

APPLICATION OF GAME THEORY, FUZZY LOGIC AND NEURAL NETWORKS FOR ASSESSING RISKS AND FORECASTING RATES OF DIGITAL CURRENCY

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ABSTRACT

In this scientific work is aimed to obtain mathematical tools for solving the problem of finding optimal investment strategies in digital cryptocurrencies (hereinafter referred to as the CX) or a CX set from the side of investor/investors were proposed. The solution was found on the basis of the application of the games theory, the theory of fuzzy sets and artificial neural networks (ANN). The developed model, which allows one to obtain an algorithm for the success forecast assessment of the investment procedure in the CX by the investor, which can be then implemented in one of the modules of the intellectual information system for the CX rates forecasting. The scientific novelty of the results is that for the first time to solve the problem of the CX market evaluation in the context of the CX investment problem, gaming approaches based on solving a bilinear quality game in fuzzy production, as well as ANN were used.

Keywords: *Digital Cryptocurrency, Forecasting, Games Theory, Fuzzy Logic, Neural Networks*

1. INTRODUCTION

In matters regarding the assessment of the digital cryptocurrencies (hereinafter referred to as the CX) investing prospect, in addition to the difficulties of legal regulation of this market, additional issues arise. So, for example, the issues of the risk evaluation of the investment process in such assets. Such an assessment, according to a number of experts, can be based on the apparatus of fuzzy logic. Indeed, as previously shown in the first section of the work, the CX rates are subject to sufficiently strong fluctuations, and rapid rises were replaced by no less rapid falls. Even many industry experts do not have a general opinion, regarding the degree of riskiness of operations related to investment in the digital cryptocurrencies [1, 2], although in parallel, many believe that investments in the digital cryptocurrencies can give investors good profit. The main advantages of such investments are that transactions based on blockchain technology, which have become the basis for the development of the CX, are transparent and safe. At the same time, the traditional approach to analyzing the investment strategies in the CX implies, as a rule, consideration

of options for only two strategies for investing in the CX. In the first case, the investor who chose the “outgrowth” strategy, purchasing the digital cryptocurrencies, for real money, is ready to wait for an increase in the CX rate. In such a case, the investor believes that the digital cryptocurrencies rate will certainly grow, and he, as a player in the CX market, will make his profit. The second strategy involves conducting operations with the digital cryptocurrencies exchange market. And if the investor has the experience of such operations, then he has the opportunity to receive return on investments at once, and don't expect any of the dividends in the future. Note that the choice of investment strategy already implies an analysis of the situation from the point of view of the theory of games. This is what makes one look for a solution to the problem of evaluating risks and forecasting the digital cryptocurrencies rates, using the combined method based on the application of the game theory, fuzzy logic and neural networks.

2. LITERATURE REVIEW AND ANALYSIS

Many scientists have been trying to find a universal way to predict trends of this market in their

research from the moment of the CX emergence [1-3]. Not only individual investors, but also large companies show interest in this market [3, 4]. Researchers distinguish a number of factors affecting this market. So, for example, in the scientific works [5, 6], the methodology of empirical analysis was considered, which takes into account the relationship between the dynamics of GDP and the dynamics of the CX. In the scientific works [7-9], a systematisation of the macroeconomic factors influence on the digital cryptocurrencies rates and prediction of its trends were performed. A number of authors focus on the influence of explosion factors on the digital cryptocurrencies rates [10, 11]. However, such an approach is not without subjectivity, because for the reliability of the analysis results it is necessary for the data to be absolutely accurate. In recent years, a series of publications on the application of the theory of games [12-14], the apparatus, and the fuzzy logic [15-17], artificial neural networks [18-21] to solve the digital cryptocurrencies rates prediction problems emerged. Special attention can be devoted to scientific papers published in 2022. Among which, [38] on the usage of the deep learning algorithms for CX price fluctuation prediction. Another work [39] provides the fundamental research on deep learning approach usage for digital cryptocurrencies volatility prediction.

Given the above, as well as the polemic in the scientific environment for this issue, new studies devoted to the development of new methods and models for forecasting the CX market can be presented as relevant.

3. RESEARCH GOAL

The main goal of current scientific research is to develop a combined method for assessing risks and predicting digital currencies based on the use of the game theory, fuzzy logic and neural networks. The combined method should be suitable to use in the further research or development of the automated standalone software tool for digital cryptocurrencies rate prediction and, therefore, solving the problem of finding optimal investment strategies in digital cryptocurrencies.

4. MODELS AND METHODS

Thus, at the first stage of solving the general problem related to the forecasting of the digital cryptocurrencies rate, one shall consider its financial component.

In the context of this paragraph, the financial component is the expenses and income measures that provide profit for the digital cryptocurrencies investor, regardless of the chosen strategy.

Let one formulate the task that allows one to find rational investment strategies into the CX.

Let one introduce the following designations.

Expenses $H_1(0)$ consist of expenses for the investment operations into the CX market. For example, an investor may face the problem of double expenses. Double expenses in this case imply a situation in which the attacker (or fraudster) requires re-payment, citing the lack of a successful transaction as an argument at the first payment for the digital cryptocurrencies. And although modern mining technologies make such situations almost impossible, novice players on the CX market may face such a problem.

Revenues $H_2^\xi(0)$ consist of income brought to the investor by the CX.

One believes that the allocated financial resources were spent on the optimal set of CX (for example, Bitcoin, Litecoin, Ethereum, Ripple). The set was formed at the first stage of the solution.

Let one denote through L - the number of CX in the set of the investor.

Let the profitability in the case of the investment process in each CX, i.e. $(income)/(expenses) = (r_1)_i, i = 1, \dots, K$. Similar to the case of the costs minimization process of each specific CX, i.e. $(income)/(expenses) = (r_2)_j, j = 1, \dots, L$.

Consider the budgeting procedure for the CX set in the context of the financial flows of the investor as a player on the CX market. One set the time for the budget planning for the CX set. It is believed that time changes discreetly $t = 0, 1, \dots, T$ (T is a natural number).

Since losses are possible (there are losses from improper configuration of the digital cryptocurrencies set a result of the incorrect forecast assessment of the CX market, in particular, on the basis of the ANN use, which will be discussed below), for the initial amount of the optimal CX set, one takes a variable $H_2^\xi(0)$, which is set by a fuzzy set. Such an income variable was determined due to the consideration of the procedure for changes in expenses and income within the framework of the "fuzzy" sets, which, in principle, describes the procedure for budgeting expenses and income in the CX investment processes.

The fuzziness of the revenues variable is very well described by possible losses, not only from the loss of investors financial resources (hereinafter FR), but also the fact that the elements of the CX set can be selected incorrectly. For example, an assessment of the amount of possible losses associated with the action of an investor with the CX can be described in the format of the following fragment of the knowledge base for the intellectual system (IS) of the

CX rates and risk assessment for the investor, see table 1.

Table 1: Linguistic Variables for Assessing the Magnitude of all possible Forms of Losses from Loss of FR During CX Investment Process (in c.u.)

№	Designation	Value
1	PL_VH	very large
2	PL_H	large
3	PL_Sg	significant
4	PL_M	medium
5	PL_L	low
6	PL_VL	insignificant

The determination of the possible losses amount can be carried out in relation to the investor budget for the CX, the level of risks for these assets, the frequency of events associated with exchange rate fluctuations, the reputation of a particular CX and others.

Building a game model with elements for assessing the general level of investment risks into the digital cryptocurrencies using a linguistic approach can ensure an effective solution in order to optimize the problem of an investor's strategies

finding in the CX market under the conditions of fuzzy information about the importance of criteria for assessing risk factors. It makes it possible to distinguish significant risk factors, their consequences under the conditions of investor actions on the CX market, and thereby determine alternative ways in order to avoid the negative impact of risks.

Thus, the implementation of fuzzy sets in the playing model to describe the risks from the loss of the investor's FR on the digital cryptocurrencies market, will make it possible to build clear forecasts for quantitative parameters for the analysed CX for the investor.

To illustrate the effectiveness of the fuzzy sets, the Fuzzy Logic Matlab tools were used.

The output mechanism in the simplest case contains two entrances: one - to input the probability of FR loss, the second - to input expenses (losses) for the CX, see Fig. 1.

Then each of the inputs can be set by its own function of belonging, as shown on Fig. 2. For losses (loss), see Fig. 2 a) and probabilities (probability), see Fig. 2 b). After setting up the fuzzy sets in the Fuzzy Logic interface, one can configure the list of rules (see Fig. 3), which will visualize the work of these rules with various combinations of parameters, in the viewing window, see Fig. 4

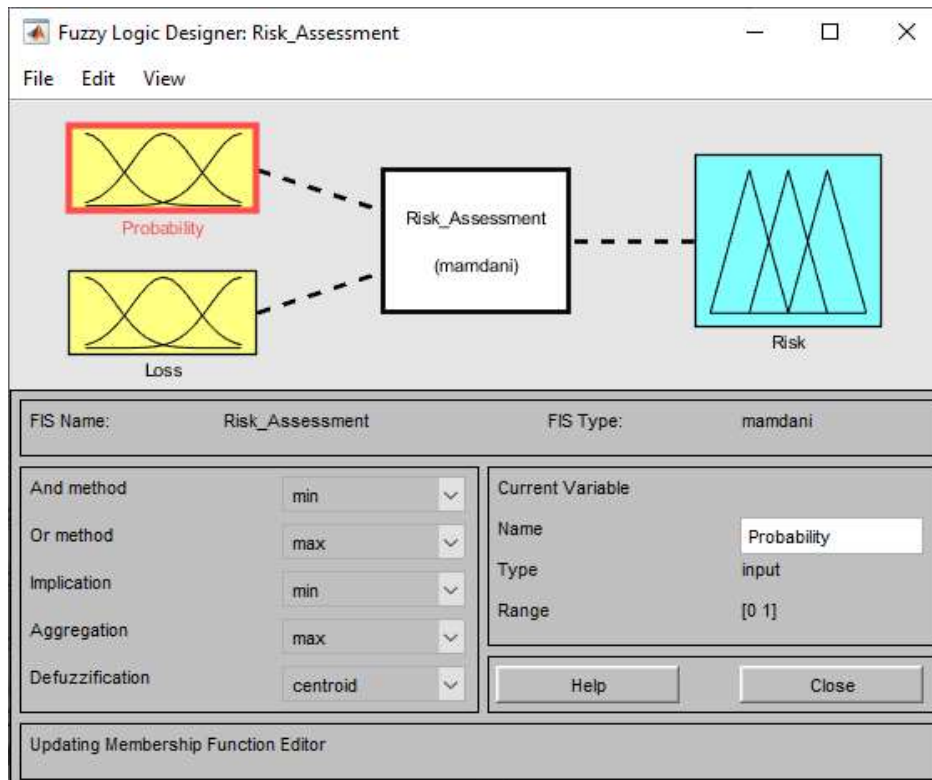


Figure 1. General View of the FUZZY Logic Interface for the Parameters Check of Fuzzy Sets Used in the Game Model.

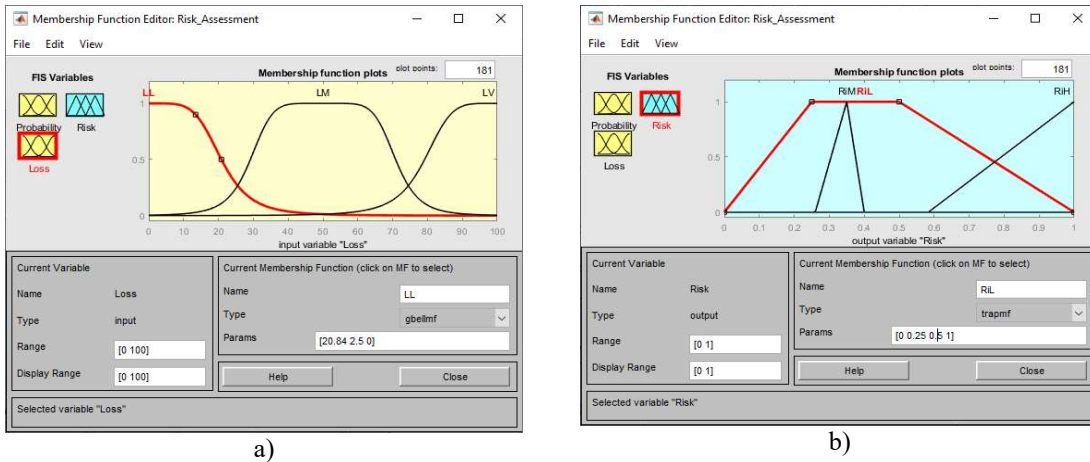


Figure 2. Functions of Belonging for the Inputs of a Fuzzy Model, for a) Losses (Loss) and b) Probability (Probability).

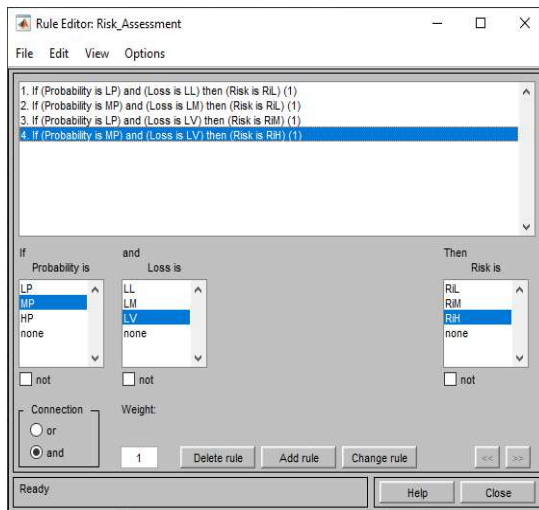


Figure 3. The Interface Window for Setting up Rules.

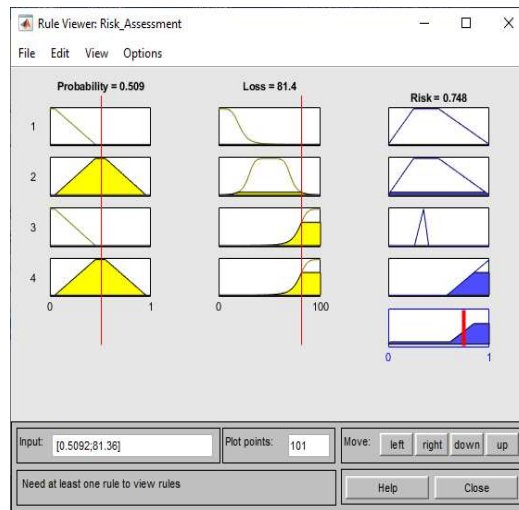


Figure 4. A Window for Visualizing the Work of the Rules with Various Combinations of Input Parameters.

One can interpret the data obtained during the modelling:

1. If the probability of FR loss - large (HP) and damage from non -investment into the CX - Large (LV), then the risk = rih (large);
2. If the probability is large (HP) and damage - medium (LM), then the risk = RIM (medium);
3. If the probability is large (HP) and the damage - low (LL), then the risk = n (RIL) (low);
4. If the probability is medium (MP) and damage - large (LV), then the risk = (RIM) (average);
5. If the probability is the average (MP) and damage - the average (LM), then the risk = (RIM) (medium);
6. If the probability is medium (MP) and damage - low (LL), then the risk = (RIL) (low);
7. If the probability is low (LP) and the damage - large (LV), then the risk = (RIL) (low);
8. If the probability is low (lp) and damage - medium (LM), then the risk = (RIL) (low);

9. If the probability is low (LP) and the damage of low (LL), then the risk = (RIL) (low).

Thus, the theory of fuzzy sets instruments can be used at the intermediate stage of the game model, as an effective means for the risks of the FR loss evaluation under the conditions of the uncertainty of the risk indicators values, as well as when choosing a risk for a CX set.

Further, the implementation of the combined method for the effectiveness and the risks evaluation of investment process into the CX involves the development of the game model based on the solution of the system of bilinear differential equations [22-41].

Let one assume that the first player controls the process of expenses realization (hereinafter referred to as the player I), and the second player (hereinafter referred to as the player II) controls the process of receiving income (player II).

The player II owns information about possible fluctuations on the CX market, and, consequently, risks. The latest circumstances determine the size of the conditional win/loss (income/loss) of investors from CX.

At the time t , the player I selects a value $u(t) \in [0,1]$, that determines the value of the CX cost $u(t) \cdot g_1(t) \cdot h_1(t)$, which he will produce at the interval $[t, t + 1]$ during the CX investment process.

The cost of expenses $u(t) \cdot g_1(t) \cdot h_1(t)$ consists of expenses in the CX set

$$\alpha_i \cdot u(t) \cdot g_1(t) \cdot x(t), i = 1, \dots, K;$$

$$\alpha_i \geq 0, \sum_{i=1}^K \alpha_i = 1$$

where α_i - a share of expenses for i specific CX.

At the time t , the player II selects a value $v(t) \in [0,1]$, that determines the amount of income from the purchase of CX $v(t) \cdot g_2(t) \cdot h_2(t)$, which he will receive at the interval $[t, t + 1]$.

The amount of income from investing in the CX set $v(t) \cdot g_2(t) \cdot h_2(t)$ consists of income

$$\beta_j \cdot v(t) \cdot g_2(t) \cdot y(t), j = 1, \dots, L;$$

$$\beta_j \geq 0, \sum_{j=1}^L \beta_j = 1$$

where β_j - shares of income from investing j in a specific CX.

Let one write down the dynamics of changes in variables $h_1(t)$ (expenses) for the CX set, which must be made at the interval from the moment t before T . Similarly for $h_2^\xi(t)$ (income) received from the purchase of a CX set, which can be obtained at the interval from the moment t before T . Where $h_1(0) = H_1(0), h_2^\xi(0) = H_2^\xi(0)$.

Consequently, taking into account scientific work [22-41]:

$$\begin{aligned} h_1(t+1) &= g_1 \cdot h_1(t) - u(t) \cdot g_1 \cdot h_1(t) - \\ &- \sum_{j=1}^K (1/(r_2)_j) \cdot \beta_j \cdot v(t) \cdot g_2 \cdot h_2^\xi(t); \\ h_2^\xi(t+1) &= g_2 \cdot h_2^\xi(t) - v(t) \cdot g_2 \cdot h_2^\xi(t) - \\ &- \sum_{i=1}^L (r_1)_i \cdot \alpha_i \cdot u(t) \cdot g_1 \cdot h_1(t), \end{aligned} \tag{1}$$

where g_1, g_2 - are correcting coefficients that can take into account inflation, devaluation, etc.;

$u(t)$ - the managing influence of the player I who chooses the share of his expenses for the CX set, which he will produce at the $[t, t + 1]$ interval;

$v(t)$ - the managing exposure of a player II who chooses a share of his income from a CX set. Similarly, one can consider the influence on the $[t, t + 1]$ interval;

α, β - accordingly, the share of expenses for the CX set and income from the FR implementation for CX set (for a specific CX set).

The above dynamics sets the interaction of two players. Such interaction will be described as a bilinear multi -step game with fuzzy information [22-37].

In contrast to a game with complete information, the player I does not exactly know the initial state of the player II , but it is known that the information belongs to the fuzzy set:

$$\{X, m(\cdot)\}$$

where X is a subset of R_+

$m(\cdot)$ is the membership function of the state $h_2^\xi(0)$ to the set $X, m(h_2^\xi(0)) \in [0,1]$, for $h_2^\xi(0) \in X$.

The unknown state of the player II , is interpreted as the possible maximum income minus possible losses (see Table 1). Then the linguistic variables for the elements evaluation of the fuzzy set $\{X, m(\cdot)\}$

that is describing the initial states of the player II can be described in Table 2.

Obtaining the fuzzy sets is similar to the procedure described above for the risks and losses from the formation of an investor's digital cryptocurrencies set.

Table 2: Linguistic Variables for the Elements Evaluation of a Fuzzy set $\{X, m(\cdot)\}$ that is Describing the Initial Player II states.

No	Designation	Value
1	$m(1)$	very large
2	$m(2)$	large
3	$m(3)$	significant
4	$m(4)$	medium
5	$m(5)$	low
6	$m(6)$	insignificant

Investment strategy for CX choosing problems involves determination of a base fuzzy rules, at the

input of which, for example, other variables may be present in addition to the damage from investments in a certain type of CX. For example, it is possible to take into account the impact on the level of risk of CX rates, individual threats, in particular reputational ones. One can also additionally take into account other factors that affect the CX rate: Economic; Technical; Media.

In addition, implementations of the strategy $v(\tau)$ for $\tau < t$ are known at every moment t , as well as the parameters that determine the game on the CX market.

The reasoning has been done from the position of the player I . Thus, no assumptions are made about the awareness of the player II . This can be interpreted as follows - the player II has any information, and first of all, that which concerns, for example, possible losses from investing in a particular CX or a CX set.

Players move at the same time.

The interaction ends when the following conditions are met:

$$((h_2^{\xi}(t) < 0), (h_1(\tau) > 0)), \text{ with certainty} \geq p_0 \quad (2)$$

$$((h_2^{\xi}(t) < 0), (h_1(\tau) > 0)), \text{ with certainty} < p_0 \quad (3)$$

Let one describe how the game goes.

At a moment in time t , the player I multiplies the value $h_1(t)$ by the coefficient (rate of change, growth rate) g_1 and selects the value $(u(t) \in [0,1])$. This value determines the share of the I player's expenses $g_1 \cdot h_1(t)$, that he will make in the interval $[t, t+1]$ during the CX set investment process.

The player II does the same. At the moment of time t , the player II multiplies the value $h_2^{\xi}(0)$ by the coefficient (rate of change, growth rate) g_2 and selects the value $(v(t) \in [0,1])$. This value determines the amount of the II player's income $g_2 \cdot h_2^{\xi}(t)$, that he will receive in the interval $[t, t+1]$ for investing in a particular CX or CX set.

The allocation of expenses and incomes by the players causes the allocation of additional amounts of expenses and incomes by the players. This is a consequence of the profitability of investing in one CX or another, which determines the relationship between the costs and incomes of investors (players).

Therefore the states of the players at the moment of time $t+1$ will be determined from relations (1).

If it turns out that condition (2) was satisfied, then one can state that in the procedure under consideration the player I has achieved the desired result with certainty $p \geq p_0$ and the procedure for investing in CX or CX set has been completed.

If it turns out that condition (3) was satisfied, then one can state that in the procedure under consideration the player I has achieved the desired result with certainty $p < p_0$ and the procedure for investing in CX or CX set has been completed.

If neither condition (2) nor condition (3) has been met, then the procedure for budgeting the CX continues.

The player I tends to find a set of his initial states that have the following property [22–40].

The above described model for effectiveness and risks evaluation of investing in CX based on a combination of game theory and fuzzy logic is more interesting for investors who are trying to form an investment strategy in CX. However, the game model itself does not provide an answer to the question of how the situation on the CX market will change over a certain period of time. To solve this subtask, it is necessary to supplement this model with tools that will allow one to predict the CX market.

Forecasting the CX rate is an important practical task. One can see its solution based on the development of the ANN apparatus together with the support vector machine.

Prediction of CX rates is usually based on a large number of predictors. However, such an approach has limitations. It is due to the fact that the use of a large number of macroeconomic indicators in the predictive model, for example, such as:

- 1) Gold price
 - 2) Silver price
 - 3) Platinum price
 - 4) Price of palladium
 - 5) Brent oil price
 - 6) Euro/dollar ratio
 - 7) The ratio of the English pound sterling / dollar
 - 8) S&P quotes
 - 9) Short-term obligations of the US Treasury;
- etc.

influence the interest of investors (players in terms of the game model considered in [22-41] to the CX market.

A high ratio between the number of potential predictors and the number of observations may lead to the fact that there will be a constant need to constantly adjust the forecast model itself or

constantly update the samples, taking into account the dynamics of changes in demand for other assets alternative to CX.

The investor is primarily interested in low errors of the forecast model. And a low error, in turn, can be achieved in the course of correct ANN training based on a correct predictive model.

Note that almost all predictors present in the predictive models of the CX market depend on events in the global economy. And it leads to a deterioration in predictability for long time boundaries. Predictors that perform well in short-term forecasting of the CX market may not work in a predictive model for a medium-term or long-term forecast.

As noted earlier in scientific works [1-6], for short-term forecasts of the CX market, models based on linear regression have proven themselves well, for example:

$$y = X \cdot b + e, \tag{4}$$

where y is the vector of CX rate values for a certain period of time;

X – a matrix of supply values in the markets of alternative assets, for example, bank metals;

b – vector of regression coefficients;

e – vector characterizing stochastic deviations.

However, CX predictive models based on classical linear regression are not suitable in situations of volatility in alternative CX markets. It is due to the fact that regressors in such a situation become random variables. They are influenced by stochastic factors. And besides, the regressors are often interdependent, such as the Euro / dollar ratio and the price of gold.

In such a situation, regression-factorial models of the form [1-4] showed themselves better:

$$y = F \cdot c + u, \tag{5}$$

where y is the vector of CX rate values for a certain period of time;

F – a matrix of factors values that affect the CX rate for a certain period of time;

U – a matrix of random deviations of factors that affect the CX rate;

$$c = A^T \cdot b,$$

where A – is the matrix that determines the load of one or another factor of the CX rate;

b – regression coefficients;

In this study, as part of the development of a combined method for assessing risks and predicting

CX rates based on the application of game theory, fuzzy logic and neural networks, the following assumption was made.

Assumption. Let one assume that the results corresponding to the logarithmic profitability of the CX in the current period of a short-term period of time, for example, an hour or a day (generally t), will determine the results of the profitability in the next day. Then, for each 20-30 values of the profitability of the CX, one will use the ANN to determine the direction of the linear trend using a logarithmic evaluation scale.

The logarithmic scale for assessing the CX trend was chosen based on the fact that it is extremely convenient for displaying large ranges of CX values or their pairs. It will eventually allow complex calculations to be carried out with an accuracy of two to three decimal places.

Therefore the predicted trend of the CX or their pairs will, in conjunction with the strategies of the players, describe the behavior of the CX quotes during the next time period (day).

To train the ANN, one can use vectors of the form:

$\vec{X} = \{X_1, X_2, \dots, X_m\}$ – independent variables, for example, the risks of investing in CX, etc.;

$\vec{Y} = \{Y_1, Y_2, \dots, Y_m\}$ – dependent variables, for example, the ratio of alternative assets (banking metals, oil, etc., as well as the strategies of players on the CX market).

In these vectors, m – the number of time intervals for which the profitability from investing in CX was determined.

Taking into account the scientific works [1-9], one can write the following expressions describing the CX trend line as follows:

$$X_n = \{LOGR_{n+1}, LOGR_{n+2}, \dots, LOGR_{n+t}\}; \tag{6}$$

$$Y_n = \{LINR_{n+t+1, n+t+2, \dots, n+T}\}; \tag{7}$$

where $LOGR_i$ – the level of profitability of CX in a logarithmic scale at the i -th point of the time interval t ;

$LINR_{j,k}$ – coefficients of the regression equation, which are built according to the indicators of profitability of CX, risks and strategies of players;

n – observation number.

The results of the ANN work will largely depend on the chosen activation function. To identify dependencies, it is better to use non-linear activation

functions. For example, one can use the functions described in [4, 5, 8, 9].

One can supply data to the ANN input using the window method, see fig. 5. The first input window is necessary to provide data that underlies the forecast, including the preferred strategies of players on the CX market, as it was discussed in the previous paragraph of the work. Second, the output window will contain the data that will have to be obtained in the forecasting process. Windows shown in orange are the entrance; green - exit.

Thus, each window can be interpreted as a carrier of information on the set of data included in the training set:

$$W_i = \{x(t_i)\}_{i=1}^N, \quad (8)$$

where N – the dimensions of the moving window relative to the time axis, see fig. 5;

x – quotes of the CX (or pair) at the moment of time t_i

For the primary processing of data on CX markets, we will use data that are published on specialised portals, for example, <https://coinmetrics.io/community-network-data/>.

This resource contains data on trading by all CXs, as well as their pairs. This data is in *. Csv, which allows one to load them, for example, into packages such as Neuro-Fuzzy Designer (Matlab), Neural Networks (STATISTICA) for further processing or ANN training.

In this study, since the Matlab package was used to solve the system of bilinear differential equations, one can also use the Neuro-Fuzzy Designer (Matlab). First, let one load the data. After that, one can supplement them with simulation results based on the solution of equations (1-3), and then one can build an artificial neural network in Neuro-Fuzzy Designer based on trading statistics data and the simulation result to find rational strategies for players on the CX market.

There are two learning algorithms to train an artificial neural network in Neuro-Fuzzy Designer. These are, respectively, backpropagation and hybrid learning. Based on the specifics of setting research objectives, hybrid learning has been chosen. It is due to the fact that with such type of training, the artificial neural network can be formed in a small number of passes. Although for the training sample, the resulting forecast will still differ from the real one, but as further learning progresses, the deviations between the forecast and real quotes will decrease. After training the ANN and its testing on the data fragments examples of which are shown in

Table 3, outside the sample the root-mean-square error should not exceed 500-100 points of the CX cost.

Thus, the result of training based on a combined method based on the application of game theory, fuzzy logic and ANN has become a multilayer hybrid NN that will be able to predict CX rates, not only based on quote statistics data, but also taking into account the risks of these investment operations, and investment strategies chosen by the players.

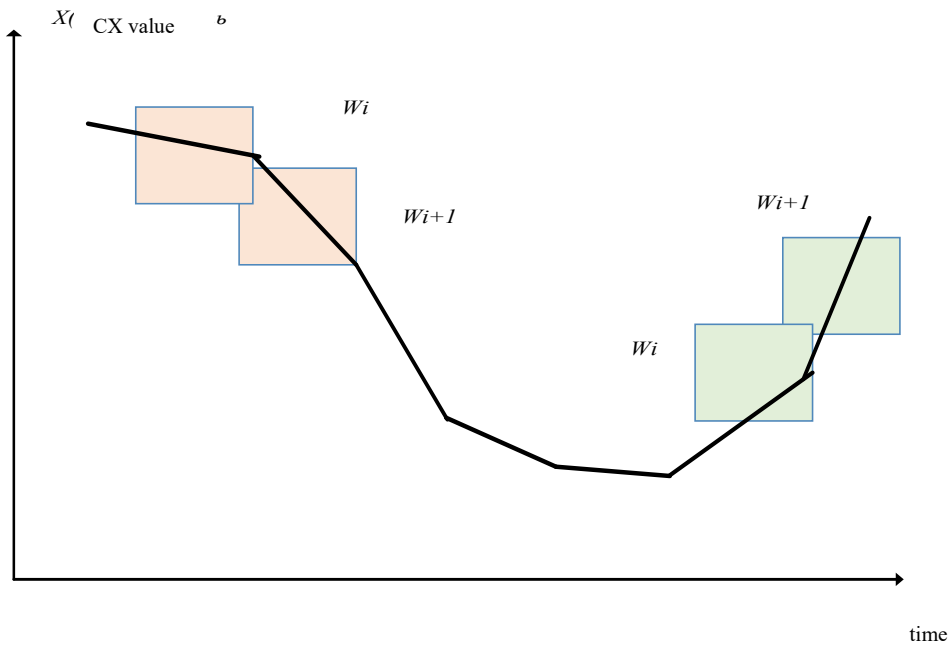


Figure 5. Scheme of Windows Movement for the Predictive Model of CX Quotes

Table 3: Fragment of Training Sample for ANN.

(based on trading statistics data (see <https://coinmetrics.io/community-network-data/>) and model-based computational experiments, see expressions 1-3).

Date	Value of Bitcoin	Value of Litecoin	Value of ethereum-eth_usd	Output Value (The value of the investors player 1 optimal strategy)	Output Value (The value of the investors player 2 optimal strategy)
16.09.2022	19 758,25	55,73	1 460,96	10	26
15.09.2022	19 798,84	56,92	1 497,71	9	29
14.09.2022	19 964,12	59,64	1 597,84	9	39
13.09.2022	20 340,42	59,75	1 616,41	8,5	38,5
12.09.2022	22 426,66	61,46	1 726,23	8,77	38,77
11.09.2022	21 537,77	62,36	1 752,49	9,5	39,5
10.09.2022	21 413,10	63,39	1 731,62	9,89	39,89
09.09.2022	21 276,02	60,90	1 722,28	8,6	38,6
08.09.2022	19 378,28	58,21	1 646,91	9,78	29,78
07.09.2022	19 344,57	56,94	1 640,69	8,56	38,56
06.09.2022	18 938,30	55,10	1 575,41	9,35	39,35
05.09.2022	19 770,90	60,23	1 596,38	9,34	39,34

Table 4: ANN Training Parameters

№	Parameter	Function notation	Value
1	Maximum number of learning cycles	net.trainParam.epochs	200
2	Limit value of the ANN learning criterion	net.trainParam.goal	1e-3

3	ANN learning rates	net.trainParam.lr	0.1
4	Information output interval	net.trainParam.show	3
5	Panic parameter	net.trainParam.mc	1

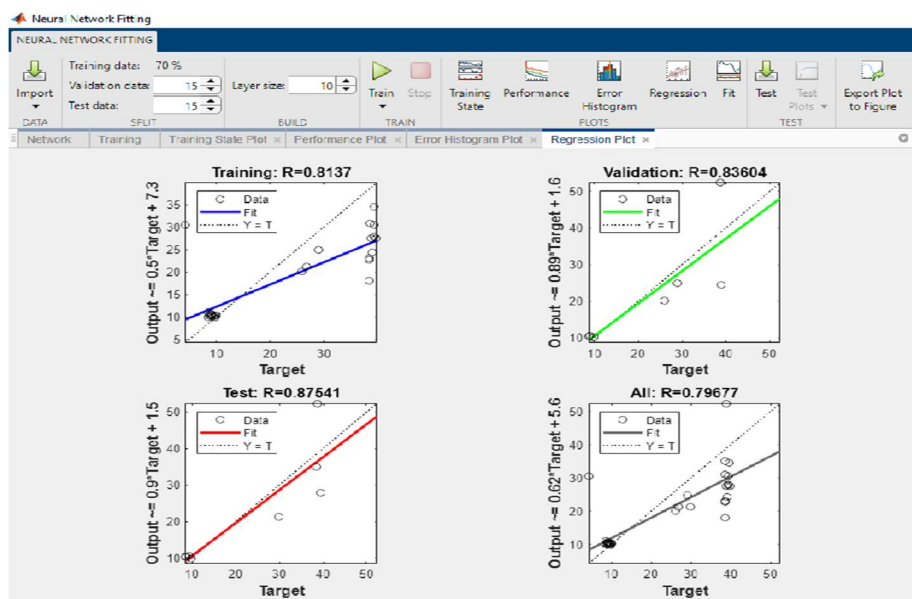


Figure 6. Diagrams that Reflect the Learning Ability of the Created ANN

Let one set the training parameters of artificial neural network, see table 4.

The following figure 6 shows the diagrams that reflect the learning ability of the artificial neural network in Matlab.

The artificial neural network training schedule based on the combined method of the effectiveness and risks evaluation of investing into the digital cryptocurrencies has been shown in Figure 7.

It can be seen from figure 6 that the given artificial neural network has been trained and is suitable for predicting the trend of the digital cryptocurrencies rate/rates or their pairs, see fig. 8. The artificial neural network training schedule coincides with the initial data on trading on the digital cryptocurrencies market for the period from October 1, 2022 to October 5, 2022.

Let one forecast the digital cryptocurrencies rate for two weeks from the 1st to the 15th day of the next month. To do this, one can set the data similar to the data shown in Table 3, but not fragmentarily, using the full sample involved in the learning process.

Figure 8 shows the digital cryptocurrencies prediction data obtained using a given artificial neural network.

Thus, using the current values of the parameters similar to those in Table 3, one can obtain a graph of digital cryptocurrencies rate forecasts in a short period of time with a minimum error, which makes it possible to obtain the most accurate forecasts in the future as the network learns.

The proposed artificial neural network can be saved as a script, see fig. 9.

This allows one to use this artificial neural network in the future, periodically checking its relevance and, if necessary, making adjustments to the training sample.

To assess the accuracy of the time series forecast on the digital cryptocurrencies market, the average relative error in percent (MAPE) was used. It made it possible to compare the results described in this article with similar results of studies [10-19].

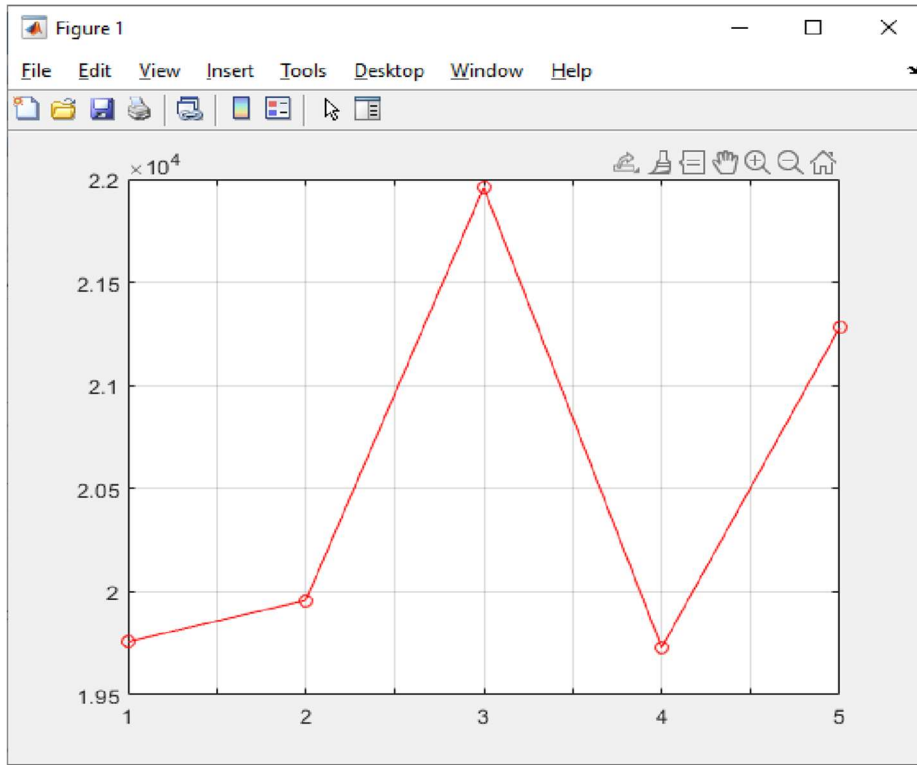


Figure 7. ANN Training Schedule Based on the Combined Method of the Effectiveness and Risks Evaluation of Investing Into the CX

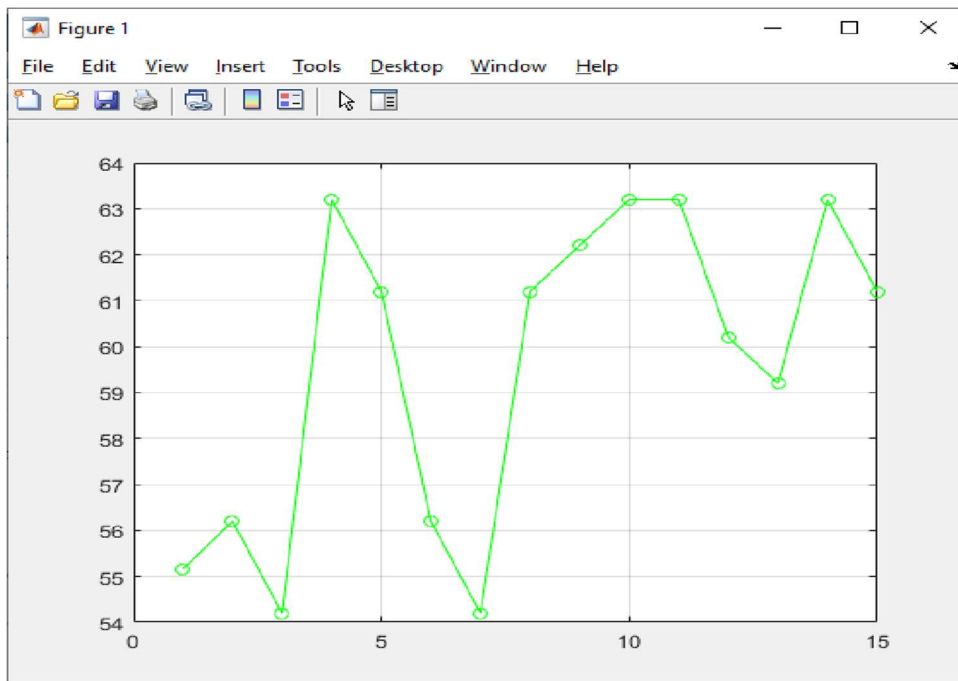
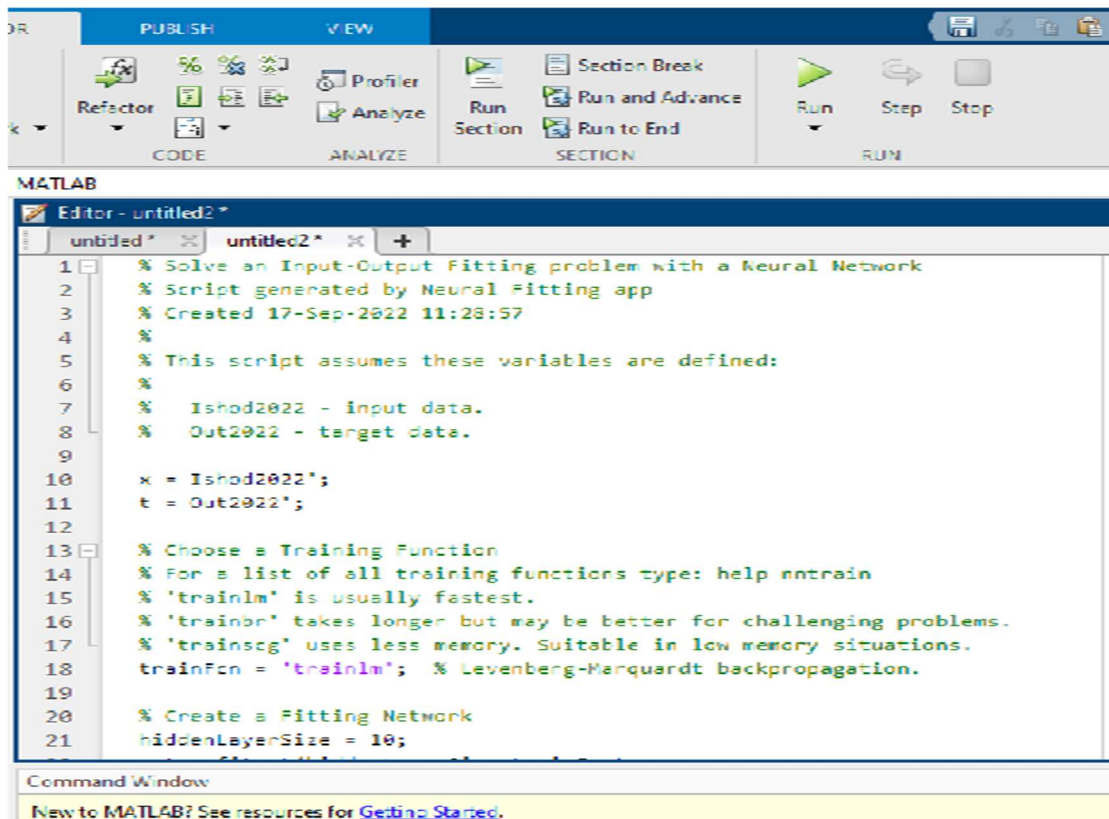


Figure 8. CX Forecasting Data Obtained Based on the ANN Output.



```

1 % Solve an Input-Output Fitting problem with a Neural Network
2 % Script generated by Neural Fitting app
3 % Created 17-Sep-2022 11:28:57
4 %
5 % This script assumes these variables are defined:
6 %
7 %   Ishod2022 - input data.
8 %   Out2022 - target data.
9 %
10 x = Ishod2022';
11 t = Out2022';
12 %
13 % Choose a Training Function
14 % For a list of all training functions type: help ntrain
15 % 'trainlm' is usually fastest.
16 % 'trainbr' takes longer but may be better for challenging problems.
17 % 'trainscg' uses less memory. Suitable in low memory situations.
18 trainfcn = 'trainlm'; % Levenberg-Marquardt backpropagation.
19 %
20 % Create a Fitting Network
21 hiddenLayerSize = 10;

```

Figure 9. Saved ANN Script

5. CONCLUSIONS

As a result of this scientific research a combined method for assessing risks and predicting digital currencies based on the use of the game theory, fuzzy logic and neural networks has been developed. In more details one can outline following key results within:

- mathematical tools for solving the problem of finding optimal strategies for investing into digital cryptocurrencies or a CX set by the investor have been developed. The solution was found based on the application of game theory, fuzzy set theory and computer simulation systems;
- the developed mathematical model makes it possible to obtain an algorithm for predictive assessment of the success of the investment procedure into the CX or a CX set on the part of the investor, which can then be implemented in one of the modules of the intelligent information system for predicting digital cryptocurrencies rates;
- the developed combined method for assessing risks and predicting digital currency rates based on the application of game theory, fuzzy logic,

and neural networks, as well as a model for predictive assessment of the success of an investment procedure into digital cryptocurrencies or digital cryptocurrencies set allow optimising decision-making processes for the digital cryptocurrencies market evaluation;

- the scientific novelty of the results obtained lies in the fact that for the first time to solve the problem of the digital cryptocurrencies market estimations in the context of the problem of investing into CXs or their sets, game approaches based on solving a bilinear game of quality in a fuzzy formulation were used. The approach developed in the work to solve the problem is new.

Obtained results can be safely classified as a suitable approach for solving the problem of finding optimal investment strategies in digital cryptocurrencies. However, there is a large room for further research and development. Further research would focus on, first of all, development of the standalone application that would combine and implement proposed methods and approaches within a single application.

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