence

$$W(n+1) = W(n) - \eta \cdot \mathrm{grad}_W \delta(W(n)) , \qquad (2)$$

where η is the step size (error correction rate coefficient).

To obtain an estimate of the learning criterion (1) and find the vector weights of the neural network (2), the Back Propagation of Error algorithm can be used. The disadvantage of this algorithm is that it can only find local minimum of the objective function (1). Since the task of finding the characteristics of a neural network that satisfies the condition $\delta(W_{\max}) = 0$ for real data is unattainable and is usually not set, the optimal solution turns into the search for a better or rational solution [14]. An effective way to find such a solution is to use the mathematical apparatus of genetic algorithms, the functioning of which is based on the mechanisms of natural evolution using selection and crossover operators of parental individuals, mutation of offspring and assessment of their fitness [12; 15–17]. Since all of these operators are collectively aimed at improving each individual, the preliminary results of the genetic algorithm will be iterative improvements in the solution population compared to the initial population, the size of which remains constant. The resulting neural network individual differs from its parent(s) and may be more or less adapted to transmit genetic information (chromosomes) to subsequent generations, which is characterized by an estimate of the fitness function. The chromosome of an individual consists of neurons — genes, each of which is represented by a set of values of its input weights [16; 18].

Let us represent individuals as a vector containing meaningful "genetic" information in the form of input and output weights of the neural network $W = (W_{inp}, W_{hid}^{j}, W_{out})$, where W_{inp} — is the vector of input weights of the neural network; W_{hid}^{j} — is the vector of weights between the *j*-th and (*j*+1)-th hidden layers of a multilayer neural network; W_{out} — is the vector of output weights of a neural network; $j = \overline{1...k-1}$, where *k* is the number of hidden layers. The dimension of *W* is equal to $(N+1)J_1 + J_1 J_2 + ... + J_{k-1}J_k + J_k M$, where J_j is the number of neurons in the *j*-th hidden layer [19].

Then, the task of building a complete neural network can be solved in two stages, each of which requires the use of a specific genetic algorithm, namely:

– a total search for the basic characteristics of the neural network topology, i.e. determining the number of hidden layers *k* and neurons in each hidden layer *J* (Fig. 1);

– optimization of the neural network configuration by determining the “best” combination of the values of the weight coefficients W of all inter-neuronal connections (Fig. 2).

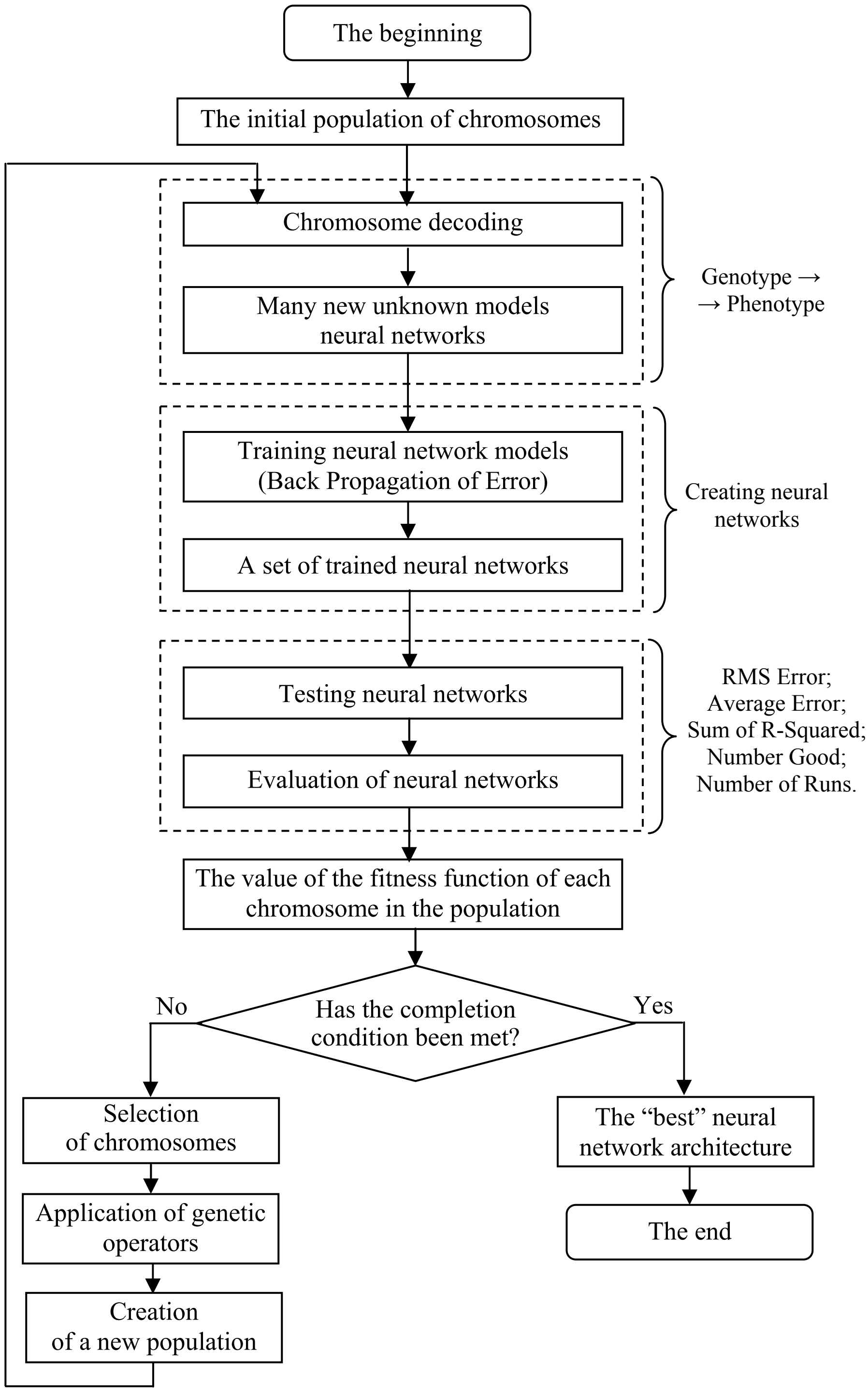


Fig. 1. Flowchart of the genetic algorithm for finding the neural network topology — evolution of architectures

Let us present four fitness functions (Table 1) for their sequential application in the genetic algorithm for optimizing the configuration of a neural network model (Fig. 2).

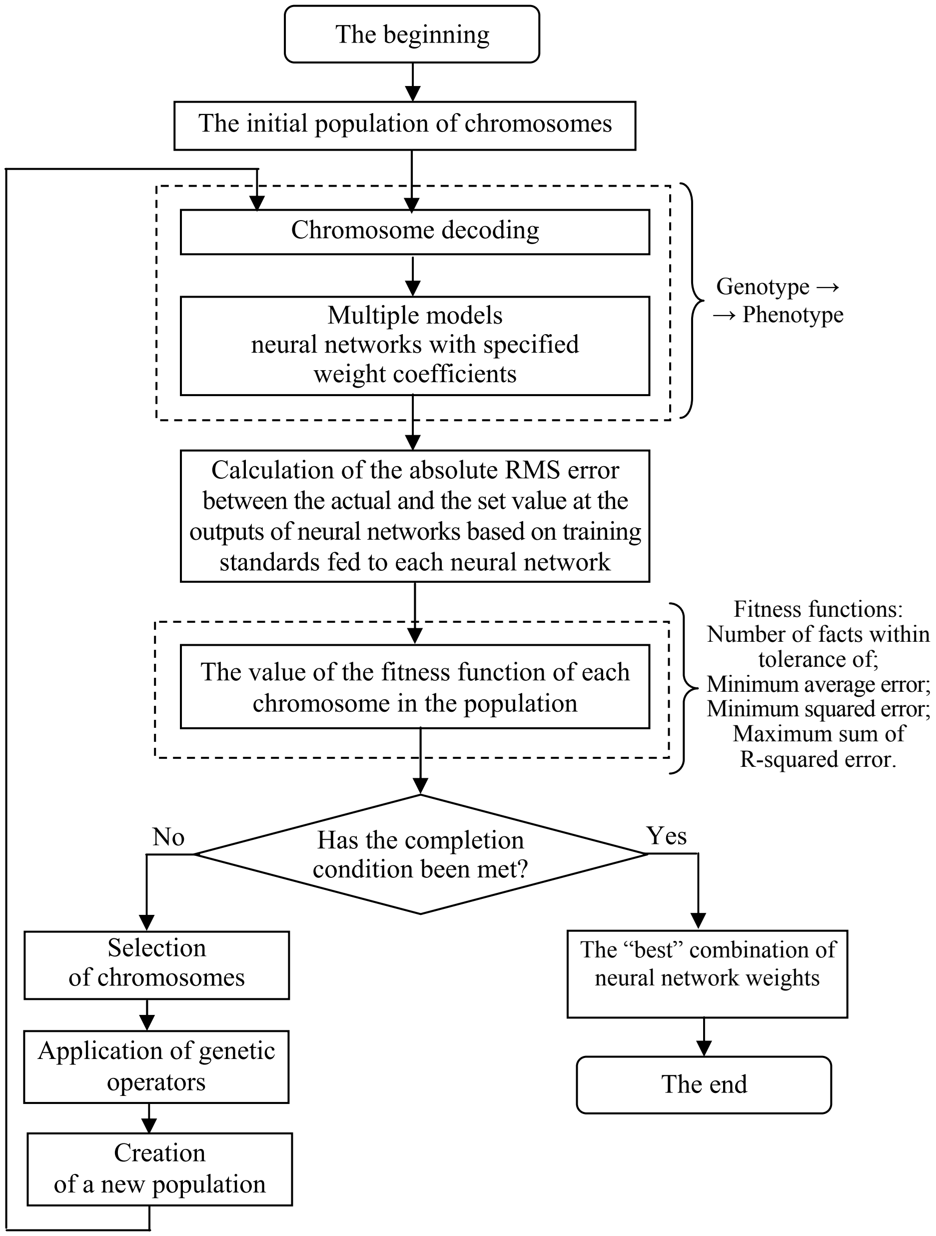


Fig. 2. Flowchart of the genetic algorithm for finding the weighting matrix of a neural network — evolution of weights

In accordance with the value of one of the selected fitness functions (Table 1), the genetic algorithm (Fig. 2) allows iteratively improving the population of neural network individuals and determining the neural network configuration that corresponds to the minimum error value (1), which can ultimately contribute to improving the accuracy of operational forecasting of time series of exchange rates.

T a b l e 1 . Types of fitness functions for the genetic algorithm for finding the matrix of neural network weighting coefficients (evolution of weights)

Criterion	Type of fitness function
Number of facts within the tolerance of	$Y' \in Y \pm TOL(Y_{\max} - Y_{\min})$, (3) where TOL is the accuracy parameter of neural network training and testing
Minimum average error	$\max\,(1 - Avg\ Error)$, (4) where $Avg\ Error = \frac{1}{n}\sum_{i=1}^{n}\lvert Y_i' - Y_i\rvert$.
Minimum squared error	$\max\,(1 - RMS\ Error)$, (5) where $RMS\ Error = \frac{1}{n}\sqrt{\sum_{i=1}^{n}(Y_i' - Y_i)^2}$
Maximum sum of R-squared error	$\max\,(\sum R^2)$, (6) where $R^2 = \frac{\left[n\sum_{i=1}^{n}(Y_i'Y_i) - \sum_{i=1}^{n}Y_i'\sum_{i=1}^{n}Y_i\right]^2}{\left[n\sum_{i=1}^{n}(Y_i')^2 - \left(\sum_{i=1}^{n}Y_i'\right)^2\right]\left[n\sum_{i=1}^{n}(Y_i)^2 - \left(\sum_{i=1}^{n}Y_i\right)^2\right]}$.

RESEARCH OBJECTIVE

This study is dedicated to improve the accuracy of neural network forecasting of the exchange rate of the currency pair hryvnia/dollar through the use of a genetic algorithm that allows to optimizing the configuration and perform an evolutionary search for the best neural networks models according to a given criterion of the quality of their training and testing.

LITERATURE REVIEW

The studies of S.A. Ayvazyan, I.G. Lukyanenko, L.I. Krasnikova, P.I. Bidyuk, O.V. Polovtsev, I.V. Baklan, V.M. Rifa, J. Johnston, J. DiNardo, G.E.P. Box, G.M. Jenkins demonstrate that the use of time series analysis methods is one of the most common approaches to forecasting the development of economic systems and processes, evaluating alternative economic strategies, as well as managing economic and financial risks [20–26].

It is known that the purpose of time series analysis is to obtain useful information from an ordered sequence of real numbers x_t, $t = 1,2,\ldots,T$, which are the results of observations of a certain value, based on a certain mathematical model [11; 27]. Such a model should explain the essence of the dynamic process, in particular, describe the nature of the data, which can be random, stationary, non-stationary, or periodic [27]. Time series of currency exchange rates or stock price movements usually contain random fluctuations and noise in varying proportions [11]. Therefore, the quality of the model is largely determined by its ability to approximate the regular (predictable) structure of the time series, separating it from the noise. To solve this problem, methods of statistical analysis of time series are effective, including linear autoregressive moving average models (ARMA), ARMA+trend models, and methods of forecasting nonlinear processes, which include artificial neural networks [9]. The peculiarity of using neural network models is the ability to reproduce any dependence of the form $\hat{x}_t = f(x_{t-1}, x_{t-2}, ..., x_{t-p}) + \varepsilon_t$ with a continuous function f based on the delay vector between current and past data $(x_{t-1}, x_{t-2}, \ldots, x_{t-p})$ in n-dimensional space of time-shifted values [11; 19].

However, under conditions of uncertainty of the future situation, associated, for example, with changes in the nature of the trend of financial indicators at different time intervals, the task of fully building a neural network model is complex both in terms of its dimensionality and in terms of ensuring the accuracy of the model during training and testing. One of the effective ways to solve this problem is to combine neural networks and genetic algorithms to find the best solution from a number of alternatives in the argument search space and determine the extremum of the objective function of the learning error (1) [12; 14]. This combination can be auxiliary when (methods are applied sequentially one after the other) or equal (simultaneous application of both methods, for example, to find the weights of inter-neural connections) [28; 29].

It is assumed that in the face of changing trends in financial indicators, the use of the principle of equal combination of a genetic algorithm and a feedforward neural network will optimize the machine learning process and, as a result, improve the accuracy of approximating the regular component of the exchange rate time series in the selected observation interval.

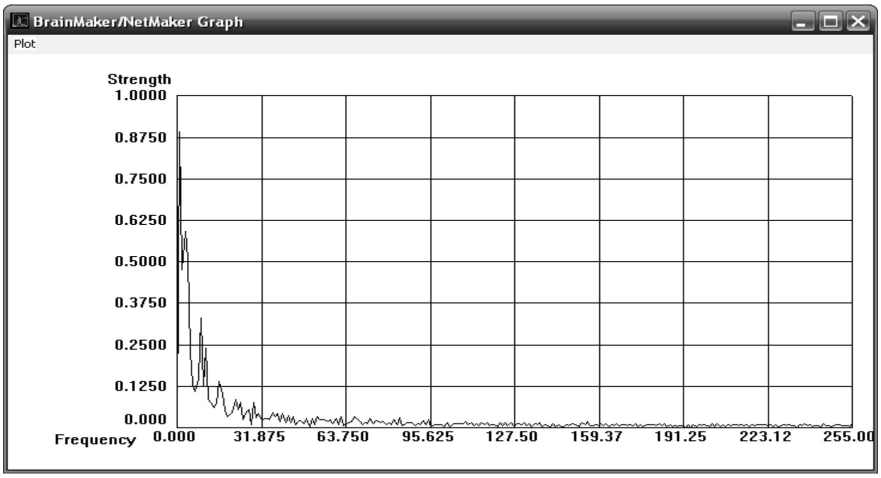
Thus, conducting a study aimed at ensuring the accuracy of neural network forecasting of non-stationary time series by using genetic algorithms in optimizing the training process of multilayer neural networks is an urgent scientific and practical task.

MATERIALS AND METHODS

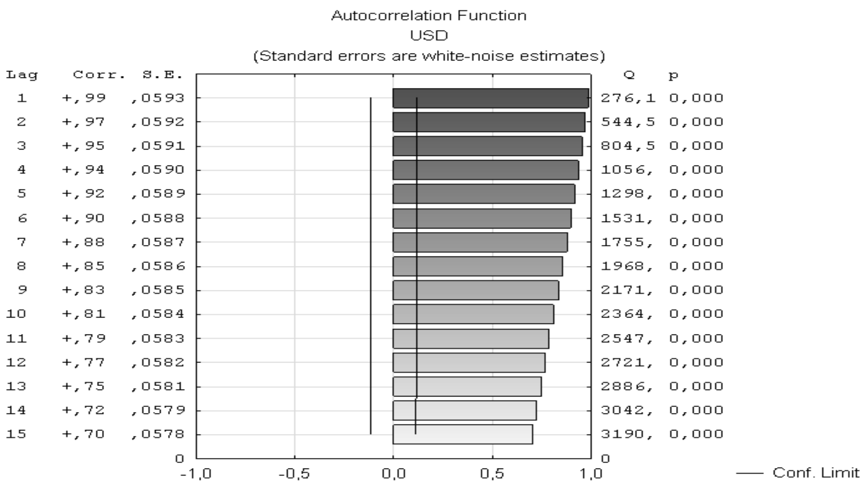
As the initial data for creating neural network forecasting models, we used factual data of the time series of the official hryvnia exchange rate against the US dollar, which were borrowed from the government electronic resource [30]. To assess the accuracy of the forecast, the principle of simulation forecasting was applied, since the actual value of the hryvnia exchange rate in relation to the one-day forecast advance period, i.e. Tuesday 06.10.2020, is known and amounts to 28.4009 hryvnia per 1 dollar. In determining the dimension of the neural network training sample, we used the methods of spectral and autocorrelation analysis of time series data, as well as the method of a branched delay line, according to which the architecture of the feedforward neural network allows us to model any finite time dependence of the following form [11]

$$Y(t) = F[X(t), X(t-1), ..., X(t-p)] . \tag{7}$$

The spectral analysis shows that the frequency of the first harmonic is approximately zero (Fig. 3, *a*). This indicates the absence of periodicity in the regular component of the time series, and, as a result, the appropriateness of setting the forecast advance period to correspond to the daily change in the hryvnia/dollar exchange rate. The result of the autocorrelation analysis (Fig. 3, *b*) characterizes the non-stationary of the hryvnia exchange rate time series, since the maximum value of the autocorrelation coefficient corresponds to the first lag (time series shift), so the use of feedforward neural networks is an appropriate way to obtain an operational simulation forecast. The observation period, which is one week and corresponds to the number of inputs of the neural network training sample, was determined taking into account the lag for which the autocorrelation coefficient exceeds 0.85 (Fig. 3, *b*) [31].



a



b

Fig. 3. Results of spectral analysis of the time series in NetMaker (*a*); autocorrelation analysis of the time series in STATISTICA 10 (*b*)

Thus, in accordance with (7) and based on the obtained estimates of the time series autocorrelation coefficients (Fig. 3, *b*), the training set of $n = 274$ examples has a dimension consisting of seven inputs (Input) USD1 $(t-7)$, USD2 $(t-6)$,...,USD7 $(t-1)$ and one output (Pattern) USD8 (*t*). Testing of the USD_11.net neural network model with the 7:10:1 architecture, trained in the BrainMaker Professional system for 67 epochs of training (Run), showed that all 27 facts of the test sample (10% of the number of examples of the training sample) are classified as Good, i.e., within the tolerance range when condition (3) is met for the value of the TOL parameter $= 0.10$ [31]. The result of the simulation neural network forecasting was obtained using a training example that characterizes the last week of the observation period before Tuesday 06.10.2020 (t), i.e. the value of the hryvnia exchange rate from 29.09.2020 $(t-7)$ to 05.10.2020 $(t-1)$. To ensure the convergence of the results of neural network forecasting, training and testing of models with the 7:10:1 architecture was repeated $L = 5$ times with the value of the TOL parameter $= 0.10$. The evaluation of the results of testing neural network models (Table 2) and the accuracy of the simulation forecast for Tuesday 06.10.2020 (Table 3) was carried out according to the criterion of the mean absolute percentage error (*MAPE*)

$$MAPE = \frac{100}{n}\sum_{i=1}^{n}\frac{\left|Y_i' - Y_i\right|}{Y_i}, \tag{8}$$

where Y', Y are respectively the predicted (Out) and actual (Ptn) values of the i-th example selected for testing, $i = 1,\ldots,n$.

Table 2. The value of the *MAPE* criterion, %, based on the results of testing USD neural network models created in BrainMaker Professional

USD_11.net	USD_12.net	USD_13.net	USD_14.net	USD_15.net
0.784	0.761	0.822	0.726	0.664

The analysis of the data presented in Table 2 shows that for the test sample, the value of the *MAPE* criterion is in the range (0.664...0.822%), and the lowest value of this criterion corresponds to the USD_15.net neural network model (Table 3).

Table 3. Evaluation of the accuracy of forecasting results using neural network models created in BrainMaker Professional

Model	Run	Good	Result	*MAPE*, %
USD_11.net	67	27	27.875	1.85
USD_12.net	129	27	27.912	1.72
USD_13.net	83	27	27.888	1.81
USD_14.net	98	27	27.878	1.84
USD_15.net	62	27	27.883	1.82

The analysis of the data presented in Table 3 shows a high speed of neural network training (Run parameter) and finding all the facts of the test sample within the training tolerance (Good parameter) in accordance with condition (3). At the same time, the interval of the *MAPE* criterion is (1.72...1.85%), the lowest value of which corresponds to the USD_12.net model.

Attempts to create neural network models with a further reduction of the training tolerance allowed us to establish that for a sample of initial data when the value of the TOL parameter is set to 0.06, the machine learning process using the Back Propagation of Error algorithm in the BrainMaker Professional system does not converge. Therefore, the task of improving the accuracy of neural network forecasting of the hryvnia/dollar exchange rate was solved by evolutionary modeling in the Genetic Training Option (GTO) software using genetic algorithms

(Figs. 1, 2) and a smaller training tolerance compared to the models presented in Table 3. At the same time, the assumption of increasing the accuracy of neural network forecasting can be confirmed by fulfilling the following condition

$$\max_{L} MAPE^{\mathrm{GTO}\,l} < \min_{L} MAPE^{\mathrm{USD}\,l}\,, \qquad (9)$$

where is the l-th model of a neural network created with (GTO_l) and without (USD_l) genetic algorithm, $l = 1,\ldots,L$.

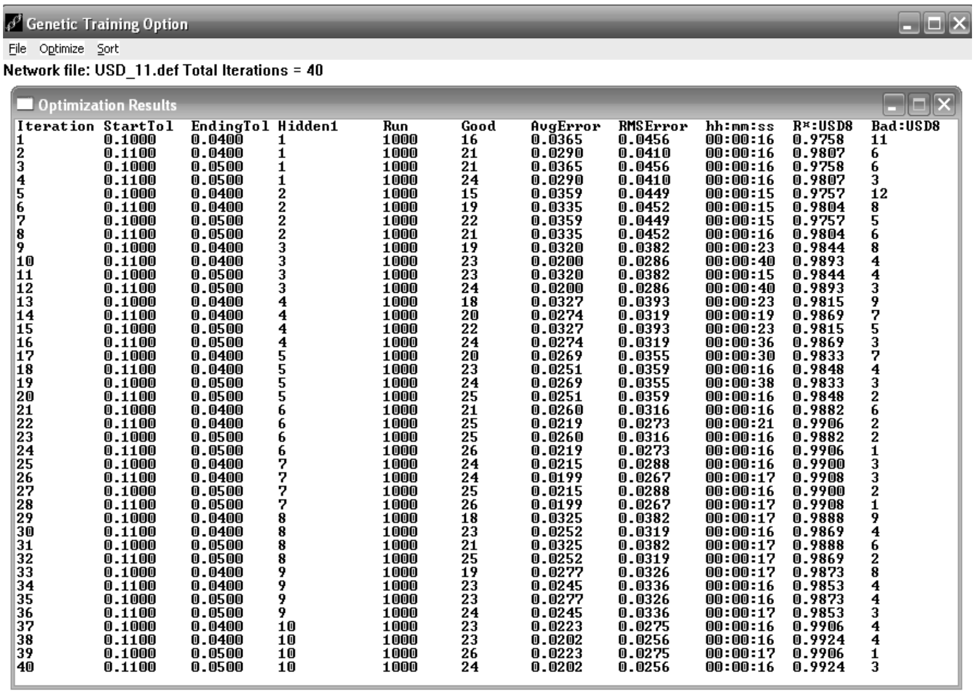
CONDUCTING COMPUTATIONAL EXPERIMENTS USING EVOLUTIONARY MODELING METHODS

The experimental studies were devoted to confirming the assumption that it is possible to improve the accuracy of neural network forecasting by using evolutionary modeling methods. Computational experiments were carried out according to a methodology that includes two stages, namely:

1) use of genetic algorithms in GTO (Figs. 1, 2) for the neural network model formed in BrainMaker Professional with randomly selected weights;

2) using the BrainMaker Professional system to automatically complete the machine learning process.

The use of the total search algorithm in GTO (Fig. 1) with a change in the TOL parameter and a given range of the number of neurons in the hidden layer of the neural network allowed us to obtain the result of training the neural network population (Fig. 4) and the model of the neural network GTO.net, all the facts of the test sample of which, according to condition (3), are within the training tolerance $\mathrm{Good} = 27$.


Genetic Training Option
File Optimize Sort
Network file: USD_11.def Total Iterations = 40
Optimization Results

Iteration	StartTol	EndingTol	Hidden1	Run	Good	AvgError	RMSError	hh:mm:ss	R*:USD8	Bad:USD8
1	0.1000	0.0400	1	1000	16	0.0365	0.0456	00:00:16	0.9758	11
2	0.1100	0.0400	1	1000	21	0.0290	0.0410	00:00:16	0.9807	6
3	0.1000	0.0500	1	1000	21	0.0365	0.0456	00:00:16	0.9758	6
4	0.1100	0.0500	1	1000	24	0.0290	0.0410	00:00:16	0.9807	3
5	0.1000	0.0400	2	1000	15	0.0359	0.0449	00:00:15	0.9757	12
6	0.1100	0.0400	2	1000	19	0.0335	0.0452	00:00:15	0.9804	8
7	0.1000	0.0500	2	1000	22	0.0359	0.0449	00:00:15	0.9757	5
8	0.1100	0.0500	2	1000	21	0.0335	0.0452	00:00:16	0.9804	6
9	0.1000	0.0400	3	1000	19	0.0320	0.0382	00:00:23	0.9844	8
10	0.1100	0.0400	3	1000	23	0.0200	0.0286	00:00:40	0.9893	4
11	0.1000	0.0500	3	1000	23	0.0320	0.0382	00:00:15	0.9844	4
12	0.1100	0.0500	3	1000	24	0.0200	0.0286	00:00:40	0.9893	3
13	0.1000	0.0400	4	1000	18	0.0327	0.0393	00:00:23	0.9815	9
14	0.1100	0.0400	4	1000	20	0.0274	0.0319	00:00:19	0.9869	7
15	0.1000	0.0500	4	1000	22	0.0327	0.0393	00:00:23	0.9815	5
16	0.1100	0.0500	4	1000	24	0.0274	0.0319	00:00:36	0.9869	3
17	0.1000	0.0400	5	1000	20	0.0269	0.0355	00:00:30	0.9833	7
18	0.1100	0.0400	5	1000	23	0.0251	0.0359	00:00:16	0.9848	4
19	0.1000	0.0500	5	1000	24	0.0269	0.0355	00:00:38	0.9833	3
20	0.1100	0.0500	5	1000	25	0.0251	0.0359	00:00:16	0.9848	2
21	0.1000	0.0400	6	1000	21	0.0260	0.0316	00:00:16	0.9882	6
22	0.1100	0.0400	6	1000	25	0.0219	0.0273	00:00:21	0.9906	2
23	0.1000	0.0500	6	1000	25	0.0260	0.0316	00:00:16	0.9882	2
24	0.1100	0.0500	6	1000	26	0.0219	0.0273	00:00:16	0.9906	1
25	0.1000	0.0400	7	1000	24	0.0215	0.0288	00:00:16	0.9900	3
26	0.1100	0.0400	7	1000	24	0.0199	0.0267	00:00:17	0.9908	3
27	0.1000	0.0500	7	1000	25	0.0215	0.0288	00:00:16	0.9900	2
28	0.1100	0.0500	7	1000	26	0.0199	0.0267	00:00:17	0.9908	1
29	0.1000	0.0400	8	1000	18	0.0325	0.0382	00:00:17	0.9888	9
30	0.1100	0.0400	8	1000	23	0.0252	0.0319	00:00:16	0.9869	4
31	0.1000	0.0500	8	1000	21	0.0325	0.0382	00:00:17	0.9888	6
32	0.1100	0.0500	8	1000	25	0.0252	0.0319	00:00:17	0.9869	2
33	0.1000	0.0400	9	1000	19	0.0277	0.0326	00:00:17	0.9873	8
34	0.1100	0.0400	9	1000	23	0.0245	0.0336	00:00:16	0.9853	4
35	0.1000	0.0500	9	1000	23	0.0277	0.0326	00:00:16	0.9873	4
36	0.1100	0.0500	9	1000	24	0.0245	0.0336	00:00:17	0.9853	3
37	0.1000	0.0400	10	1000	23	0.0223	0.0275	00:00:16	0.9906	4
38	0.1100	0.0400	10	1000	23	0.0202	0.0256	00:00:16	0.9924	4
39	0.1000	0.0500	10	1000	26	0.0223	0.0275	00:00:17	0.9906	1
40	0.1100	0.0500	10	1000	24	0.0202	0.0256	00:00:16	0.9924	3

Fig. 4. The result of GTO at the stage of total search for the basic characteristics of the neural network when ordering the population of models by the criterion of the number of neurons of the hidden layer Hidden 1

The main purpose of the GTO.net model, whose training was completed at the minimum value of the TOL parameter=0.056≤0.060, is to be used to perform crossover and mutation operators using the two best models that form the initial population of neural networks (Fig. 4). In the process of implementing genetic operators, in particular, it was assumed that each neural network would be trained for 100 epochs (Run) and 30 generations would be changed. To evaluate the neural network's adaptability, we used the results of both training and testing of the already trained neural network model. At the same time, 50% of all neurons were subjected to crossover and 10% to mutation. It was also assumed that the neurons were directly crossed by 50% and 25% using a uniform and normal random variable distribution law, respectively. The mutation of neurons was carried out in the same proportion as when performing the crossover operator. The fitness (quality) of the neural network model was assessed by one of the four GTO statistical criteria (Table 1).

The result of evaluating the quality of training for the 30 formed neural networks according to criterion (5), ordered from the highest to the lowest value, showed that the neural network model corresponding to the value $\max(1 - RMS\ Error) = 0.9735$ is the "best". The application of the created neural network model allowed us to obtain the forecast value of the exchange rate for Tuesday 06.10.20, which is equal to 28.071 hryvnias per 1 dollar. The final result of the genetic algorithm is the automatic saving of the five best out of 30 neural network models GTO001.net, GTO002.net, GTO003.net, GTO004.net, GTO005.net with a TOL value of 0.056. Evaluation of the results of testing the models created using the genetic algorithm and the accuracy of neural network forecasting according to criterion (8) is presented in Table 4 and Table 5, respectively.

Table 4. The value of the *MAPE* criterion, %, based on the results of testing USD neural network models created in GTO

GTO001.net	**GTO002.net**	**GTO003.net**	**GTO004.net**	**GTO005.net**
0.349	0.348	0.369	0.357	0.388

The analysis of the data presented in Table 4 shows that for the test sample, the value of the *MAPE* criterion is in the range (0.348...0.388%), and the lowest value of this criterion corresponds to the GTO002.net neural network model. Thus, based on a comparison of the results in Table 2 and Table 4, condition (9) is proved to be met.

Table 5. Evaluation of the accuracy of forecasting results using neural network models created by evolutionary modeling methods using GTO software and BrainMaker Professional system

Model	**Run**	**Good**	**Result**	***MAPE*, %**
GTO001.net	100	27	28.071	1.16
GTO002.net	100	27	28.075	1.15
GTO003.net	100	27	28.077	1.14
GTO004.net	100	27	28.063	1.19
GTO005.net	100	27	28.082	1.12

The analysis of the data presented in Table 5 shows that at the same speed of the neural network model training process ($\text{Run} = 100$), all the facts of the test sample in accordance with condition (3) are within the training tolerance $(\text{Good} = 27)$. At the same time, the result of the evaluation of criterion (8) is in the interval (1.12...1.15%), the lowest value of which corresponds to the GTO005.net neural network model.

Comparison of the results in Table 3 and Table 5 shows that the accuracy of the point forecast of the hryvnia exchange rate obtained using neural network models created by evolutionary modeling methods is higher than that of models created without the use of a genetic algorithm. To exclude the possibility of obtaining a random result of neural network forecasting using evolutionary modeling methods and to confirm the convergence of the neural network training and testing process, computational experiments in GTO were repeated five times using different statistical criteria: RMS Error; Average Error; Sum of R-Squared; Number Good; Number of Runs (Fig. 1).

Thus, at the first stage of applying the GTO evolutionary algorithm to find the basic characteristics and obtain the initial population of neural networks, in addition to the result with a different number of neurons in one hidden layer (Fig. 4), we obtained five more variants of ordering the initial population of neural network individuals. Thus, given the Hidden 1 ordering criterion, the total number of computational experiments was six. At the second stage, for the obtained six variants of the initial population of neural networks and four criteria (3)–(6), we repeated computational experiments to assess the adaptability of neural network models when optimizing their configuration using a genetic algorithm (Fig. 2).

RESULTS OF COMPUTATIONAL EXPERIMENTS

An assessment of the accuracy of the results of the daily forecasting of the hryvnia/dollar exchange rate for Tuesday 06.10.2020, obtained on the basis of neural network models created using a genetic algorithm, is presented in Tables 6–9 and Figs. 5–8.

Table 6. *MAPE* values, % for neural network models created on the basis of the criterion Number of facts within tolerance of

Ordering criterion	**Model**				
	GTO001	GTO002	GTO003	GTO004	GTO005
Hidden 1	1.34	1.24	1.20	1.14	1.11
RMS Error	1.34	1.12	1.15	1.25	1.18
Average Error	1.19	1.25	1.28	1.28	1.24
Sum of R-Squared	1.34	1.12	1.16	1.14	1.23
Number Good	1.19	1.32	1.21	1.22	1.15
Number of Runs	1.19	1.15	1.26	1.17	1.14

Table 7. *MAPE* values, % for neural network models created on the basis of the criterion Minimum average error

Ordering criterion	**Model**				
	GTO001	GTO002	GTO003	GTO004	GTO005
Hidden 1	1.24	1.19	1.19	1.23	1.26
RMS Error	1.23	1.22	1.26	1.23	1.26
Average Error	1.22	1.26	1.16	1.23	1.14
Sum of R-Squared	1.28	1.19	1.16	1.25	1.15
Number Good	1.17	1.13	1.31	1.25	1.28
Number of Runs	1.26	1.24	1.27	1.26	1.22

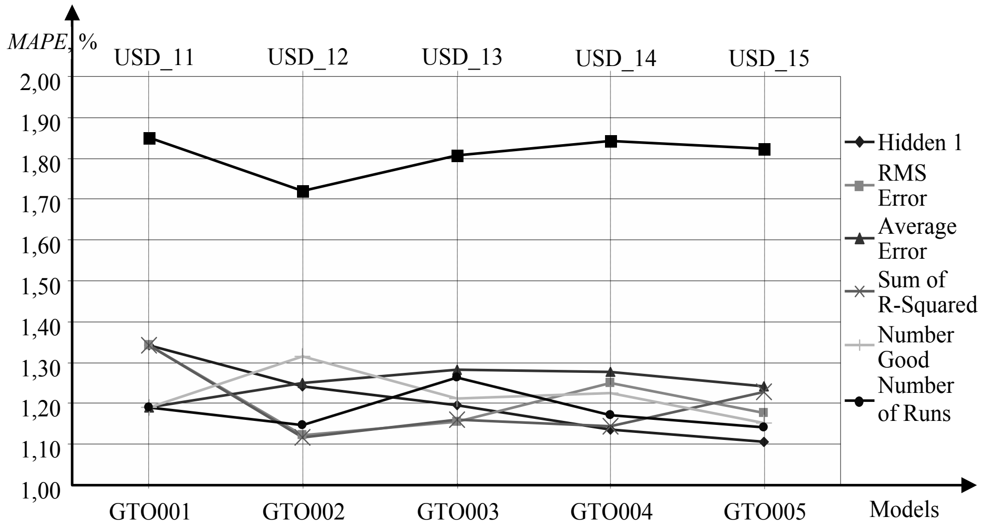


Fig. 5. MAPE values for forecasting the hryvnia exchange rate using five USD neural network models and five GTO neural network models created on the basis of the criterion Number of facts within tolerance of

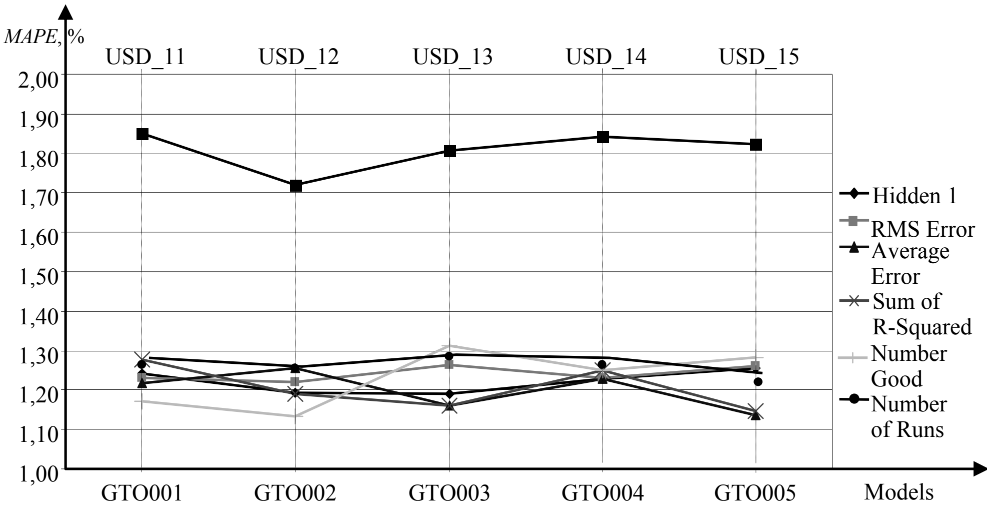


Fig. 6. MAPE values for forecasting the hryvnia exchange rate using five USD neural network models and five GTO neural network models created on the basis of the criterion Minimum average error

Table 8. *MAPE* values, % for neural network models created on the basis of the criterion Minimum squared error

Ordering criterion	**Model**				
	GTO001	GTO002	GTO003	GTO004	GTO005
Hidden 1	1.16	1.15	1.14	1.19	1.12
RMS Error	1.20	1.25	1.28	1.24	1.27
Average Error	1.20	1.15	1.22	1.27	1.18
Sum of R-Squared	1.22	1.18	1.24	1.17	**1.12**
Number Good	1.20	1.16	1.26	1.15	1.20
Number of Runs	1.13	1.17	1.18	1.17	1.15

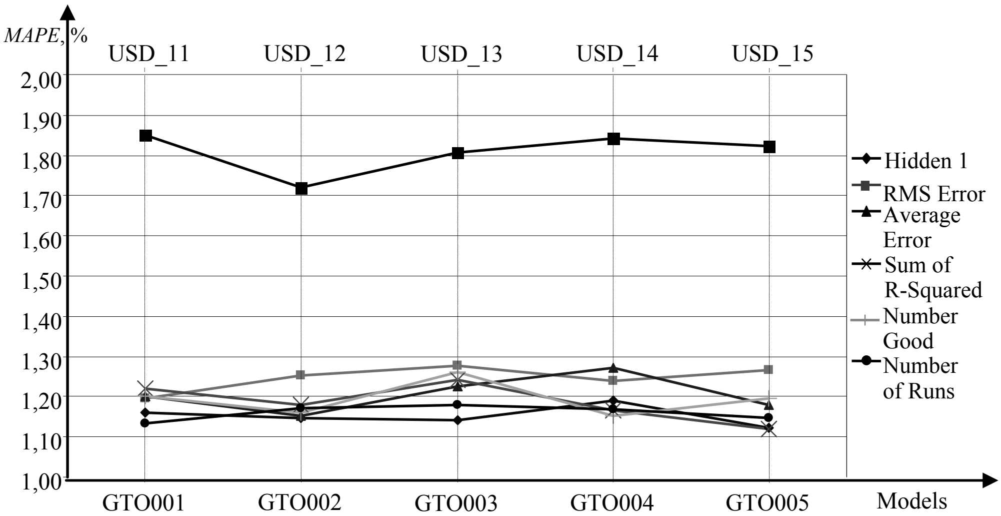


Fig. 7. MAPE values for forecasting the hryvnia exchange rate using five USD neural network models and five GTO neural network models created on the basis of the criterion Minimum squared error

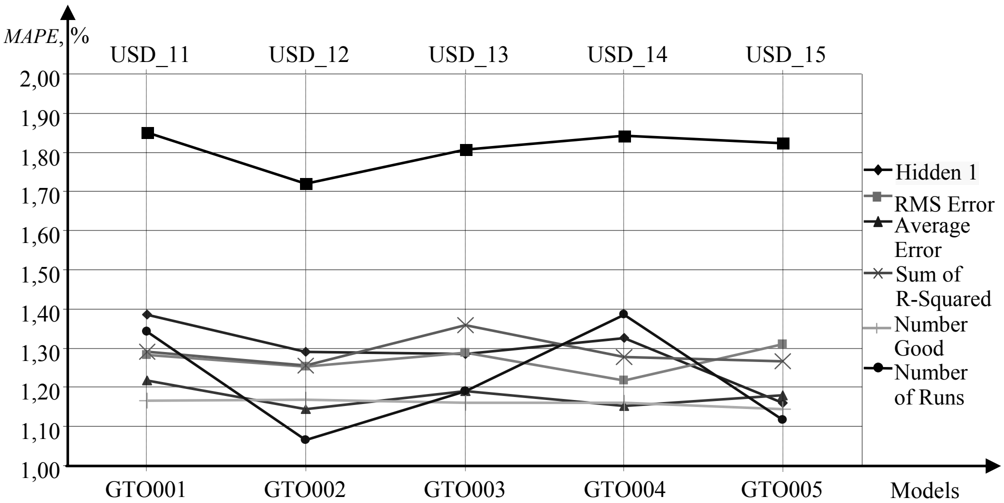


Fig. 8. MAPE values for forecasting the hryvnia exchange rate using five USD neural network models and five GTO neural network models created on the basis of the criterion Maximum sum of R-squared error

Table 9. *MAPE* values, % for neural network models created on the basis of the criterion Maximum sum of R-squared error

Ordering criterion	Model				
	GTO001	GTO002	GTO003	GTO004	GTO005
Hidden 1	1.39	1.29	1.28	1.33	1.16
RMS Error	1.28	1.25	1.29	1.22	1.31
Average Error	1.22	1.14	1.19	1.15	1.18
Sum of R-Squared	1.29	1.26	1.36	1.28	1.27
Number Good	1.17	1.17	1.16	1.16	1.14
Number of Runs	1.34	1.07	1.19	1.39	1.12

DISCUSSION OF THE OBTAINED RESULTS

Data analysis (Tables 6–9, Figs. 5–8) shows that the intervals of MAPE values for neural network models trained according to criteria (3)–(6) are, respectively: (1.11…1.34%); (1.13…1.31%); (1.12…1.28%); (1.07…1.39%), and for neural network models trained without the use of a genetic algorithm (1.72…1.85%) (Table 3).

Thus, on the basis of six computational experiments, the convergence of the process of re-training, testing and selection of the best neural network models was confirmed, and it was found that any of the 120 neural network models $(5\times 6\times 4=120)$ created by evolutionary modelling methods can improve the accuracy of the daily forecast of the hryvnia/dollar exchange rate (Figs. 6–9). Since the smallest interval of the *MAPE* value (1,12…1,28%) meets the criterion (5) — Minimum squared error (Table 8), the forecasting results with a one-week advance warning period were obtained using the best model of the GTO005.net neural network (Table 10) for the Sum of R-Squared ordering criterion (*MAPE*=1,12%, Table 8).

Table 10. The result of forecasting the hryvnia exchange rate using neural network models based on the criterion Minimum squared error

Ordering criterion	**Model**				
	GTO001	GTO002	GTO003	GTO004	GTO005
Hidden 1	28.071	28.075	28.077	28.063	28.082
RMS Error	28.061	28.045	28.038	28.049	28.041
Average Error	28.060	28.074	28.053	28.040	28.066
Sum of R-Squared	28.054	28.066	28.048	28.070	**28.083**
Number Good	28.060	28.071	28.043	28.074	28.061
Number of Runs	28.079	28.068	28.066	28.069	28.075

The GTO005.net model (Table 10) is characterized by the lowest forecast error value $|\Delta|=0.318$, where $|\Delta|$ is the a posteriori value of the deviation of the forecast value of the hryvnia/dollar exchange rate of 28.083 from the actual value of 28.4009 hryvnia per 1 dollar. The results of the estimates for the weekly forecast lead time obtained using the most accurate neural network model USD_12.net (Table 3), which was created without the use of a genetic algorithm, and the selected most accurate model GTO005.net are shown in Table 11.

Table 11. Evaluation of the neural network forecasting result with a warning period of one week from 07.10.2020 to 13.10.2020

Date	**Hryvnia exchange rate**	**USD_12.net**	**GTO005.net**	$MAPE_{USD\_12}$	$MAPE_{GTO005}$
07.10.2020	28.364	27.913	28.082	1.590	0.994
08.10.2020	28.324	27.916	28.099	1.440	0.794
09.10.2020	28.284	27.921	28.096	1.282	0.663
10.10.2020	28.284	27.925	28.079	1.268	0.723
11.10.2020	28.284	27.913	28.058	1.310	0.798
12.10.2020	28.210	27.903	28.052	1.088	0.559
13.10.2020	28.248	27.895	28.055	1.250	0.684

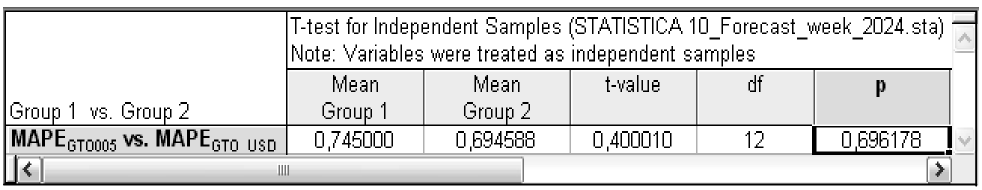
Taking into account all the values of the weekly forecast lead time for the USD_12.net and GTO005.net models (Table 11), the estimated mean absolute percentage error (8) is 1.318% and 0.745%, respectively. Thus, for the GTO005.net model, the *MAPE* estimate is approximately 1.77 times lower than the *MAPE* estimate for the USD_12.net model. Thus, the analysis of the results obtained (Table 11), as well as in the case of the daily point forecast, shows that the accuracy of the weekly forecast of the hryvnia/dollar exchange rate has improved.

The adequacy of the results was checked, as well as the reliability and validity of the neural network forecast was assessed using the inverse verification method on a new retrospective period of the hryvnia/dollar exchange rate time series — from 02.10.2023 to 19.03.2024. To obtain a weekly forecasting result based on the data of the observation period from 02.10.2023 to 12.03.2024, the neural network was trained in the GTO system using the Sum of R-Squared ordering criterion at the stage of total search for its basic characteristics, and the Minimum squared error criterion to select the best neural network models (5). The evaluation of the obtained forecasting result is shown in Table 12.

Table 12. Evaluation of the result of neural network forecasting with a warning period of one week from 13.03.2024 to 19.03.2024

Date	Hryvnia exchange rate	GTO_USD.net	$MAPE_{\text{GTO\_USD}}$
13.03.2024	38.4924	38.379	0.295
14.03.2024	38.7878	38.399	1.002
15.03.2024	38.6854	38.518	0.433
16.03.2024	38.6854	38.453	0.601
17.03.2024	38.6854	38.451	0.606
18.03.2024	38.7998	38.499	0.775
19.03.2024	38.9744	38.526	1.150

The estimate of the *MAPE* criterion, taking into account all values of the weekly forecast advance period for the GTO_USD.net model (Table 12), is 0.695%, which is less than the value of 0.745% for the GTO005.net model (Table 11). At the same time, the test of the statistical hypothesis that there is no significant difference between $MAPE_{\text{GTO005}}$ and $MAPE_{\text{GTO\_USD}}$, which was performed in STATISTICA 10 based on a *t*-test for independent variables $(p \approx 0.696 > 0.05)$, confirms the reliability of the result of improving the accuracy of the neural network forecast (Fig. 9).


T-test for Independent Samples (STATISTICA 10_Forecast_week_2024.sta)
Note: Variables were treated as independent samples

Group 1 vs. Group 2	Mean Group 1	Mean Group 2	t-value	df	p
$MAPE_{\text{GTO005}}$ vs. $MAPE_{\text{GTO USD}}$	0,745000	0,694588	0,400010	12	0,696178

Fig. 9. Screenshot of the result of testing the statistical hypothesis that there is no significant difference in the *MAPE* estimates for the GTO005.net and GTO_USD.net models

Thus, the analysis of all the results obtained for different periods of retrospection of the time series of the hryvnia/dollar exchange rate under the condition of changing the nature of its trend confirms the reliability of the results obtained and allows us to recommend the use of evolutionary modeling methods in training and optimizing feedforward neural networks to improve the accuracy of operational neural network forecasting of time series of exchange rates.

CONCLUSIONS

1. In order to obtain an operational forecast of the hryvnia/dollar exchange rate with a one-day and one-week lead time for different observation periods in 2020 and 2024, feedforward neural network models with the Back Propagation of Error learning algorithm were developed using the BrainMaker Professional system and the Genetic Training Option software.

2. Computational experiments have shown that the use of a genetic algorithm in training neural networks can improve the accuracy of operational forecasts by optimizing the configuration and carrying out an evolutionary search for the best neural network models in accordance with a given criterion for the quality of their training and testing compared to neural network models created without the use of a genetic algorithm. The validity of the obtained forecast results is confirmed by assessing their reliability by the method of inverse verification carried out for different retrospective periods of the hryvnia/dollar exchange rate using the statistical criterion *MAPE*.

REFERENCES

1. Hidayat Muhammad, Defitri Siska Yulia, and Hilman Haim, "The Impact of Artificial Intelligence (AI) on Financial Management," *Management Studies and Business Journal (PRODUCTIVITY)*, vol. 1 (1), pp. 123–129, 2024.
2. Agrawal Ajay, Gans Joshua, and Goldfarb Avi, *Artificial intelligence in the service of business. How machine prediction helps to make decisions*. M.: Mann, Ivanov & Ferber, 2019, 336 p.
3. V.V. Pryimuk, "Implementation of artificial intelligence in the financial activity of the enterprise," *Collection of scientific works of the State Tax University*, 2023 (1), pp. 183–198.
4. B.E. Grabovetskyi, *Economic Forecasting and Planning: a textbook*. K.: Centre for Educational Literature, 2003, 188 p.
5. "*Prognostics. Terms and definitions*. Committee for Scientific and Technical Terminology, issue 109. M.: Nauka, 1990, 56 p.
6. John T. Barkoulas, Anthony G. Barilla, and William Wells, "Long-memory exchange rate dynamics in the euro era," *Chaos, Solitons & Fractals*, vol. 86 (C), pp. 92–100, 2016.
7. Yu-chin Chen, Kwok Ping Tsang, "What Does the Yield Curve Tell Us about Exchange Rate Predictability?" *The Review of Economics and Statistics*, vol. 95, pp. 185–205, 2013.
8. A.A. Chistyakova, B.V. Shamsha, "Information technology for forecasting non-stationary time series using singular spectral analysis," *East European Journal of Advanced Technologies*, no. 2/4 (68), pp. 24–30, 2014.
9. P.I. Bidyuk, I.V. Baklan, and V.I. Lytvynenko, *Modelling and forecasting of nonlinear dynamic processes*. K.: EKMO, 2004, 120 p.
10. A.A. Chistyakova, "Development of methods for analysing heterogeneous dynamics series based on statistical characteristics," *East European Journal of Advanced Technologies*, no. 5/4 (71), pp. 35–43, 2014.
11. D.-E. Bastens, W.-M. Van den Berg, and D. Wood, *Neural Networks and Financial Markets: Decision Making in Trading Operations*. M.: TVP Scientific Publishing House, 1997, 236 p.
12. D. Rutkovskaya, M. Pilinsky, and L. Rutkovsky, *Neural Networks, Genetic Algorithms and Fuzzy Systems*; Translated from Polish by I.D. Rudinsky. M.: Hotline-Telecom, 2004, 452 p.
13. Andreas S. Weigend, Bernardo A. Huberman, and David E. Rumelhart, "Predicting the future: a connectionist approach," *International Journal of Neural Systems*, vol. 01, no. 03, pp. 193–209, 1990.
14. V.V. Korneev, A.F. Gareev, S.V. Vasyutin, and V.V. Raikh, *Databases. Intelligent information processing*. M.: Nolige, 2000, 352 p.
15. L.A. Gladkov, V.V. Kureichik, and V.M. Kureichik, *Genetic algorithms*; 2nd ed. M.: Fizmatlit, 2006, 320 p.
16. V.F. Sytnyk, M.T. Krasnyuk, *Intelligent data analysis (data mining)*. K.: KNEU, 2007, 376 p.
17. N.M. Kussul, A.Y. Shelestov, and A.M. Lavreniuk, *Intelligent computing: a textbook*. K.: Naukova Dumka, 2006, 186 p.

18. "Genetic Training Option," *California Scientific Software*. Nevada City, CA 95959, 1996, 54 p.
19. 19. P.I. Bidyuk, O.I. Savenkov, and I.V. Baklan, *Time series: modelling and forecasting*. K.: EKMO, 2004, 144 p.
20. S.A. Aivazyan, V.S. Mkhitaryan, *Applied Statistics and Fundamentals of Econometrics*. M.: UNITY, 1998, 1006 p.
21. I.G. Lukianenko, L.I. Krasnikova, *Econometrics: a textbook*. K.: Znannya Society, KOO, 1998, 494 p.
22. P.I. Bidyuk, O.V. Polovtsev, *Analysis and Modelling of Economic Processes in Transition*. K.: NTUU "KPI", 1999, 230 p.
23. P.I. Bidyuk, I.V. Baklan, and V.N. Rifa, "Systematic approach to the construction of a egression model on time series," *Systemic Research and Information Technology*, no. 3, pp. 114–131, 2002.
24. J. Johnston, J. DiNardo, *Econometric methods*. New York: McGraw-Hill, 2007, 531 p.
25. G.E.P. Box, G.M. Jenkins, *Time Series Analysis: Forecasting and Control*. San Francisco: Holden-Day, 1976, 575 p.
26. G.E.P. Box, G.M. Jenkins, and G.C. Reinsel, *Time Series Analysis: Forecasting and Control*; 4th ed. US: John Wiley & Sons., 2008, 784 p.
27. Y.P. Lukashin, *Adaptive methods of short-term forecasting of time series: a textbook*. M.: Finance and Statistics, 2003, 416 p.
28. Z. Guo, R.E. Uhrig, "Use of genetic algorithms to select inputs for neural network," *Proceedings of International Workshop on Combinations of Genetic Algorithms and Neural Networks, COGAN-92*, pp. 223–234, 1992.
29. D. Whitley, T. Starkweather, and C. Bogart, "Genetic algorithms and neural networks: Optimising connections and connectivity," *Parallel Computing*, vol. 14, issue 3, pp. 347–361, 1990.
30. *National Bank of Ukraine. Official exchange rate of the hryvnia against foreign currencies. US dollar.* [website]. Available: https://bank.gov.ua/ua/markets/ exchangerate-chart?cn%5B%5D=USD (accessed 21.04.2024)
31. S.S. Fedin, *Artificial Intelligence Systems and Data Analysis Technologies: Workshop*; 2nd ed. K.: Interservice, 2021, 848 p.

Received 02.04.2024

INFORMATION ON THE ARTICLE

Serhii S. Fedin, ORCID: 0000-0001-9732-632X, National Transport University, Ukraine, e-mail: sergey.fedin1975@gmail.com

ПІДВИЩЕННЯ ТОЧНОСТІ НЕЙРОМЕРЕЖЕВОГО ПРОГНОЗУВАННЯ ВАЛЮТНОГО КУРСУ МЕТОДАМИ ЕВОЛЮЦІЙНОГО МОДЕЛЮВАННЯ / С.С. Федін

Анотація. Створено комплекс моделей прямошарових нейронних мереж для отримання оперативних прогнозів часового ряду валютного курсу гривні/долара. Показано, що використання еволюційного алгоритму тотального пошуку базових характеристик і генетичного алгоритму пошуку значень матриці вагових коефіцієнтів нейромереж дає змогу оптимізувати конфігурацію та відібрати кращі нейромережеві моделі за різними критеріями якості їх навчання та тестування. На основі верифікації результатів прогнозування встановлено, що використання відібраних методом еволюційного моделювання нейромережевих моделей дозволяє підвищити точність прогнозу курсу гривні/долара порівняно з нейромережевими моделями, які були створені без застосування генетичного алгоритму. Достовірність одержаних результатів прогнозування підтверджено методом інверсної верифікації за даними різних ретроспективних періодів часового ряду з використанням критерію середньої абсолютної відсоткової похибки прогнозу.

Ключові слова: валютний курс, генетичний алгоритм, еволюційне моделювання, нейронна мережа, оптимізація, прогнозування, точність, часовий ряд.