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MODELING COMPANY'S FINANCIAL SUSTAINABILITY WITH THE USE OF ARTIFICIAL NEURAL NETWORKS

For enterprises in market conditions, not only the sum of profit is important, but also their financial capacity to continue its activity. The ability of a company to counteract the threat of bankruptcy is an essential condition for its long-term functioning and sustainable development. The financial sustainability of an enterprise is a complex characteristic that can't be described by the value of a single simple indicator. In modern conditions, for its diagnosis, a comprehensive analysis using various financial indicators is used. When a human does it, such an assessment may be subjective and depends on the level of the analyst's qualification and competence.

The article proposes the use of artificial neural networks to build an economic and mathematical model of company's financial sustainability, which is designed to remove the human factor, and to increase the speed and accuracy of the companies' bankruptcy threat diagnosis. An example of such a model is presented that is relevant for Ukrainian companies in the current conditions of the period after the economic crisis of 2014-2015. To model financial sustainability, a three-level artificial neural network of direct signal propagation was constructed. As input factors it is proposed to use 17 financial indicators that should give the most complete assessment of the company's financial sustainability. The study shows that prediction of bankruptcy is possible in the time horizon up to 3 years from the date of filing annual financial statements. The constructed model allows not only to accurately classify enterprises as "financially sustainable" and "potential bankrupt" but also opens up opportunities for further researches about the mutual dependence between the values of financial indicators while maintaining a certain level of financial sustainability. The model may be useful for financial institutions, investment funds, audit firms and companies themselves for timely prediction of the company's bankruptcy.

Key words*: financial sustainability, bankruptcy, neural networks, economic and mathematical modeling, classification, bankruptcy diagnostics, financial indicators, limit of financial sustainability, neuro-network modeling, perceptron, neuron, enterprise*

Introduction. The freedom of enterprise and choice is a fundamental basis for conducting productive activities in a market economy, which is today the most widespread form of economic organization in the world. The role of the state is only in the general direction of development and transformation of a national economy and in setting certain restrictions. The very system of distribution of goods and services is formed through free decisions by consumers and suppliers. Economic actors have

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a wide freedom to manage their limited economic resources at their own discretion. Accordingly, the consequences of economic decisions are also part of the responsibility of economic actors. Thus, any company that seeks profit or attain another some other desired effect, in order to achieve its goals, should rationally manage its resources and take into account the threats that can lead to undesirable consequences.

One of the key tasks of a company is to speed up the growth of its profits, which can be attained, in particular, via additional third-party financing and accompanied by increased financial risks. Therefore, in such a case, the risk of failure, for the company, to repay in time, that is, its bankruptcy, increases. Avoiding financial collapse is the company's other key concern. Continuous monitoring of the financial position and timely decisions regarding the elimination of threats of the loss of the company's financial capacity to continue its operations is an indispensable condition for its sustainable development. Monitoring procedures are quite expensive, and the reliability of the results significantly depends on the level of qualification and competence of the personnel. Therefore, in our opinion, the most efficient solution is to automate the process, which can significantly reduce its cost, improve accuracy and eliminate the risks associated with the human factor. It is proposed to use artificial neural networks to simulate the financial sustainability of a company.

Analysis of researches and publications. The issues of assessment, management and simulation of the company's financial sustainability have been investigated by: E. Altman [1], K. Beerman [2], G. Tishow [3], R. Taffler [3], J.S. Soileau [4], T.A. Al-Cassara [4], P.K. Ozil [5], O.D. Sharapov [6], O.O. Tereshchenko [7], A.V. Matviychuk [8–10], O.V. Pavlovskaya [11], A.M. Poddyeriogin [12, 13], L.Yu. Naumova [12], G.V. Davidova [14], O.Yu. Belikov [14], L.D. Buriak [13, 15], G.G. Nam [13], O.G. Yakovenko [16], A.M. Pavlikovsky [15], V.G. Vershigora [17] and others.

Among the existing attempts to simulate financial sustainability, the most widespread are discriminant models. The first model of its kind was introduced by American scientist Edward Altman in 1968, it was relevant to the conditions of the US economy at that time, and its first version included five factors [1, p. 589–609]. With this model, a Z-score is calculated, whose range of possible values is divided into areas of high bankruptcy probability, low bankruptcy probability and uncertainty areas. Subsequently this approach was further developed and applied to construct other discriminant models for different countries. Examples include Beerman's models for Germany (ten factors) [2, p. 118–121], models by Tafler and Tishaw for the United Kingdom (four factors) [3, p. 50–54], and those by O.O. Tereshchenko (six factors) [7, p. 38–45] and A.V. Matvijchuk (seven factors) [8, p. 24-46] for Ukraine and others. A.V. Matvijchuk [9, p. 229–231] presents the results of experiments on the use of some of these models for the Ukrainian economy. The classification accuracy of the Matvijchuk's model on the sample that was used to create it was 82.5% (92% – bankrupts, 72.4% – financially sustainable ones), and on independent sample - 80.1% (89.2 and 71.2%) respectively) [9, p. 229]. On the same data, the Altman model showed the accuracy of 54.3% (54.1% - bankrupts, 54.5% – financially sustainable ones), while it could not estimate the conditions of 11.7% of companies [9, p. 230]. The Tereshchenko model failed to provide any estimate for 51.4% of the companies, while for the evaluated enterprises the accuracy was 67.6% [9, p. 230–231]. Therefore, in our opinion, the results of some of the above models are too low to be used in the current practice of the Ukrainian economy, others may be used, but it makes sense to try to create new, more accurate models of bankruptcy forecasting.

In addition to discriminant models, other methods to forecast company bankruptcy have been proposed. Thus, A.V. Matvijchuk proposes to apply comprehensive financial analysis of companies based on fuzzy logic theory. This approach involves constructing a fuzzy model of company bankruptcy diagnostics. Attempts to build such models attained an overall accuracy of 92.7%, which implies the accuracy of the correct classification of bankruptcies of 100%, and the accuracy of the correct classification of financially sustainable companies of 85.7% (with the beta error of 14.3%) [10, p. 96]. In our opinion, this is a good result, but it is worth acknowledging that the beta error of this model is quite significant and reducing it is an important task for further research. Also, A.V. Matvijchuk in [10, p. 100–101] presents the results of attempts to build neural network models of financial sustainability, in particular, a classification accuracy of 98.6% was attained (100% – bankrupts, 97.0% – financially sustainable companies), which is a high result. It should be noted that the constructed model used data from the pre-crisis period, that is, the period before the decline of Ukraine's economy in 2014–2015. In our opinion, one cannot be sure that the resulting model still remains sufficiently effective and retains its accuracy under the current financial and economic conditions in Ukraine. However, this model demonstrates a high feasibility of using artificial neural networks to solve the problem of classifying companies into "financially sustainable" and "potential bankrupts".

The article by O. L. Tymoschuk and K. M. Dorundyak [18, p. 26–28] presents an artificial neural network for assessing the probability of a company's bankruptcy. The model uses the values of the company's financial performance to attribute their financial status to one of three classes: "1 – nothing threatens the company because it is financially sustainable; 2 – there are certain financial difficulties, and a low probability of bankruptcy; 3 – the company has a high risk of becoming bankrupt" [18, p. 27]. The classification accuracy was 97.7%. It should be noted that for training the neural network using the «supervised» method, the values of the source variable (the class, to which the company should be attributed) were calculated "based on the methodology of the Ministry of Finance of Ukraine" [18, p. 28]. It is worth noting that this methodology, most likely, has its own error and aims at unifying the estimation of the depth of the crisis in Ukrainian enterprises. Thus, when using the presented model, the time of bankruptcy cannot be ascertained, nor the time horizon can be established when the company will go bankrupt or retain its financial capacity to continue operations. It should be emphasized that the construction of this model also demonstrates the high suitability of neural networks to build models of company financial sustainability, since it can reproduce with great precision the relationships between the factors and the resulting variable, which are specified in the above mentioned methodology of the Ministry of Finance of Ukraine.

It is worth noting other current researches related to economic and mathematical modeling of financial sustainability. Thus, O.A. Levchenko's article [19, p. 105–113] presents a model for evaluating the financial sustainability of a leasing financing mechanism based on Bayesian logistics models with a normal type of conditional probability distribution. The article by V.M. Kuzyko and M.O. Mikhailuk [20,

p. 24–30] proposes the use of a sixteen-component indicator of financial stability, which, according to the authors, allows a thorough analysis of company financial sustainability and reveal problems with business and warehouse inventories, as well as with medium-term payables [20, p. 29].

There are also works proposing to use a taxonomic indicator as an integral estimator when simulating financial sustainability [21, p. 199–207; 22, p. 195–199].

Despite the large volume of works on company financial sustainability, no studies have been conducted to construct a model that could predict whether a company would go bankrupt in a given time horizon. Such a research would be relevant for Ukraine's financial and economic conditions after the 2014–2015 crisis and would have a rather high prediction accuracy. In particular, in our opinion, this problem has not been sufficiently addressed from the point of view of constructing an artificial neural network using a large number of versatile financial indicators.

An article [23, p. 86–91] considers the current interpretation of the concept of financial sustainability and suggests that the term means the ability of a company to withstand any financial threats that could lead to bankruptcy.

Another research [24, p. 112–119] presents a first attempt of the author of this article to construct a multifactor artificial neural network for the classification of companies by financial sustainability. 21 financial indicators were taken as factors. For training and testing the network, we used data from Ukrainian enterprises for the early 2000s. As a result, a neural network was obtained with 100% accuracy in the training sample and 88% in the test sample.

The purpose of the article is to build a fully connected three-layer artificial neural network relevant for the current realities of the Ukrainian economy, which could classify companies by the level of financial sustainability into "financially sustainable ones" and "potential bankrupts". The accuracy of the model's work should be determined.

Presenting the main content. First of all, for this type of research, particular attention should be given to the quality of the dataset, which should be sufficiently reliable and orderly. Using the neural network modeling method to classify companies by financial sustainability, the models' author should set such parameters of the neural network's design and training, which could provide the highest possible classification accuracy. Some of these parameters can be chosen at the researcher's discretion. However, many of them, in our opinion, should be chosen through a series of experiments.

A dataset was created that contains financial statements of 126 enterprises. The annual reports of these companies start from 2015 and end with the statements for 2017. Half of the observations are the companies' statements submitted some time before the court decision on their bankruptcy and the start of the liquidation procedure. The other half are companies that for some time after the submission of the statements were not declared bankrupts by the court. The date of bankruptcy is the date of the court's announcement of the commencement of liquidation proceedings. For bankrupt companies, the time from the statement submission to the start of the liquidation procedure varies from four months to three years. For the financially sustainable companies, the time from the statement submission to the time of inclusion of the observation in the dataset varies from one to three years.

A set of factors presented in the study [24, p. 116] was reviewed. It was decided to leave a sufficient number of financial indicators in the order to preserve the versatility in the neural network's evaluation of the companies' financial sustainability leave the possibility to study the interchangeability of the indicators' values if the company is on the verge of financial stability, as presented in the work [25, p. 59–66]. Thus, before the classifier was built, 17 financial indicators were adopted as neural network factors:

1) asset mobility;
2) own working capital availability;
3) current assets turnover;
4) fixed assets turnover;
5) equity turnover;
6) financial dependency;
7) own capital maneuverability;
8) general liquidity;
9) fast liquidity;
10) accounts payable turnover;
11) coverage (general), (current liquidity);
12) asset coverage;
13) attracted capital concentration;
14) investments coverage;
15) fixed assets depreciation;
16) receivables turnover;
17) debt repayment with own capital.

The essence of the classification consists in drawing a boundary that separates the observations of one class from the observations of the other one. In our case, the number of factors is 17, which means that the boundary of financial stability must be drawn in the 17-dimensional real vector space R^{17}. For each of the companies we have a set of financial indicators that act, in our model, as factors shaping the vector of the coordinates of a point in the above described space. That is, each such point describes the position of an individual enterprise in the space of financial sustainability. Hypothetically financially sustainable companies form a set of points that is generally sufficiently distant from the set of points describing a bankruptcy enterprise, so that those two sets can be separated from one another by a particular hypersurface. Such a hypersurface will be considered as the boundary of financial sustainability. Hence the boundary of financial sustainability divides the above space into two parts, that is, the semi-hyperspace of financial sustainability and the semi-hyperspace of potential bankruptcy.

It should be emphasized that the main objective of this study is to achieve the highest accuracy in the classification of companies. In this case, it was considered appropriate to refuse to receive other information that may be provided by the network when using this method. The function of such information can be performed by the prediction of time before the bankruptcy or the likelihood of bankruptcy, as demonstrated by A.V. Matvijchuk [9, p. 250-266].

To create and train the neural networks, software package STATISTICA 12 (including the built-in SANN package) was used. When attempting to construct neural networks of different architecture as an activation function, on the hidden and output layers, combinations of the following functions were used: identical function, logistic function, hyperbolic tangent, exponential function, sine, Gaussian. Given the results of the large number of experiments on the construction of a neural network, and also considering the results of the study [24, p. 117], it was decided to use the hyperbolic tangent function as an activation function on the hidden and output layers, since it was this function that provided the highest classification accuracy. So we can say that the boundary between classes will represent a nonlinear hypersurface. The search for the specified boundary is that after finding it, the maximum number of companies will be in the semi-hyperspace to which they belong. Thus, our goal is to search for a function or equation that sets the position of the boundary of financial sustainability. Such a function or equation can be obtained by applying the method of artificial neural networks.

The main options that define the architecture of the artificial neural network and its training methods are the following:

- neural network type: multilayer perceptron (MLP), radial basis function (RBF);
- error function: sum of squares, cross entropy;
- activation functions:
  – in the hidden layer;
  – in the input layer;
- number of hidden layer neurons;
- training algorithm:
  – type of algorithm: gradient descent method, Broyden–Fletcher–Goldfarb–Shanno method (BFGS), conjugate gradient method;
  – number of training cycles;
  – training speed;
  – momentum;
- parameters of initial weight initialization;
- stop training criteria.

Although some of the values of these parameters can be chosen by logical assumption, based on the features of the object of simulation, the choice of others can be made mostly relying on the results of experiments on the construction of neural networks with different combinations of these parameters. The best combination was considered to be the one that provides the highest classification accuracy.

As a result of a series of neural network experiments in STATISTICA 12 package and based on a number of logical judgments, it was concluded that the best parameters to build artificial neural network that classifies companies as "financially sustainable" and "potential bankrupts" will be the following:

network type: multilayer perceptron (MLP);
activation function of the hidden layer neurons: hyperbolic tangent (tanh);
error function: sum of squares of the error (SOS);
training algorithm: Broyden–Fletcher–Goldfarb–Shanno method (BFGS);
initialization of weights: normal randomization, mean: 0, variance: 0.1.

The distribution of the dataset from 126 observations into sub-samples was each time conducted in the following proportion: training sample – 70%, testing sample – 15%, and validation sample – 15% of observations. In each of the sub-samples, the proportion of 50% sustainable companies and 50% bankrupts was maintained. Distribution into sub-samples was random. The dataset distributed into sub-samples was used in a number of experiments to find the best parameters of the neural network. During these attempts, there were situations where a randomly distributed dataset was not suitable for neural network training, which was reflected in the absence of models with approximately identical classification accuracy in each sub-sample (training, testing, and validation). In such cases, it was acknowledged that the dataset was poorly distributed, and the drop in accuracy was probably caused by accidental occurrence of similar observations in one sub-samples with a simultaneous lack of such examples in other sub-samples, which made it impossible for the network to perform high quality training, testing or validation. If such a situation occurred during the experiments, the dataset was again randomly distributed into new sub-samples, and the experiments were repeated and continued. But each time testing, training, and validation were performed on different observations of the dataset.

After many attempts to construct neural networks, the best of them was chosen, which showed the highest classification accuracy. It should be noted that during the training of an artificial neural network, the classification accuracy is expressed simultaneously by three values:

• classification accuracy on the training sample;
• classification accuracy on the testing sample;
• classification accuracy on the validation sample.

The ideal result is 100% accuracy, whose achievement means that during the training we managed to draw a boundary (in our case a hypersurface) between observations of classes in such a way that each company is in the half-space where only representatives of its class are located. However, we must understand the complexity of this task, the great variability of the situation at real economic entities, the limited possibilities of approximation, and so on. Thus, each of the above indicators of accuracy reflects what share of companies find themselves in their respective semi-hyperspace after the completion of the network training.

Accuracy of the classification of observations in the training sample reflects how well the boundary between classes separates the observations of the different classes that are known during the training, on which the adjustment of the neural network weights takes place. Accuracy of the classification on the testing sample shows the highest accuracy attained during the intermediate testing of the error during training. Accuracy of the classification on the validation sample indicates the share of companies in the validation sub-sample correctly classified after the completion of training, that is, unknown during neural network optimization.

When choosing the best neural network, one should require small variations between these three estimates. There is no point in choosing a network that has a high classification accuracy on the training sample and a low accuracy on the test or validation sample. Such a combination of estimates indicates that the boundary for financial sustainability was drawn well for the training sample, but such a neural network is not able to classify new, unknown companies, which is actually its main task. Low classification accuracy on the training set with high accuracy on the validation sample indicates the inconsistency of the boundary to the majority of observations, since the share of observations of the training sample in our study is 70% of the total sample. Low accuracy on the testing sample with high other estimates is surprising and most likely due to unfortunate coincidence that occurs during the distribution of observations into sub-samples for training, testing, and validation. Low scores on all sets indicate the network's inability to classify with sufficient accuracy. High and close estimates of classification accuracy in all sub-samples indicate that the obtained neural network accurately classifies most observations than we have in our research, classifies well the observations unknown during training, and provides confidence that during random distribution into the sub-samples of training, testing and validation there were no random conflux of similar observations in one of the sub-sample, that is, the distribution of different variants of observations occurred relatively evenly among the sub-samples of training, testing and validation. Otherwise, when there is conflux in one of the sub-samples, or if there are no representatives of one or other types of observations in one sub-section, we will have large deviations between the indicators of classification accuracy in the sub-samples of training, testing and validation, and cannot be sure in the quality of the obtained model.

During the construction of the neural network, it was decided to use two neurons at the output layer. During the network's working, the first one should actively respond in case of financially sustainable companies, and the second one– if the company is a potential bankrupt. When using two neurons on the last layer in our model, when estimating each observation that is unknown during the training, two hypotheses are put forward: 1) the enterprise is financially sustainable; 2) the enterprise is a potential bankrupt. It is clear that in reality these hypotheses are alternative to each other. Nevertheless, given that in most cases the estimation of financial sustainability cannot be made with one hundred percent accuracy, in assessing one company, each of the two options is considered separately. In this case, for each estimation variant, its own level of reliability of the fact that the company belongs to particular class is calculated. After that, the output signals of the neurons of the last layer are compared, and the company is assigned to the class, whose neuron acquires the larger output value. In other words, the estimate is made in accordance with the hypothesis that the neural network recognizes the more reliable one.

Thus, during the network training, each bankrupt company is assigned corresponding values of the neurons of the output layer: bankrupts class $y_n = 1$, sustainable companies class $y_s = -1$. And if the company is financially sustainable, then $y_n = -1$, and $y_s = 1$. At the same time, after the current network has undergone training, the model does not always return exactly such values. In practice, they range from –1 to 1. It should be noted that the sum of these values is often not equal to 0, that is, the value of one of the neurons of the output layer is not an antagonistic reflection of the value of the other one. That is, classifying a company, the network can not only find in it features that are characteristic of financially sustainable companies, but also identify signs of possible bankruptcy. In this case, the enterprise belongs to the class to whose representatives it is more similar. It is also worth noting that the individual features by themselves of a company's financial sustainability can indicate both that it is bankrupt and that it is financially sustainable. The decisive factor in this case is the combination of these features with other financial parameters of the company. In our view, the use of a neural network with a single neuron at the output layer reduces the model's ability to evaluate the impact of different variants of factor values, but further studies can compare the accuracy of models with two neurons at the input layer with one-neuron models.

Thus, out of the whole set of neural networks that we built, the MLP 17-5-2 was chosen, which contains five neurons in the hidden layer (Fig. 1). Its accuracy on the training sample is 91.11%, on the test sample – 94.44%, and on the validation sample – 94.44%. During the training, it took 48 cycles using the BFGS algorithm.

The result of the classification of companies by financial sustainability is defined as follows:

$$y_s = f\left(\sum_{j=1}^{5}\left[f\left(\sum_{i=1}^{17}[x_{i,1} \cdot w_{i,j}] + a_j\right) \cdot v_{j,s}\right] + d_s\right), \quad (1)$$

$$y_b = f\left(\sum_{j=1}^{5}\left[f\left(\sum_{i=1}^{17}[x_{i,1} \cdot w_{i,j}] + a_j\right) \cdot v_{j,b}\right] + d_b\right), \quad (2)$$

$$f(p) = \frac{2}{1 + e^{-2p \cdot k}} - 1, \quad (3)$$

$$z(y_s, y_b) = \begin{cases} sustainable, & y_s > y_b \\ bankrupt, & y_s \le y_b \end{cases}, \quad (4)$$

where $x_{i,1}$ is input signal, which is transmitted by the neuron i of the first layer and reflects the value of the financial indicator that corresponds to this neuron;

j – hidden layer neuron index;

$w_{i,j}$ – the weight of the synaptic connection between the neurons i and j of the input and hidden layers; and

a_j –bias of the sum of signals of the hidden layer neurons;

d_s and d_b –biases of aggregators of the input layer neurons (the neuron corresponding to financial sustainability and that corresponding to the risk of bankruptcy);

s and b – denote the neurons of the output layer (s – sustainable, b – bankrupt);

$v_{j,s}$ and $v_{j,b}$ – the weights of synaptic connections between the neurons of the hidden (j) and output (s and b) layers;

y_s and y_b – calculated signals of the output layer neurons;

p – the sum of the weighted input signals of the neuron using the aggregator's bias;

k – coefficient of compression-stretching;

$f(p)$ – hyperbolic tangent function;

z – the conclusion of the neural network on the financial sustainability of the represented company.

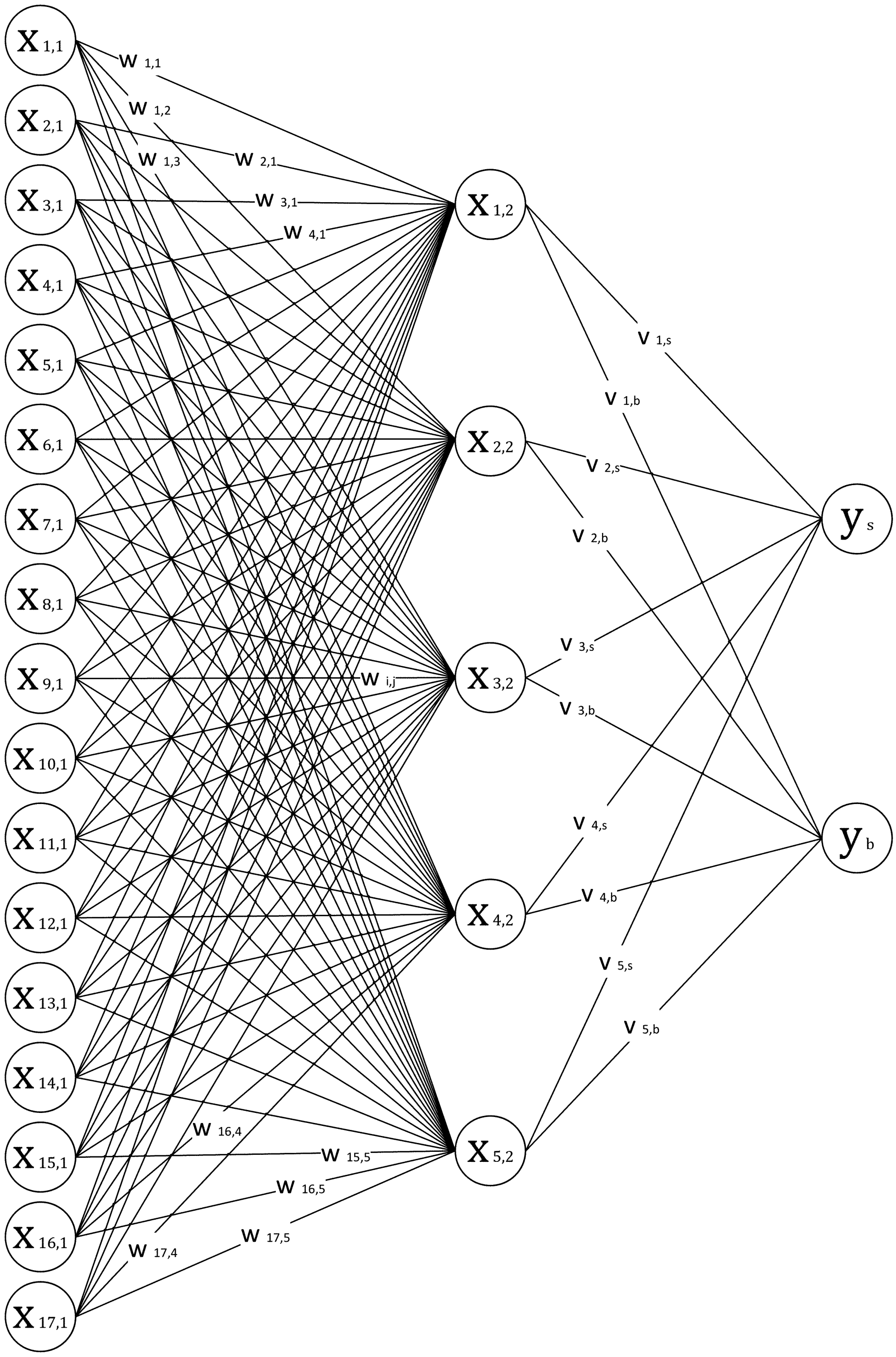

Fig. 1. Fully connected neuron network of direct propagation
Source: developed by author.

In Table 1, we can see that out of 90 training sample companies, 82 are classified correctly, of which 42 are bankrupts and 40 are financially sustainable companies. Thus, the classification error in the training sample is 8.89%. The α-error was 11.11% and β-error was 6.67%. Thus, we understand that when drawing the boundary of financial sustainability separating bankrupts from financially sustainable companies, we could not mathematically set a hypersurface that would correctly separate absolutely all representatives of the sets. As we can see, five financially sustainable companies are in the semi-hyperspace of bankrupts, and three bankrupts are in the semi-hyperspace of financial sustainable companies. The described error levels indicate a certain mathematical imperfection of the boundary, but, given the accuracy of the classification on the training set (91.11%), we can consider them acceptable.

Table 1

Detailing the classification accuracy in the training sample

Indicator	Bankrupts	Financially sustainable companies	Total
Total observations	45	45	90
Correctly classified	42	40	82
Erroneously classified	3	5	8
Correctly classified, %	93.33	88.89	91.11
Erroneously classified,%	6.67	11.11	8.89

Source: developed by author.

From Table 2 we can see that while conducting intermediate testing during the training, we managed to reach an error of 5.56%, which testifies to the high accuracy of classification. We can see that we only failed to correctly classify one of the 18 companies, which was actually bankrupt, but was classified as financially sustainable one.

Table 2

Detailing the classification accuracy in the test sample

Indicator	Bankrupts	Financially sustainable companies	Total
Total observations	9	9	18
Correctly classified	8	9	17
Erroneously classified	1	0	1
Correctly classified, %	88.89	100.00	94.44
Erroneously classified,%	11.11	0.00	5.56

Source: developed by author.

According to Table 3, which reflects the error structure in the validation sub-sample, when working with unknown companies during the training stage, the neural network correctly classified all financially sustainable companies, and only made one error in the classification of nine bankrupt companies. The classification error of new companies, which were unfamiliar for the network amounted to 5.56%, which is a high result.

Table 3

Detailing the classification accuracy in the validation sample

Indicator	**Bankrupts**	**Financially sustainable companies**	**Total**
Total observations	9	9	18
Correctly classified	8	9	17
Erroneously classified	1	0	1
Correctly classified, %	88.89	100.00	94.44
Erroneously classified,%	11.11	0.00	5.56

Source: developed by author.

In Table 4 we can see how accurately the financial sustainability is defined in all our observations. Of the 126 enterprises, 116 are classified correctly. Thus, the classification accuracy is 92.06% (both Sen (sensitivity) and Spe (specificity) are 92.06%). That is, the α- and β-errors are 7.94%. This means that, in the general population of Ukrainian companies, the neural network will classify, with equal accuracy, both potential bankrupts and financially sustainable companies with an accuracy of 92.06%, which we consider a sufficiently high result.

Table 4

Detailing the classification accuracy in the general sample

Indicator	**Bankrupts**	**Financially sustainable companies**	**Total**
Total observations	63	63	126
Correctly classified	58	58	116
Erroneously classified	5	5	10
Correctly classified, %	92.06	92.06	92.06
Erroneously classified, %	7.94	7.94	7.94

Source: developed by author.

If we look at the receiver operating characteristic curve (ROC curve) of the obtained neural network (Fig. 2), we will see that there are possibilities to adjust it to 100% sensitivity or to 100% specificity (or close to 100%). However, it is obvious that an increase in one of these characteristics would cause the other one to fall.

Sensitivity ratios are used to understand the relative importance of neural network variables. Each coefficient is calculated as the ratio of the network error in the absence of the factor to the network error with the available input. If this ratio is less than or equal to 1, the network will actually work better if this factor is excluded from the set of variables.

The most influential factors of financial sustainability in the obtained model were the following indicators: financial dependence, concentration of attracted capital, coverage (general), accounts payable turnover, and asset coverage. This is evidenced by the coefficients of sensitivity of the target indicator to the change in the factors' values (Fig. 3).

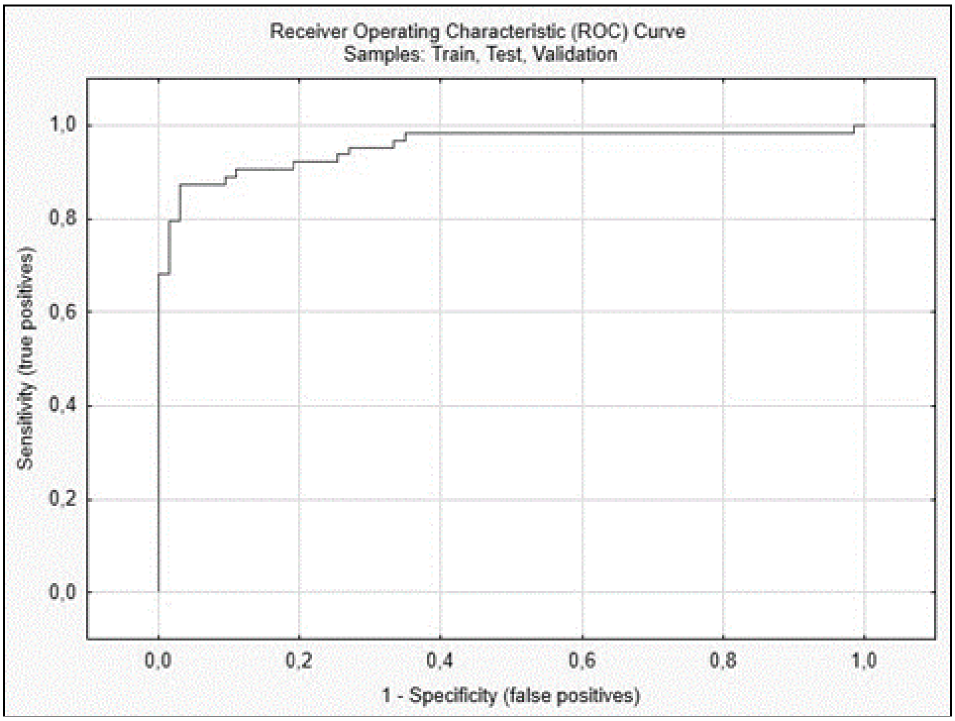

Fig. 2. The ROC curve of the obtained rule of companies classification by financial sustainability

ource: developed by author.

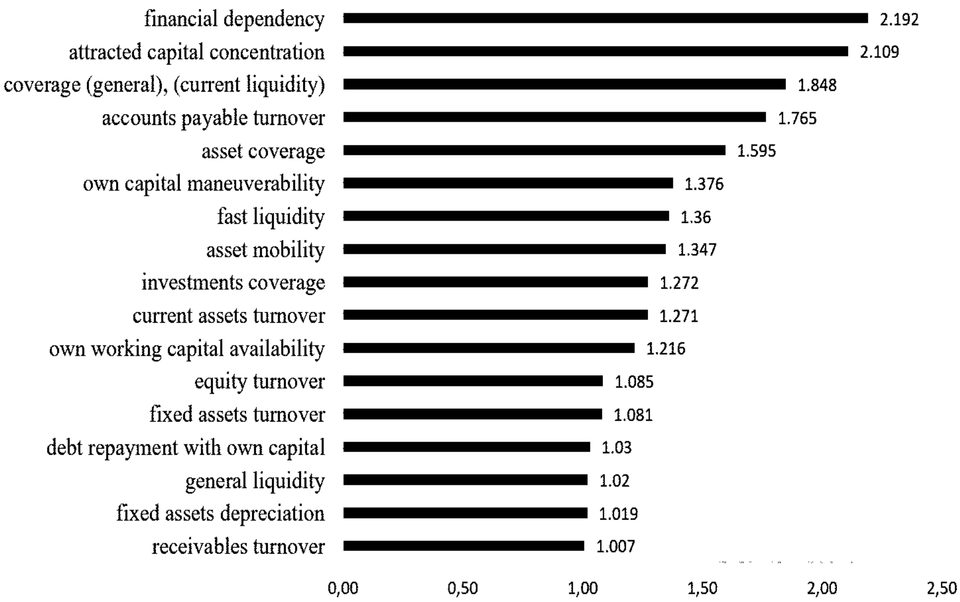

Fig. 3. Sensitivity of financial sustainability to changes in the factors' values

Source: developed by author.

It should be noted that exactly such values of the sensitivity coefficients can be conditioned, among other things, by the composition of the presented set of financial indicators. The point is that some indicators are dependent on each other because their values are calculated using the same financial statements. For example, calculations of the indicators of asset mobility and maneuverability of own capital involve using the volume of non-circulating assets, indicators of the turnover of circulating assets and turnover of fixed assets (net income from sales, etc.). Thus, changes in the values of these indicators are interrelated, and therefore, the impact of the value of each of them on a company's financial sustainability appears lesser than it actually is. However, given the sustainability of neural networks to multicollinearity, such a set of indicators can well be used. The order of influence shown in Fig. 3 demonstrates how important each factor is in itself in this model, and how indispensable it is. The indicators with the lowest sensitivity are the most interconnected ones, which means that when trying to reduce the number of factors, they cannot simply be dropped one by one as the sensitivity increases. When reviewing a set of factors, at least one representative from each group of related indicators should remain, otherwise the neural network will lose the ability to detect the effects described by the group of such indicators, which may result in the loss of classification accuracy. It should be noted that none of the factors in the model has a corresponding sensitivity factor of less than 1, indicating that none of them reduces accuracy, and the exclusion of any of them, will the loss of any of them will lower the accuracy. However, this circumstance is only relevant for this network, hence further research may attempt to construct new networks, except for some of the factors with the lowest sensitivity.

Conclusions and prospects for further research

A neural network of company classification by financial sustainability has been built. At the input, the network accepts 17 financial indicators of the company, and at the output it attributes the company either to the class of financially sustainable ones or to the class of bankrupts. The classification accuracy of the network is 92.06%, the α- and β-errors are 7.94%. The nature of the dataset used to create the network makes it possible to argue that a model has been obtained that is capable of providing a sufficiently accurate estimates of the company's ability to maintain financial sustainability for one year or the possibility of its bankruptcy during three years after the date of the annual financial statement, whose data serve as a basis for the estimation.

In the future it is worth trying to construct a neural network with one neuron on the input layer and to compare the accuracy of such a network with the accuracy of the model presented in this article. It may also make sense to conduct new experiments to reduce the number of factors by excluding the least sensitive input variables of the presented network, which could simplify the model without losing classification accuracy.

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МОДЕЛЮВАННЯ ФІНАНСОВОЇ СТІЙКОСТІ ПІДПРИЄМСТВ ЗА ДОПОМОГОЮ ШТУЧНИХ НЕЙРОННИХ МЕРЕЖ

У ринкових умовах підприємства переймаються не тільки величиною прибутку, а й фінансовою спроможністю до продовження діяльності. Здатність

компанії протистояти загрозі банкрутства становить невід'ємну умову тривалого функціонування та сталого розвитку. Фінансова стійкість підприємства – складна характеристика, яку неможливо описати за допомогою одного простого показника. В сучасних умовах для діагностування фінансової стійкості використовується комплексний аналіз із використанням різних фінансових показників. У разі його проведення людиною така оцінка може бути суб'єктивною та залежатиме від рівня кваліфікації й компетентності аналітика.

Для побудови економіко-математичної моделі фінансової стійкості підприємств, яка покликана вилучити людський фактор, підвищити швидкість та точність діагностування загрози банкрутства у статті пропонується використати штучні нейронні мережі. Наводиться приклад такої моделі, що є актуальною для українських компаній у сучасних умовах після економічної кризи 2014–2015 рр. Для моделювання фінансової стійкості було побудовано трирівневу штучну нейронну мережу прямого розповсюдження. Як вхідні фактори пропонується використовувати 17 фінансових показників, що допомагають якнайповніше оцінити фінансову стійкість підприємства. Проведене дослідження показує, що передбачення банкрутства з високою точністю можливе в часовому горизонті до трьох років з моменту подачі річної фінансової звітності. Отримана модель дозволяє не тільки достатньо точно класифікувати підприємства на «фінансово стійкі» та «потенційні банкрути», а й відкриває можливості щодо проведення подальших досліджень взаємозалежності значень фінансових показників при збереженні певного рівня фінансової стійкості. Модель може бути корисною для кредитно-фінансових установ, інвестиційних фондів, аудиторських компаній та самих підприємств задля вчасного передбачення загрози банкрутства.

Ключові слова: фінансова стійкість, банкрутство, нейронні мережі, економіко-математичне моделювання, класифікація, діагностика банкрутства, фінансові показники, межа фінансової стійкості, нейро-мережеве моделювання, персептрон, нейрон, підприємство

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МОДЕЛИРОВАНИЕ ФИНАНСОВОЙ УСТОЙЧИВОСТИ ПРЕДПРИЯТИЙ ПРИ ПОМОЩИ ИСКУССТВЕННЫХ НЕЙРОННЫХ СЕТЕЙ

В рыночных условиях предприятия озабочены не только величиной прибыли, но и финансовыми возможностями для продолжения деятельности. Способность компании противостоять угрозе банкротства является неотъемлемым условием длительного функционирования и устойчивого развития. Финансовая устойчивость предприятия – сложная характеристика, которую невозможно описать с помощью одного простого показателя. В современных условиях для диагностирования финансовой устойчивости используется комплексный анализ с использованием различных финансовых показателей. При его проведении человеком такая оценка может быть субъективной и зависеть от уровня квалификации и компетентности аналитика.

Для построения экономико-математической модели финансовой устойчивости предприятий, задача которой – исключить человеческий фактор, повысить скорость и точность диагностирования угрозы банкротства, в статье предлагается использование искусственных нейронных сетей. Приводится пример такой модели, которая весьма актуальна для украинских компаний в современных условиях периода, следующего за экономическим кризисом 2014–2015 гг. Для моделирования финансовой устойчивости было построено трехуровневую искусственную нейронную сеть прямого распространения сигнала. В качестве входящих факторов предлагается использовать 17 финансовых показателей, которые помогают наиболее полно оценить финансовую устойчивость предприятия. Проведенное исследование демонстрирует, что с высокой точностью предсказать банкротство возможно во временном горизонте до трех лет с момента подачи годовой финансовой отчетности. Полученная модель позволяет не только достаточно точно классифицировать предприятия на «финансово устойчивые» и «потенциальные банкроты», но и открывает возможности проведения дальнейших исследований взаимозависимости значений финансовых показателей при сохранении определенного уровня финансовой устойчивости. Модель может быть полезной для кредитно-финансовых учреждений, инвестиционных фондов, аудиторских компаний и самих предприятий, чтобы своевременно выявить угрозу банкротства компании.

Ключевые слова: финансовая устойчивость, банкротство, нейронные сети, экономико-математическое моделирование, классификация, диагностика банкротства, финансовые показатели, предел финансовой устойчивости, нейросетевое моделирование, персептрон, нейрон, предприятие