Artificial Neural Network Model for Systems of Economic Security of Bank

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Abstract— **Relevancy of the scientific work is due to necessity in studying problems of securing economic security, as in the modern market conditions the process of successful functioning and development of the bank system depends, to a large extent, on selection and perfection of measures to ensure its financial stability. The purpose of the research is to substantiate theoretically and practically the necessity in researching and developing additional mechanisms, improving the level of financial sector economic security. In accordance with the purpose, the work sets out and consecutively solves the following tasks: review of modern assessment methods of bank sphere economic security level, substantiates the necessity in perfection of existing approaches to provide high level of economic security. The work, using the method of neural modeling, analyzes macroeconomic indices of the Russian bank system during 2000-2017. The re-search results can be used for development of strategic landmarks of financial sector, perfection of mechanisms, improving economic security level. The value of the work is in accentuating the attention on the use of neural networks for analysis of economic networks, which can bring about major economic effect as these technologies can substantiate, by quantity, management decisions, which are taken as a rule, based on intuition.**

Keywords— **Economic Security, Bank, Artificial Neural Network.**

1. Introduction

One of the key tasks of the state economic policy is to provide stable economic security of the national economy, in particular, economic security of the bank system. In modern conditions the financial sector covers the interests of practically all subjects of the national economy (investments, payments between economic agents etc.), and in this situation, frustration of the bank system functions can destabilize economic ties in the country and have a negative impact on internal economic processes [1, 2, 3]. This calls for obligatory solution of the following tasks: studying modern assessment methods of the bank sphere economic security level, optimizing existing approaches to comprehend the essence of the phenomenon under review [4]. Comparative analysis of modern economic & statistical modeling methods identified as a priority the neural approach to modeling economic security of the bank system [5, 6]. Most important to our opinion, from the point of studying specific features of neural technology application to assess economic security level of complex economic structures are works by A.I. Galushkin, M.G. Akhmedov, V.V. Borisov and other [7, 8]. Researchers point out the following stages of neural modeling: Establishing the requirements to the network structure; Determining the quantity of neurons in inlet and outlet layers; Selection of training parameters [9, 10]. The purpose of the research is to specify scientific & methodological and practical recommendations on implementing neural algorithms when modeling economic processes.

2. Materials and Methods (Model)

During development of the neural model, the researchers face as a rule the problem of selecting input parametersв, as their multicollinearity hampers the modeling process. A major task in this case is to establish the neural network structure, which could ensure the required model quality. An error in selection of configuration is discovered by comparing target and forecast values [11, 12, 13]. Thus, we can state that neural modeling is a process of model adaptation, realized by the network, to available training data. F^{ES}_{min}, F^{ES}_{max} – are current minimal and maximal values of economic security function F_{ES} respectively.

$$\begin{cases} \dfrac{\partial F_{ES}}{\partial x_1} = f_1(x_2, x_3, x_4, x_5) \cdot (F_{ES} - F_{ES}^{min}) \cdot (F_{ES} - F_{ES}^{max}), \\[2mm] \dfrac{\partial F_{ES}}{\partial x_2} = f_2(x_1, x_3, x_4, x_5) \cdot (F_{ES} - F_{ES}^{min}) \cdot (F_{ES} - F_{ES}^{max}), \\[2mm] \dfrac{\partial F_{ES}}{\partial x_3} = f_3(x_1, x_2, x_4, x_5) \cdot (F_{ES} - F_{ES}^{min}) \cdot (F_{ES} - F_{ES}^{max}), \\[2mm] \dfrac{\partial F_{ES}}{\partial x_4} = f_4(x_1, x_2, x_3, x_5) \cdot (F_{ES} - F_{ES}^{min}) \cdot (F_{ES} - F_{ES}^{max}), \\[2mm] \dfrac{\partial F_{ES}}{\partial x_5} = f_5(x_1, x_2, x_3, x_4) \cdot (F_{ES} - F_{ES}^{min}) \cdot (F_{ES} - F_{ES}^{max}), \end{cases} \quad (1)$$

Having solved each differential equation relative to economic security function F_{ES}, we get (see 2). Let us review the functions of five variable values.

$$F_{ES} = \frac{e^{2\frac{\partial f_i}{\partial x_i} + 2\phi_i} - 1}{e^{2\frac{\partial f_i}{\partial x_i} + 2\phi_i} + 1}, \quad i = 1, \ldots, 5. \quad (2)$$

Arguments of this function x_1, x_2, x_3, x_4, x_5 are not independent from one another, that is why the dependence of macro variables can be presented as follows (see 3).

$$\frac{\partial f_i}{\partial x_i} + \phi_i = \frac{x_1 \cdot x_2 \cdot x_3 \cdot x_4 \cdot x_5}{x_1 + x_2 + x_3 + x_4 + x_5}, \quad i = 1, 2, ..., 5 \tag{3}$$

Based on the above, the function of economic security can be presented as follows (see 4):

$$F_{ES} = \frac{Ae^{2B\frac{x_1 \cdot x_2 \cdot x_3 \cdot x_4 \cdot x_5}{x_1 + x_2 + x_3 + x_4 + x_5}} - 1}{Ae^{2B\frac{x_1 \cdot x_2 \cdot x_3 \cdot x_4 \cdot x_5}{x_1 + x_2 + x_3 + x_4 + x_5}} + 1}, \quad где \quad A, B = const. \tag{4}$$

Eventually, F_{ES} function can be analyzed for extremum, for this we need to identify a multitude of critical points [14, 15]. Critical points of economic security function in this context should be viewed as possible variations in development, dynamics, both positive and negative. In critical points, F_{ES} is unstable.

3. RESULTS AND DISCUSSION

Let us review assessment of bank system economic security level. To illustrate the use of neural technology for modeling financial sector economic security, we used macroeconomic indices of the Russian bank system in the period of 2000-2017.

Random data give a combination of the following values: average crediting interest rate for non-financial sector, % per annum (x1); share of long term credits in the total of credits, per annum (x2); share of bank credits for industrial enterprises, per annum (x3); official US dollar rate to ruble as per the Bank of Russia (x4); average per annum Brent oil price per barrel in USD (x5). For neural network training, it is necessary to prepare training samples, having as input values - selected macroeconomic indices, and as preferable output ones – corresponding value of economic security function FES. Table 1 shows training data for the network. Data analysis was performed on analytical platform Deductor Studio Academic. This software is a powerful tool for visualization and intellectual analysis of data assets. The neural model was built by Neuronetwork processor. Each line of the Table has a training example (x_1, x_2, x_3, x_4, x_5 – network input values) and expected output value (F_{ES}).

Table 1. Macroeconomic indices of the Russian bank system[a], values F_{ES}.

Years	Input parameters of neural network					Output
	x_1	x_2	x_3	x_4	x_5	F_{ES}
2000	24.4	1.4	77.2	28.13	28.66	0.0067
2001	17.9	1.1	77.5	29.17	24.46	0.0036
2002	15.7	1.2	78.3	31.35	24.99	0.0038
2003	13.0	1.5	76.2	30.69	28.85	0.0044
2004	11.4	1.9	74.5	28.81	38.26	0.0057
2005	10.7	2.6	69.7	28.28	54.57	0.0090
2006	10.4	4.0	65.3	27.18	56.16	0.0127
2007	10.0	5.8	65.6	25.57	72.44	0.0196
2008	12.2	8.5	64.7	24.81	96.94	0.0389
2009	15.3	11.7	65.5	31.68	61.74	0.0616
2010	10.8	11.6	65.4	30.74	79.61	0.0506
2011	8.5	12.6	65.3	29.35	11.26	0.0503
2012	9.1	13.4	62.6	31.07	111.63	0.0580
2013	11.5	15.2	59.5	31.82	108.56	0.0791
2014	17.3	18.2	40.0	37.97	98.9	0.1109
2015	13.8	20.9	40.5	60.7	52.4	0.0983
2016	12.8	21.3	39.3	66.33	44.0	0.0849
2017	11.6	22.4	37.7	58.29	55.4	0.0851

[a.] Based on statistical bulletin of the Bank of Russia 2000-2017.

Neural network processor can process data assets, establishing a certain procedure of links between elementary calculation elements (neurons). Having built a neural model, we received a model, consisting out of five input signals, two open layer neurons, which are to process input signals, and one output neuron, responsible for network activity (see Fig. 1).

Quality of neural model can be estimated by dissipation diagram (see Fig. 2). Visual analysis makes it possible to conclude that deviation of forecast values of economic security at the neural network output from values of F_{ES} function, received in the process of modeling, does not exceed the permitted 5% confidence interval, which confirms high quality of the model. Neural training based on training sample data makes it possible to build with required precision the forecast model. Next step in process modeling is verification of built mode adequacy. There are several ways to verify adequacy. Basically, model adequacy depends upon the results, received on the model basis, whether they reflect sufficiently the situation to achieve the goal. One can waste a

lot of time to improve model solution, which is not justified by target setting. For example, this can be due to precision degree of empirical data. In particular, if available baseline data contain certain errors, it is not feasible to consider a model, providing less error. Besides, often an approximate modeling result of a social & economic phenomenon can be more efficient than a more precise answer, which would take more time to get.
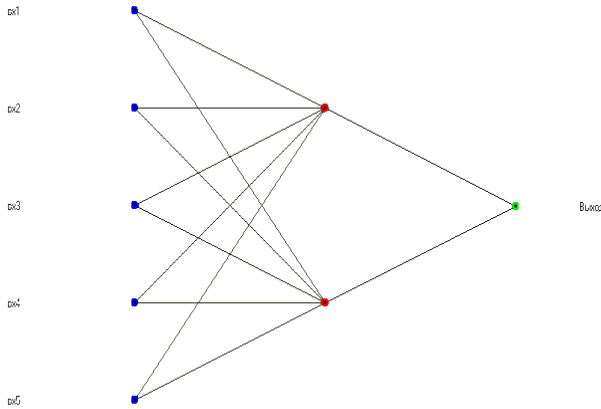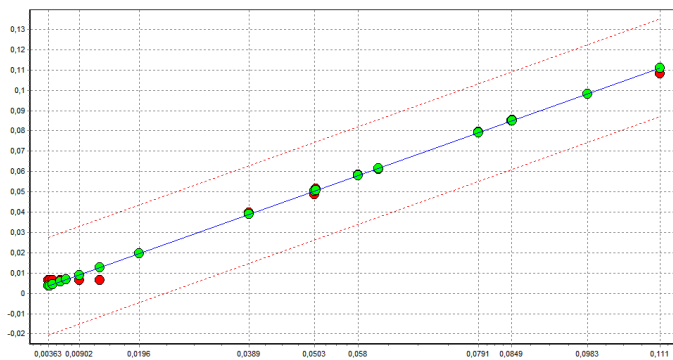

Fig. 1. Neural network.

Fig. 2. Dissipation diagram of trained neural network.

So, to have a model not contradictory and complying with consistency of phenomenon described, we should estimate the difference between calculated results of economic security function and results of neural modeling. Let us check the built model for adequacy. We compare economic security functional values of the bank system at the neural network output with experimental values. The comparative analysis testifies to high quality of approximation, as the built model fully repeats the experiment row trends. After neural network training we set certain values for network weigh scale and thresholds minimize errors of forecast, produced by the network. To assess the built neural model, we use a test multitude. We analyze dissipation diagram while testing. Test multitude is formed by processing all available data, considering training results. Looking at the diagram, we see

that although the deviation of forecast values from original ones has increased, they are still within the boundaries of 5% confidence interval (see Fig. 3).
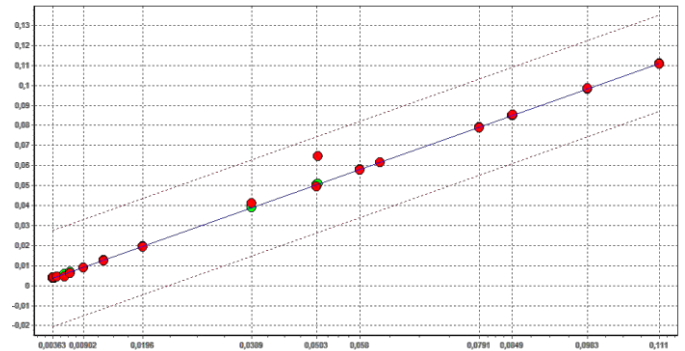

Fig. 3. Dissipation diagram of neural network during test.

4 Conclusion

The practical importance of the proposed approach is in possibility to use neural technologies when modeling economic processes for building models with high degree of approximation, which ensures unbiased analysis of experimental data. The use of neural networks for analysis of economic system functioning can yield a major economic effect, as such technologies can substantiate, by quantity, management decisions, which are taken as a rule, based on intuition. Based on the neural approach to analysis of economic phenomena, we can build a self-training expert system, capable of modeling decision making situations [16, 17, 18].

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