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DESIGN OF ASSESSMENT AND FORECASTING OF A COUNTRY'S FINANCIAL SECURITY IN A CHANGE MANAGEMENT CONDITIONS

Abstract. *The competitiveness of any country depends directly on the efficiency of its financial sector. Moreover, the level of financial security determines a country's ability to further develop on an innovative basis. An important need is to model the assessment and forecasting of a country's financial security in order to make timely adjustments to government decisions and allocate resources to improve the country's financial capacity. Methods of monitoring financial security, especially at the macro level, are underdeveloped in the academic world. The tools for selecting the indicators, which are needed to assess financial security, need to be deepened. In addition, in times of innovative discoveries and technologies, the methods of such assessment need to be progressive and unconventional.*

The materials for this article were statistical indicators that characterise the financial development of Ukraine. It is possible to assess the level of security in a timely manner and to calculate forecasts, using these indicators. The authors have proposed such a grouping of these indicators, which will fully cover the financial activity of the country. We propose to model the assessment and forecasting of the country's financial security with the usage of artificial networks. Application package Matlab including the Network Data Manager program was used for making neural networks, their training and application for forecasting the dynamics of financial security indicators. This program allows us to optimally form and select neural networks, topology, activation and training algorithm.

The assessment and forecast of financial security have shown the need for increased government attention to the allocation and accumulation of financial resources. According to our estimates, the banking security indicators are expected to stabilise in 2023–2025. The indicators of the ratio of bank loans to deposits in foreign currency, the share of foreign capital in the share capital of banks, the ratio of long-term loans to deposits, and the share of assets of the 5 largest banks in the total assets of the banking system will stabilize at the level of 2020. Return on assets will slightly decrease and become negative, while the liquid assets to short-term liabilities ratio will increase to 95.6%. The ratio of total public debt service and repayment to government budget revenues is projected to increase significantly. The proposed design for assessing and predicting countries' financial security is based on the usage of artificial neural networks, which are particularly relevant in the present context. The modelling logic is quite user-friendly and understandable for those interested and can be used by government officials to systematically determine the level of a country's financial security. The proposed design can also be adapted for use in other countries to determine the level of financial security and to adjust the existing financial development strategies of the state.

Keywords: *financial security, neural network, forecasting, financial market, loans, liquidity, insurance, public debt, national monetary unit.*

1. Introduction

The sustainable development of a country depends on a timely diagnosis of its current financial situation. Furthermore, security and socio-economic development are integral requirements of a progressive, innovation-driven economy. At the same time, an international assessment of financial security will make it possible to see a country's position in relation to others and to make timely management decisions necessary to improve it. There is a need to identify a set of indicators that will assess the current financial condition of the country best. It is important that these indicators are relevant for all countries to be assessed because otherwise, the results will be misleading. The above issues emphasise the relevance of the subject matter of our research and determine its prospects. The aim of the study is to determine the optimal model for assessing a country's financial security.

Many researchers have dealt with the problem of a comprehensive assessment of a country's financial security. In the work of Zolkover *et al.*, [1], the level of gross output, economic security and innovation capacity of the regions were determined. The authors have developed a mechanism to stimulate economic growth in different regional clusters. The methods used by the authors are interesting for our article: tree-like clustering based on selected Euclidean distances, statistical, indicator grouping, discriminant analysis, etc. The researchers compared the results with EU countries and revealed the problems of non-harmoniousness of gross output and economic development of Ukrainian regions. Sun and Xu, [2], focus their attention on the security, investment and financing of China's energy sector. A genetic algorithm was used in the methodology to assess the financial security of the Chinese energy industry. An innovative way to assess Chinese energy security is to use neural networks, which we will also test in our study. Shah *et al.*, [3], examine the relationship between energy efficiency, trade, financial development and government integrity in G7 economies over the period from 1996 to 2015. By effectively combining a system of indicators, the authors make a significant contribution to statistical analysis theory. The usage of the Driscoll and Cray method strengthens the level of scholarship of the study D'Orazio, [4], has carried out an empirical analysis of the financial policies of G20 countries, which are concerned with global energy usage and CO2 emissions. The author conducts a cluster analysis from 2000 to 2018 and assesses the carbon intensity of the economy and its impact on climate change. Leuz *et al.*, [5], carried out an international assessment of revenue management in 31 countries. Using a system of indicators, the authors predicted individual financial indicators, which led them to conclude that there was an endogenous relationship between corporate governance and the number of revenues. Unconventional approaches to financial analysis were used in their study by Xu *et al.*, [6], who traced the dynamics of financial payments for healthcare at the interstate level. This allowed the authors to identify the direction of policy measures needed for effective healthcare. Using data from 59 countries, the researchers conducted a regression analysis of the variables associated with healthcare costs. In the article, a number of unconventional modelling tools that deserve our attention were used. Kruk and Freedman, [7], evaluated healthcare system efficiency and proposed indicators, which are most important for measuring the effectiveness of online health databases. Interesting for our study is the authors' grouping of indicators into three categories: efficiency, equity and profitability. This grouping and set of indicators are particularly useful for those designing public healthcare policies and assessing the impact of several cost-sharing strategies in developing countries. Chang *et al.*, [8] provide a high-level, scholarly analysis of changes in the affordability index and the energy efficiency index. What is important for our study is the set of indicators the authors analyse. Moreover, the system of such indicators is simple and adaptive for measuring financial security. Tete *et al.*, [9], through a multi-criteria analysis of decisions, value energy security in the electricity sector of the West African Economic and Monetary Union. Using 18 country-reporting indicators for 2010–2019, the researchers assess governance performance, environmental sustainability, and energy security. Moreover, there is some academic interest in the indicators system and how it is assessed. Cheng and Chien, [10], conduct research on the relationship between financial development, the spread of information and communication technologies and economic growth. The authors have used a broad panel of statistics from 72 countries around the world for the years 2000–2015 and have used non-standard approaches to assess them. Among other achievements, the authors have also thoroughly analysed the Cobb-Douglas model and evaluated it in the present context. A thorough analysis of the scientific literature has shown a lively interest among scholars in the issue of assessing a country's financial security. There is a relevant discussion regarding the selection of the optimal group of financial indicators that will fully reflect the level of financial security. Defining a methodology that will be suitable for assessing security is equally important.

2. Materials and Methods

We propose to use artificial neural networks to assess the level of financial security of countries. We divide the set of financial security indicators Q into 6 subsets:

Q_1 — banking security indicators;

Q_2 — non-banking financial market safety indicators;

Q_3 — debt security indicators;

Q_4 — budget security indicators;

Q_5 — currency security indicators,

Q_6 — monetary security indicators

Let us denote the j indicator in the set Q_i, by q_{ij}. The list of indicators selected to assess the level of financial security is shown in Table 1.

To study the dynamics of these indicators, we will take the retrospective period 2010–2020. Let us mark with t the number of the year in the retrospective period, and with $q_{ij}(t)$ the value of the indicator q_{ij}, in the t year. The values of indicators q_{ij}, during the retrospective period are given in Table 2.

The Matlab application package was used to create neural networks, train them and use them in forecasting the dynamics of financial security indicators, including the Network Data Manager program. This software allows creating neural networks, defining their topology, selecting the activation function and the effective learning algorithm.

A Feed-forward back propagation type neural network is used to predict the dynamics of q_{ij} indicators. This network has three layers of neurons. The input layer picks up signals from the external environment

Table 1

Indicators reflecting the level of financial security of a country

Designation	Content of the indicator
Banking security indicators (Q_1)	
q_{11}	Share of overdue loans in the total volume of loans granted by banks to residents of Ukraine, %
q_{12}	Ratio of bank loans to deposits in foreign currency
q_{13}	Share of foreign capital in the share capital of banks, %.
q_{14}	Ratio of long-term (over 1 year) loans and deposits, times
q_{15}	Return on assets, %
q_{16}	The ratio of liquid assets to short-term liabilities, %
q_{17}	Share of assets of the 5 largest banks in total assets of the banking system, %
Non-banking financial market safety indicators (Q2)	
q_{21}	Insurance penetration rate (insurance premiums to GDP), %
q_{22}	Volatility level of the PFTS index, number of critical deviations (−10%)
q_{23}	Share of insurance premiums received by the 3 largest insurance companies in the total volume %
Debt security indicators (Q_3)	
q_{31}	Ratio of public and publicly guaranteed debt to GDP, %
q_{32}	Ratio of gross external debt to GDP, %
q_{33}	Weighted average yield on domestic government bonds in the primary market, %.
q_{34}	EMBI + Ukraine Index
q_{35}	Ratio of official international reserves to gross external debt, %
Budget security indicators (Q_4)	
q_{41}	Ratio of the state budget deficit and surplus to GDP, %
q_{42}	Deficit/surplus of budgetary and extra-budgetary funds of the general administration sector, as a percentage to GDP
q_{43}	The level of GDP redistribution through the consolidated budget, %
q_{44}	Ratio of total payments on public debt servicing and repayment to state budget revenues, %
Currency security indicators (Q_5)	
q_{51}	Index of changes in the official exchange rate of the national currency against the US dollar, average for the period
q_{52}	Gross international reserves of Ukraine, in months of imports
q_{53}	Share of loans in foreign currency in total loans granted, %
q_{54}	Balance of purchase and sale of foreign currency by households, billion USD
q_{55}	Level of dollarisation of the money supply, %
Monetary security indicators (Q_6)	
q_{61}	Specific weight of cash outside banks in the total money supply (M0/M3), %
q_{62}	Difference between interest rates on loans granted by depository corporations to residents of Ukraine in the reporting period and interest rates on deposits attracted by depository institutions
q_{63}	Weighted average interest rate on loans granted by depository corporations (other than the NBU) in national currency relative to the consumer price index
q_{64}	Share of consumer loans to households in the total structure of loans to residents
q_{65}	Specific weight of long-term loans in total loans granted (adjusted for exchange rate differences), %
q_{66}	The volume of legal outflow of financial resources outside the country, billion USD

Source: Indicator grouping system proposed by the authors

Table 2

Values of the country's financial security indicators in 2010–2020

Indicator	Years of the retrospective period										
	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
q_{11}	11	10	9	11	16	25	28	55	53	48	41
q_{12}	190	153	119	124	153	169	134	109	117	83	68
q_{13}	41	42	39	34	32	44	49	49	28	29	28
q_{14}	4	3	2	2	3	4	4	3	4	4	3
q_{15}	-1	-1	1	0	-4	-5	-13	-2	2	4	2
q_{16}	1	1	90	89	86	93	92	98	93	91	87
q_{17}	37	37	39	40	43	54	56	60	60	61	59
q_{21}	2	2	1	2	2	1	1	1	1	1	1
q_{22}	2	4	1	0	1	0	0	0	0	0	0
q_{23}	14	14	10	13	16	15	19	21	15	14	16
q_{31}	40	36	37	40	69	79	81	72	61	50	61
q_{32}	86	77	77	77	94	129	120	103	88	79	81
q_{33}	13	9	14	13	15	17	15	15	18	17	10
q_{34}	400	900	550	763	2226	2375	763	564	533	492	651
q_{35}	29	25	18	14	6	11	14	16	18	21	23
q_{41}	-6	-2	-4	-4	-5	-2	-3	-2	-2	-2	-5
q_{42}	-1	-1	-1	0,1	-0,2	-0,1	0,1	0	-0,2	0	1
q_{43}	28	31	32	30	29	32	32	34	33	32	33
q_{44}	18	23	28	33	48	94	34	60	38	46	47
q_{51}	151	100	100	100	149	184	117	104	102	95	104
q_{52}	4	4	3	3	2	3	3	3	3	5	5
q_{53}	46	40	37	34	46	56	49	44	43	37	37
q_{54}	-10	-13	-10	-1	2	1	2	2	1	0	1
q_{55}	29	30	32	27	33	32	33	32	29	29	27
q_{61}	31	28	26	26	30	28	28	27	28	27	28
q_{62}	7	7	4	5	4	6	5	6	6	5	7
q_{63}	6	8	18	17	5	-27	5	2	8	12	11
q_{64}	17	16	15	15	13	11	10	12	14	18	18
q_{65}	29	25	22	19	17	15	24	26	22	20	18
q_{66}	9	11	13	14	11	3	7	10	12	14	11

Source: Calculated by the authors

and passes them on to neurons in the intermediate layer, without converting them. Neurons of the intermediate layer receive signals from neurons of the input layer, transform them and transfer the transformed signals to neurons of the output layer. Neurons in the output layer generate output signals that have to match the existing standards during the learning phase of the network. The intermediate layer contains two neurons N_1 and N_2, each with one input. Neuron N_k corresponds to weighting factor v_k, offset of a_k and activation function of f_k. Having received input signal X, neuron N_k produces output signal $G_k = f_k(v_kX + a_k)$, which is transmitted to the output layer neuron. The output layer contains one neuron N_0, which has two inputs and receives output signals from neurons of the intermediate layer. The inputs of the neuron N_0, perceiving signals from neurons N_1 and N_2 correspond to the weights coefficients w_1 and w_2. Neuron N_0 produces an output signal $G_0 = f_0(w_1G_1 + w_2G_2 + b)$, where f_0 is the activation function of this neuron and b is its offset. We choose the same activation function $tansig(x) = 2(1 + e^{-2x})^{-1} - 1$ for all neurons in the network. This function is monotonically increasing, the set of its values is the interval $(-1, 1)$, it follows to 1 at $x \to \infty$ and follows to -1 at $x \to -\infty$. Thus, the current state of the network is determined by the parameters v_1, v_2, w_1, w_2, a_1, a_2 and b. When training the network, each value of the input signal X from the defined set is matched with a known value of the output signal L. In the process of network training, the output signal values G_0 obtained by the network, are compared with the corresponding reference values L, the error $\Delta = |L - G_0|$ is determined and the network parameters are changed depending on its value. This ensures that the resulting output signals are sufficiently close to the known reference values.

We select the trainlm function to train the network. This function updates the weights coefficients v_1, v_2, w_1, w_2 and offsets a_1, a_2, b of the network neurons according to Levenberg-Marquardt optimization. We take the training parameters as follows: the maximum number of epochs to be trained is 1000, the maximum number of verification errors is 6, and the minimum performance gradient is 10^{-5} [11].

In order to use the network to predict the dynamics of q_{ij} indicators the numbers of years t of the retrospective period should be fed to the input during training and the outputs should be compared with the known values of $q_{ij}(t)$ of this indicator. After training is completed in the forecasting process, the numbers of years corresponding to the forecasting period are fed to the input of the network. The output values of the network are taken as the results of the forecasting process. However, for this network to work, the input and output signals have to be in the range [0; 1]. Hence, it is necessary to transform the data so that the values belong to this interval. Let us denote by X(t) the value of the input signal corresponding to the year with number t. For the values X(t) to belong to the interval [0, 1], we define them by equality:

$$X(t) = t/(T_0 + T),$$

where T_0 is the duration of the retrospective period and T is the duration of the forecast period. Since we use data for 2010–2020, then $T_0 = 11$.

Table 3

Input signals for neural network training and operation

t	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
X(t)	0,06	0,13	0,19	0,25	0,31	0,38	0,44	0,50	0,56	0,63	0,69	0,75	0,81	0,88	0,94	1,00

Source: proposed by the authors

Table 4

Reference values of the output signals for neural network training

Indicator	Year numbers of the retrospective period										
	1	2	3	4	5	6	7	8	9	10	11
q_{11}	0,133	0,121	0,109	0,133	0,194	0,303	0,339	0,667	0,642	0,582	0,497
q_{12}	0,667	0,537	0,418	0,435	0,537	0,593	0,470	0,382	0,411	0,291	0,239
q_{13}	0,558	0,571	0,531	0,463	0,435	0,599	0,667	0,667	0,381	0,395	0,381
q_{14}	0,667	0,500	0,333	0,333	0,500	0,667	0,667	0,500	0,667	0,667	0,500
q_{15}	0,481	0,481	0,556	0,519	0,370	0,333	0,037	0,444	0,593	0,667	0,593
q_{16}	0,007	0,007	0,612	0,605	0,585	0,633	0,626	0,667	0,633	0,619	0,592
q_{17}	0,404	0,404	0,426	0,437	0,470	0,590	0,612	0,656	0,656	0,667	0,645
q_{21}	0,667	0,667	0,333	0,667	0,667	0,333	0,333	0,333	0,333	0,333	0,333
q_{22}	0,333	0,667	0,167	0,000	0,167	0,000	0,000	0,000	0,000	0,000	0,000
q_{23}	0,444	0,444	0,317	0,413	0,508	0,476	0,603	0,667	0,476	0,444	0,508
q_{31}	0,329	0,296	0,305	0,329	0,568	0,650	0,667	0,593	0,502	0,412	0,502
q_{32}	0,444	0,398	0,398	0,398	0,486	0,667	0,620	0,532	0,455	0,408	0,419
q_{33}	0,481	0,333	0,519	0,481	0,556	0,630	0,556	0,556	0,667	0,630	0,370
q_{34}	0,112	0,253	0,154	0,214	0,625	0,667	0,214	0,158	0,150	0,138	0,183
q_{35}	0,667	0,575	0,414	0,322	0,138	0,253	0,322	0,368	0,414	0,483	0,529
q_{41}	0,000	0,667	0,333	0,333	0,167	0,667	0,500	0,667	0,667	0,667	0,167
q_{42}	0,000	0,000	0,000	0,367	0,267	0,300	0,367	0,333	0,267	0,333	0,667
q_{43}	0,549	0,608	0,627	0,588	0,569	0,627	0,627	0,667	0,647	0,627	0,647
q_{44}	0,128	0,163	0,199	0,234	0,340	0,667	0,241	0,426	0,270	0,326	0,333
q_{51}	0,547	0,362	0,362	0,362	0,540	0,667	0,424	0,377	0,370	0,344	0,377
q_{52}	0,533	0,533	0,400	0,400	0,267	0,400	0,400	0,400	0,400	0,667	0,667
q_{53}	0,548	0,476	0,440	0,405	0,548	0,667	0,583	0,524	0,512	0,440	0,440
q_{54}	0,167	0,042	0,167	0,542	0,667	0,625	0,667	0,667	0,625	0,583	0,625
q_{55}	0,586	0,606	0,646	0,545	0,667	0,646	0,667	0,646	0,586	0,586	0,545
q_{61}	0,667	0,602	0,559	0,559	0,645	0,602	0,602	0,581	0,602	0,581	0,602
q_{62}	0,667	0,667	0,381	0,476	0,381	0,571	0,476	0,571	0,571	0,476	0,667
q_{63}	0,148	0,198	0,444	0,420	0,123	0,667	0,123	0,049	0,198	0,296	0,272
q_{64}	0,630	0,593	0,556	0,556	0,481	0,407	0,370	0,444	0,519	0,667	0,667
q_{65}	0,667	0,575	0,506	0,437	0,391	0,345	0,552	0,598	0,506	0,460	0,414
q_{66}	0,429	0,524	0,619	0,667	0,524	0,143	0,333	0,476	0,571	0,667	0,524

Source: Suggested by the authors

We choose the duration of the forecast period T-5, i.e. the forecast is made until 2025. Thus, the value of t varies from 1 to 16. The corresponding values of the value X(t) are shown in Table 3.

We denote by $Y_{ij}(t)$ the reference value for comparison with the output value of the network used to predict the dynamics of q_{ij}, and corresponds to the input signal X(t). If q_{ij} indicator can only take positive values, the value of $Y_{ij}(t)$ is defined by the equality

$$Y_{ij}(t) = q_{ij}(t)/(1{,}5\max(q_{ij}(t))) \quad (1)$$

where the maximum is taken for all years of the retrospective period. A factor of 1.5 is introduced to ensure that the network outputs from the forecasting process belong to the interval [0, 1].

If among the values of q_{ij} some are negative, the following equation is used to determine the value of $Y_{ij}(t)$

$$Y_{ij}(t) = \nu_{ij}(t)/(1{,}5\max(\nu_{ij}(t))), \quad (2)$$

where $\nu_{ij}(t) = q_{ij}(t) - \min(q_{ij}(t))$, the minimum is taken over all years of the retrospective period.

The values of value $Y_{ij}(t)$ are shown in Table 4.

The result of network training for the indicator q_{11} — the share of overdue loans in the total volume of loans provided by banks to residents of Ukraine — is shown in figure 1. The R = 0.9576 value is close to 1, which confirms the quality of the predictive model.

3. Results and Discussion

As a result of training the network created to predict the dynamics of indicator q_{ij}, its parameters v_1, v_2, w_1, w_2, a_1, a_2 and b take the values given in table 5.

In order to get the forecast values of the country's financial security indicators, we feed to the input of the neural network configured to forecast a certain indicator q_{ij}, of the values X(t) at values t corresponding to the forecasting period, i.e. from 12 to 16. In the result of work, the network produces output signals $Y_{ij}(t)$. The predicted values $q_{ij}(t)$ of the indicator q_{ij}, are determined from equations (1) and (2).

For indicators taking only positive values, the following equation applies

$$q_{ij}(t) = 1{,}5Y_{ij}(t)\max(q_{ij}(t)), \quad (3)$$

and for indicators taking negative values during the retrospective period as well, the following equation applies

$$q_{ij}(t) = 1{,}5Y_{ij}(t)\max(q_{ij}(t) - \min(q_{ij}(t))) + \min(q_{ij}(t)), \quad (4)$$

where the maximum and minimum are determined for all years of the retrospective period.

The defined predicted values of the indicators are shown in Table 6.

Thus, according to the projections made, a certain stabilisation of banking safety indicators is expected between 2023 and 2025. The ratio of bank loans to deposits in foreign currency, the share of foreign capital in the share capital of banks, the ratio of long-term loans to deposits and the share of assets of the five largest banks in the total assets of the banking system will stabilise at the level of 2020, the return on assets decreases slightly, while

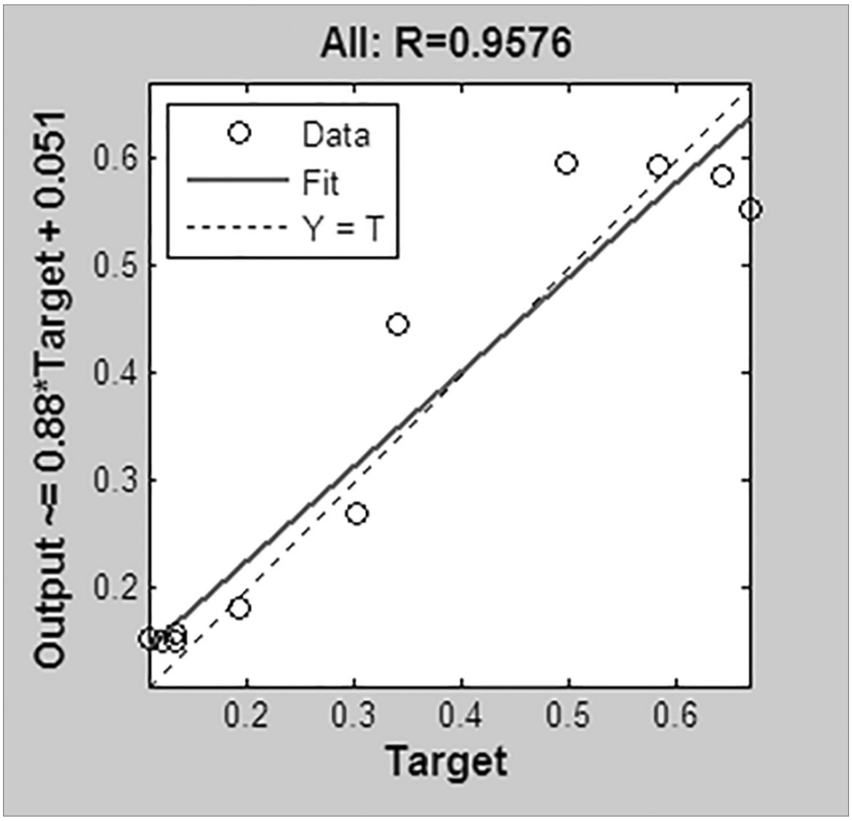

Figure 1. Result of neural network training

Source: Listing of neural network training results

Table 5

Parameters of neural networks designed to predict the dynamics of a country's financial security indicators

Indicator	Neural network parameters						
	v_1	v_2	w_1	w_2	a_1	a_2	b
q_{11}	2,8	2,8	-0,9379	1,0394	-2,8	2,8	0
q_{12}	1,5297	2,6546	-1,8664	0,19076	-1,5109	2,9343	-1,5827
q_{13}	-2,8	2,8	1,0207	-0,95821	2,8	2,8	0
q_{14}	3,5562	-2,3565	-1,4511	-2,5907	-1,5022	-3,6961	3,1974
q_{15}	-2,4827	-7,3345	1,8175	-2,1672	0,56891	2,9916	0,95424
q_{16}	2,2263	-4,0893	0,13871	-1,1384	-3,9827	-2,1621	0,64076
q_{17}	1,8623	-1,46	0,33998	-2,1402	-3,8962	-0,57455	-0,36225
q_{21}	2,8	2,8	-1,1189	0,84141	-2,8	2,8	0
q_{22}	-3,1789	4,809	0,87024	-2,0057	3,6981	2,7759	0,0078222
q_{23}	2,2551	-2,632	0,077406	-0,42383	-3,1321	-3,147	-0,46413
q_{31}	1,4239	8,4167	0,28723	0,89848	-4,0643	2,7268	-0,096515
q_{32}	-2,8	-2,8	1,0715	-0,9011	2,8	-2,8	0
q_{33}	8,7832	3,7755	-1,6716	0,51504	-8,911	1,9595	-1,6019
q_{34}	2,0324	-2,7424	-0,14362	-0,16337	-3,8209	-2,5129	-1,057
q_{35}	0,94092	4,0372	1,6193	-0,88525	-0,85414	1,7213	1,339
q_{41}	3,0871	3,2133	-0,589	0,79078	-2,516	2,4008	-0,65549
q_{42}	0,33156	-0,75058	4,1771	-2,828	0,18531	-5,6903	-3,7808
q_{43}	0,072653	4,9863	2,8168	-0,0531	-5,4753	-0,22255	-4,8214
q_{44}	3,153	3,1183	0,78448	0,96224	-4,0372	2,4864	-0,62592
q_{51}	-0,38795	-3,066	-0,37681	-1,2779	0,41669	-0,65043	-0,67931
q_{52}	-2,5815	-3,0161	1,0073	0,19389	2,8497	-2,3917	-0,12728
q_{53}	3,4543	-1,9895	-1,0062	0,69101	-2,0308	-3,5693	-0,16058
q_{54}	2,9561	-2,9019	0,043945	0,034243	-2,4595	-2,6846	1,0319
q_{55}	-2,5134	-0,81969	2,6058	-2,5099	2,4266	-4,2403	2,4724
q_{61}	2,591	2,4912	1,3565	-0,12583	-0,10255	3,0504	-0,10589
q_{62}	-2,9396	-3,3299	0,883	0,49151	2,1328	-2,1658	-0,22717
q_{63}	1,278	-2,7843	0,51951	-1,0783	-2,0877	-2,8425	-1,0041
q_{64}	-1,6832	-1,6586	-2,1283	-0,30267	1,5471	-5,3726	1,424
q_{65}	5,0355	-3,2258	0,89759	0,34351	-2,6596	-1,0312	0,98987
q_{66}	-4,1095	-0,49957	-2,8614	0,31348	-3,2879	-1,8917	-1,2118

Source: proposed by the authors

the ratio of liquid assets to short-term liabilities will increase to 95.6%. The share of overdue loans in total loans volume extended by banks to residents of Ukraine is forecast to decrease significantly and stabilise at a level of 34–36%.

Among the security indicators for the non-banking financial market, the insurance penetration level is projected to increase by 0.37–0.4%, while the remaining indicators in this group are not expected to change significantly compared to 2020.

Among the debt security indicators, the ratio of public and publicly guaranteed debt to GDP is projected to increase and stabilise at around 70%. Similarly, the gross external debt to GDP ratio is projected to increase and reach a level of 99–100%. The weighted average yield of domestic government bonds in the primary market is forecast to decrease by 1% and the ratio of official international reserves to gross external debt is forecast to increase by around 5%. The dynamic of the EMBI+Ukraine index together with the forecast for 2023–2025 are shown in Figure 2.

Among the budgetary security indicators, the ratio of total public debt service and repayment payments to public budget revenues is projected to increase substantially. Dynamics of this indicator together with the forecast for 2023–3025 is shown in Figure 3.

According to the forecast, the ratio of the state budget deficit/surplus to GDP will be −1.25 in 2025, the deficit/surplus of budgetary and extra-budgetary funds of the general government sector will stabilise at 0.36% of GDP in 2023–2025 and the redistribution level of GDP through the consolidated budget at 32.73%.

Among the currency security indicators, the index of change in the official exchange rate of the national monetary unit against the US dollar and

Table 6

Projected values of the country's financial security indicators

Indicator	Years				
	2021	**2022**	**2023**	**2024**	**2025**
Banking security indicators					
Share of overdue loans in the total volume of loans granted by banks to residents of Ukraine, %	43,73	38,32	35,75	34,80	34,48
Ratio of bank loans to deposits in foreign currency	70,29	68,93	68,49	68,32	68,25
Share of foreign capital in the share capital of banks, %	29,04	28,58	28,45	28,41	28,40
Ratio of long-term loans and deposits (over 1 year), times	4,00	4,00	4,00	4,00	4,00
Return on assets, %	0,03	-0,15	-0,21	-0,24	-0,24
Ratio of liquid assets to short-term liabilities, %	94,61	94,76	95,01	95,33	95,61
Share of assets of the 5 largest banks in total assets of the banking system, %	59,68	59,78	59,90	60,06	60,25
Security indicators of the non-banking financial market					
Insurance penetration rate (insurance premiums to GDP), %	1,63	1,47	1,40	1,38	1,37
Volatility level of the PFTS index, number of critical deviations (−10%)	0,06	0,02	0,02	0,01	0,01
Share of insurance premiums received by the 3 largest insurance companies in the total volume %	15,11	15,29	15,47	15,59	15,65
Debt security indicators					
Ratio of public and publicly guaranteed debt to GDP, %	69,25	69,31	69,43	69,62	69,95
Ratio of gross external debt to GDP, %	111,90	103,93	100,45	99,22	98,81
Weighted average yield on domestic government bonds in the primary market, %	9,05	9,04	9,04	9,04	9,04
EMBI+ Ukraine Index	750,37	739,68	721,01	694,65	667,00
Ratio of official international reserves to gross external debt, %	25,67	26,92	27,63	28,03	28,26
Indicators of budget security					
Ratio of the state budget deficit and surplus to GDP, %	-1,59	-1,39	-1,30	-1,27	-1,25
Deficit/surplus of budgetary and extra-budgetary funds of the general government sector, as a percentage of GDP	0,37	0,36	0,36	0,36	0,36
The level of GDP redistribution through the consolidated budget, %	32,73	32,73	32,73	32,73	32,73
Ratio of total payments on public debt servicing and repayment to state budget revenues, %	61,34	76,91	83,87	85,91	86,48
Currency security indicators					
Index of changes in the official exchange rate of the national currency against the US dollar, average for the period	149,27	150,83	152,29	153,65	154,92
Gross international reserves of Ukraine, in months of imports	2,57	2,19	2,06	2,02	2,01
Share of loans in foreign currency in total loans granted, %	32,60	32,58	32,57	32,57	32,57
Balance of purchase and sale of foreign currency by households, billion USD	1,10	1,11	1,11	1,11	1,11
Level of dollarisation of the money supply, %.	32,98	32,90	32,81	32,76	32,73
Monetary security indicators					
Share of cash outside banks in the total money supply (M0/M3), %	26,36	26,36	26,36	26,36	26,36
Difference between interest rates on loans granted by depository corporations to residents of Ukraine in the reporting period and interest rates on deposits attracted by depository institutions	6,86	6,86	6,86	6,86	6,86
Weighted average interest rate on loans granted by depository corporations (other than the NBU) in national currency relative to the consumer price index	12,19	13,55	15,16	16,77	18,16

Continuation of table 3

Share of consumer loans granted to households in the total structure of loans to residents	17,36	17,36	17,36	17,36	17,36
Specific share of long-term loans in total amount of loans granted (adjusted for exchange rate differences), %	18,58	18,55	18,55	18,55	18,55
The volume of legal outflow of financial resources outside the country, billion USD	11,19	11,19	11,19	11,19	11,19

Source: proposed by the authors

the level of dollarization of the money supply are projected to increase. Ukraine's gross international reserves and the share of loans in foreign currency in the total volume of loans granted are forecast to decrease. The balance of purchase and sale of foreign currency by households is forecast at the level of 1.11 billion USD.

Among the monetary security indicators, the level of the weighted average interest rate on loans extended by depository corporations (excluding the National Bank) in national currency is expected to rise relative to the consumer price index. The dynamics of this indicator, together with the forecast for 2023–3025, are shown in Figure 4.

The specific share of cash outside banks in total money supply is forecast to decrease and stabilise at 26.36%. Other monetary safety indicators according to the forecast remain close to the 2020 level.

4. Conclusions

The design of assessing and forecasting the financial security of a country is proposed to be carried out using artificial networks. For creating neural networks, their training and their application in forecasting the dynamics of financial security indicators we used the Matlab application package, including the Network Data Manager program. This program gives the possibility to optimally form and choose neural networks, topology, activation and training algorithm. The grouping of indicators characterizing financial security, we propose to distribute into 6 subsets: indicators of banking security; non-bank financial market security indicators; debt security indicators; budget security indicators; currency security indicators; monetary security indicators. Calculation of financial security level and its forecasting showed the need for increased state attention to the allocation and accumulation of financial resources. Despite the fact that according to the forecasts, some stabilisation of banking safety indicators is expected in 2023–2025, the return on assets will decrease. The weighted average yield of domestic government bonds in the primary market is projected to decrease by 1%, and the ratio of official international reserves to gross external debt is projected to increase by about 5%. The aim of

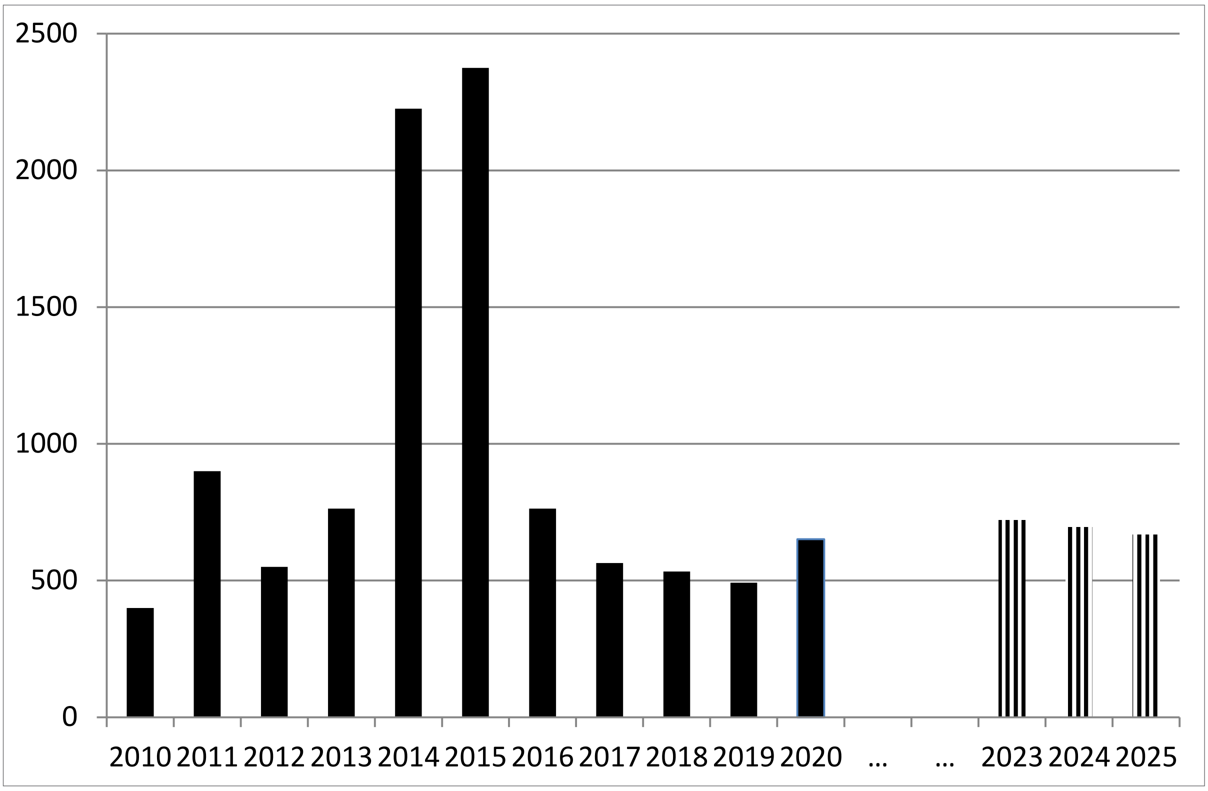

Figure 2. Dynamics of the EMBI+Ukraine Index

Source: forecast data calculated by the authors

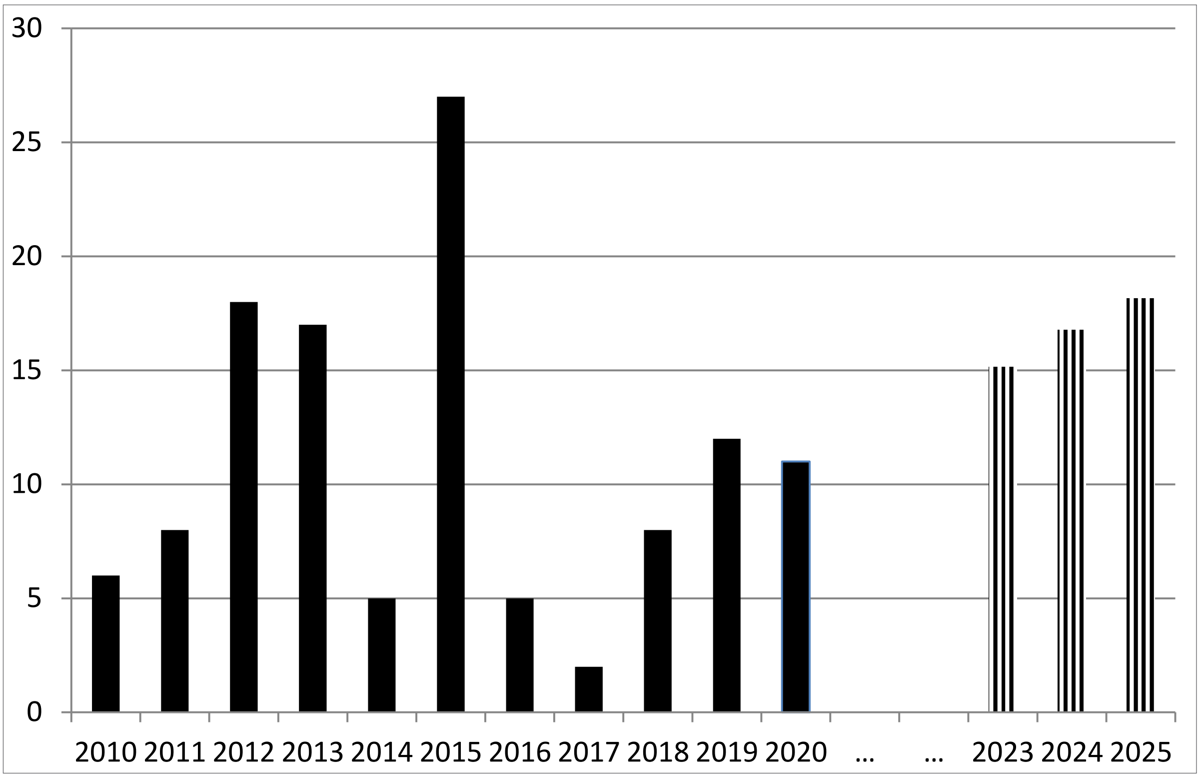

Figure 3. Ratio of total public debt service and repayment payments to public budget revenues

Source: forecast data calculated by the authors

our further researches will be to increase the system of indicators for financial security design and to expand the methodological tools to forecast the phenomenon we are analysing.

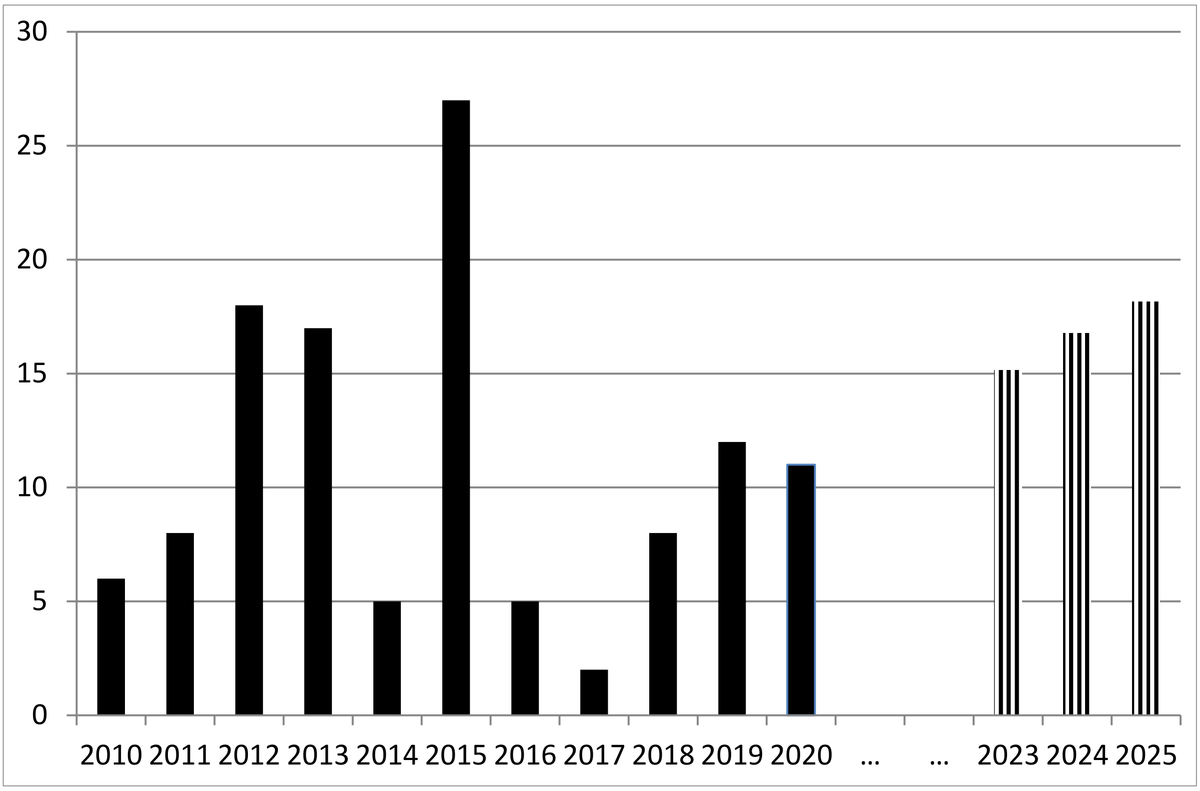

Figure 4. Dynamics of the weighted average interest rate on loans provided by depository corporations (except the National Bank) in national currency relative to the consumer price index

Source: forecast data calculated by the authors

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ДИЗАЙН ОЦІНЮВАННЯ ТА ПРОГНОЗУВАННЯ ФІНАНСОВОЇ БЕЗПЕКИ КРАЇНИ В УМОВАХ УПРАВЛІННЯ ЗМІНАМИ

Анотація. *Конкурентоспроможність будь-якої країни знаходиться у прямій залежності від ефективності роботи фінансового сектору. При чому рівень фінансової безпеки обумовлює спроможність країни розвиватися далі на інноваційних засадах. Важливою потребою є моделювання оцінювання та прогнозування фінансової безпеки країни, щоб вчасно корегувати державні рішення, розподіляти ресурси країни для підвищення її фінансової спроможності. У науковому світі не достатньо розвинуті методи моніторингу фінансової безпеки особливо на макрорівні. Потребує поглиблення інструментарій відбору показників необхідних для оцінювання фінансової безпеки. Також у часи інноваційних відкриттів та технологій, методи такої оцінки повинні бути прогресивними та нестандартними.*

Матеріалами для написання статті слугували статистичні показники, що характеризують фінансовий стан розвитку України. З використанням цих показників можливо вчасно оцінювати рівень фінансової безпеки та розраховувати прогноз. Авторами запропоновано таке групування зазначених показників, яке у найбільш повній мірі буде охоплювати фінансову діяльність країни. Моделювання оцінювання та прогнозування фінансової безпеки країни пропонуємо здійснювати з використанням штучних мереж. Для створення нейронних мереж, їх навчання та застосування при прогнозуванні динаміки показників фінансової безпеки використано пакет прикладних програм Matlab, що включає програму Network Data Manager. Ця програма дає можливість у оптимальний спосіб формувати та обирати нейронні мережі, топологію, активацію та алгоритм навчання.

Оцінювання та прогноз фінансової безпеки засвідчив необхідність підвищеної уваги держави до розподілу та накопичення фінансових ресурсів. За нашими підрахунками, у 2023–2025 роках очікується певна стабілізація показників банківської безпеки. Показники співвідношення банківських кредитів та депозитів в іноземній валюті, частки іноземного капіталу в статутному капіталі банків, співвідношення довгострокових кредитів та депозитів, частки активів 5-ти найбільших банків у сукупних активах банківської системи стабілізуються на рівні 2020 року. Рентабельність активів дещо зменшиться і стане від'ємною, а показник співвідношення ліквідних активів до короткострокових зобов'язань зросте до рівня 95,6%. Прогнозується істотне зростання відношення обсягу сукупних платежів з обслуговування та погашення державного боргу до доходів державного бюджету.

Запропонований дизайн оцінювання та прогнозування фінансової безпеки країн заснований на використанні штучних нейромереж, які є особливо актуальними в умовах сьогодення. Логіка моделювання є цілком зручною та зрозумілою для зацікавлених та може використовуватися державними посадовцями для систематичного визначення рівня фінансової безпеки країни. Також запропонований дизайн може бути адаптований для використання в інших країнах з метою визначення рівня фінансової безпеки та корегування існуючих фінансових стратегій розвитку держави.

Ключові слова: *фінансова безпека, нейронна мережа, прогнозування, фінансовий ринок, кредити, ліквідність, страхування, державний борг, національна грошова одиниця*