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Prediction of Bankruptcy in Non-financial Corporations Using Neural Network

SYLVIA JENCOVA[1], IGOR PETRUSKA[2], MARTA LUKACOVA[3] and JULIA ABU-ZAID[4]

[1] Associate Professor, University of Presov, Faculty of Management, Department of Finance, Slovakia, e-mail: sylvia.jencova@unipo.sk
[2] CSc., University of Presov, Faculty of Management, Department of Mathematical Methods and Managerial Informatics, Slovakia, e-mail: igor.petruska@unipo.sk
[3] PhD. Student, University of Presov, Faculty of Management, Department of Finance, Slovakia, e-mail: marta.lukacova@smail.unipo.sk
[4] PhD. Student, University of Presov, Faculty of Management, Department of Finance, Slovakia, e-mail: abuzaidjulia@gmail.com

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ABSTRACT

Prediction of bankruptcy is an important issue for management in corporate governance. So far, a considerable number of prediction models have been developed. In the field of the use of predictive models, one can see the growing importance of methods based on artificial intelligence. The aim of the paper is to predict the bankruptcy of companies in the electrical (SK NACE 26 and SK NACE 27) and engineering (SK NACE 25, SK NACE 28, SK NACE 29 and SK NACE 30) industry of the Slovak Republic using a multi-layer neural network (MLP – Multi Layer Percepton). This network with a Back Propagation learning algorithm is the most commonly used to solve practical tasks. Financial ratios of 754 companies in the electrical industry and 233 companies in the engineering industry in the Slovak Republic were used to train and test the neural network. For the electrical industry were used financial ratios for the year 2017 and for the engineering industry for the year 2018. An optimal model (network) was found for each industry using input layers of 11 or 8 financial ratios in combination with one or two hidden layers. The success of the models on test sets in individual indus-tries was high.

INTRODUCTION

The issue of financial health has been the object of many studies. There are many methods for predicting a company's financial health. Tamari's model (1966), the Balance Analysis System by Doucha (1996) and the Kralicek Quick Test (1991) are the scoring methods. Mathematical and statistical methods are based on one-dimensional discriminant analysis. Beaver (1966) outlined the possibility, that the use of multiple indicators may have higher predictive power than the use of just one indicator. Thus began a new era in the development of predictive bankruptcy models (Delina and Packova, 2013). Methods of multidimensional discriminant analysis are Altman's Z - score (1968), Taffler's model, Springate model and Indexes IN. Valaskova et al. (2018) deal with the issue of the debt, bankruptcy or non-bankruptcy of a company in their work. Kovacova and Kliestik (2017) introduced a bankruptcy prediction model in the Slovak Republic using logistic regression. The authors Zmeskal and Dluhosova (2015) also deal with the prediction and analysis of the financial health of companies. Among other authors, who deal with issues of financial and economic analysis include Vasanicova (2019), and Stefko & Sojka (2015).

Prediction of future development as part of the evaluation of the company's financial situation requires an expansion of the range of mathematical and statistical methods. Methods of comprehensive evaluation of a company excel in a certain transparency, but they suffer from a shortcoming due to their inaccuracy. It is therefore necessary for financial analysts to use several predictive valuation methods to clarify a company's financial health. At present, the foreground often receive model using neural networks (Jencova, 2018). Neural network models have non-linear nonparametric properties. They do not require the fulfilment of assumptions such as linearity, normality or independence of variables. The high predictive power of neural networks was confirmed by Sharda and Wilson (1996). One of the advantages of neural networks is their ability to learn the behavior (template) of very complex systems. Through learning, they transform inputs into desired outputs by adjusting the weights of signals between neurons. Most learning processes require a certain amount of computational time to count iterations.

When we model intelligence and learning using artificial neural networks (ANN), we must keep in mind, that we do not really know how the biological brain works. Neurons in the artificial neural network do not have the wealth of information contained in biological neurons. But the use of massive parallel processes, which imitate brain function, we can achieve the benefits of biological systems. The nature of neural networks as well as the fact, that their application requires special software support, creating conditions for their use especially in large enterprises. Small and medium enterprises often struggle to raise capital and are dependent on external sources. For this reason, they do not tend to spend money on the purchase of special software, which is necessary for the application of neural networks (Jencova, 2020).

1. LITERATURE REVIEW

Artificial neural networks are a general term for a group of procedures in the field of artificial intelligence, some of which can be well used as classification systems. Their most significant advantages are the ability to reveal nonlinear relationships in data and the ability to learn (Fitriyaningsih et al. 2018, Zalai et al. 2006). The basic features of neural networks are the ability to learn, ie to find connections in the trained data and to represent them using synoptic weights, as well as the ability to generalize the acquired knowledge. Adaptation is the ability to respond properly to unknown inputs for which the neural network has not been learned. A neural network consists of interconnected units, neurons (Kumar and Walia, 2006).

According to Gundova (2012), a neural network can be defined as a massively parallel processor, that tends to preserve experimental knowledge and its further use. The "backpropagation" neural network model was proposed by Rumelhart et al. (1986). It is a type of multilayer neural network. This model usually consists of an input layer, an output layer and a hidden layer. There is a connection between nodes of different layers, but there is no connection between nodes in the same layer. The neurons of the input layer receive signals, which are further divided into neurons of the next layer. In the hidden layer, neurons receive signals from other neurons, but also from the external environment. The output layer is used to transmit signals to the external environment (Terek, Hornikova and Labudova, 2010).

Neural networks are also referred to the concept of a black box. This indication is based on the fact, that it is impossible to know in detail the internal structure of the system. The black box works in two phases. In the first phase, the neural network acts as an inexperienced person, who learns to set his parameters. In the second phase, the neural network becomes an expert, because it produces outputs based on the knowledge gained in the first phase (Dostal, 2012). Neural networks have started to be used in practice due to the need to process large amounts of information in an ever shorter time. One of the basic properties of neural networks is the ability to process tasks, that we are not able to describe with sufficient accuracy. The theory of neural networks arose from the effort to develop an artificial system capable of performing complex, intelligent calculations similar to routine operations in the human brain (Kelemenova, Cernak et al., 2010). According to Sincak and Andrejkova (1996), the tasks that are often solved using neural networks include function approximation problems, solution of prediction problems, classification into classes, signal transformation and process control problems.

There are different variations of neural networks for specific tasks, such as feedforward neural networks and recurrent neural networks. The feedforward neural networks are spreading signals in only one direction. By recurrent neural networks we mean neural networks, that have synapses oriented in different directions. This means, that the neuron can be both input and output. In terminology, it is referred to as a dual neuron (Kelemenova, Cernak et al., 2010). Since the middle of the 20th century, artificial neural networks have been a popular topic in data analysis. The first work was published by W. S. McCulloch, then W. Pitts developed a model of the simplest neuron and F. Rosenblatt created a functional perceptron (Dostal, 2012). Although artificial neural networks have been around for a long time and have been used in many fields. It was not until the early 1990s, that they began to be used to model the prices of financial assets (Kaastra and Boyd, 1996). For the most relevant form for financial management considered Wang and Zha (2019), Stankovicova (2011), Stankovicova and Vojtkova (2007) and Vasanicova (2020) "backpropagation" neural network (one of the leading neural networks).

The first applications of neural networks in finance refer to Kimoto et al. (1990), who used these networks to predict the Tokyo Stock Exchange index. They used several neural networks trained to learn the relationship between the previous values of various technical and economic indicators and to predict the return of TOPIX, which is the value of the weighted average of all shares listed on the Tokyo Stock Exchange. In the literature concerning intelligent techniques used in predicting bankruptcy, Tam (1991) believes that the neural network is a competitive tool to assess the financial situation of the bank. Anyaeche and Ighravwe (2013) addressed the disappearance of performance measures using linear regression and a neural network. They used artificial neural networks as alternative predictive tools for regression to create a correlation between productivity, price recovery and profitability as indicators of performance.

Wang et al. (2016) aimed to develop a predictive model for financial time series using Elman recurrent neural network with stochastic time efficient function to test the predictive power of SSE, TWSE, KOSPI and Nikkei 225. From research evidence it suggests, that the proposed neural network in terms of the accuracy of the prediction exceeds some of the earlier models and the results are very close to real change in the market. Lin and Gong (2017) used an artificial neural network (ANN) to predict futures prices in Shanghai and Shenzhen. The results showed that the constructed neural network prediction model had high accuracy and a good prognostic effect, which provided an important reference point for investment decisions. Pang et al. (2018) proposed a neural network to predict the stock market. Using their model on the composite A-stock index in Shanghai, they compared the proposed model with the basic models.

2. ELECTRICAL AND ENGINEERING INDUSTRY IN THE SLOVAK REPUBLIC

The Slovak Republic has historically been and will continue to be an industrial state. The most important industries in the Slovak Republic include the electrical and engineering industry. Globalization has significantly influenced the electrical industry as a specific carrier of the latest science and technology results by a synergistic effect, which greatly improves the quality of production of other industrial sectors, especially the engineering industry (Sikula et al., 2003).

According to the Statistical Office of the Slovak Republic, the electrical industry registers 1 436 business entities in the SK NACE 26 - Manufacture of computer, electronic and optical products and 1 628 business entities in the SK NACE 27 - Manufacture of electrical equipment. The electrical industry employs 50.83 thousand people, which is representing almost 10% of total employment in Slovak industry. In 2017, the employment index for the SK NACE 26 – Manufacture of computer, electronic and optical products was 98.60 percentage points, for the SK NACE 27 – Manufacture of electrical equipment it was 105.40 percentage points. In 2017, revenue in absolute terms reached 9.450 billion €, costs were 9.703 billion € and profit (EBT) was 308.26 million €. In terms of sales in 2017, the manufacture of electrical equipment (SK NACE 27) was the first in the industry of the Slovak Republic, the seventh place was the manufacture of computer, electronic and optical products (SK NACE 26). According to the Aspekt Global Rating calculating for the period 2012–2016, the rating AAA (the optimal business entity) dominated and was reached by 26.27% of enterprises in electrical industry; on the other hand, 8.02% were on the brink of bankruptcy. Table 1 shows financial indicators of the electrical industry for the year 2017.

Table 1. Median of financial indicators of the electrical industry for the year 2017

Financial indicators	*SK NACE 26*	*SK NACE 27*
ROA – return on assets	3.19%	6.08%
ROE – return on equity	4.42%	10.58%
ROS – return on sales	4.53%	4.83%
TI – total indebtedness	38.96%	54.17%
TL – total liquidity	2.49	1.62
CL – current liquidity	2.13	1.36
Share of EBITDA in sales	7.18%	7.99%
Inventory turnover	0.00 days	2.61 days
Receivables turnover	57.49 days	57.16 days
Short-term trade receivables turnover	38.12 days	42.11 days
Share of value added in sales	23.01%	26.43%
Turnover of assets	0.89	1.25

Source: own processing according to Statistical Office of the Slovak Republic

The development of the electrical industry depends primarily on the automotive industry, where Slovakia is a world leader in motor vehicle production per capita. In 2018, 1.08 million motor vehicles were made in Slovakia. This was an annual increase in the number of produced vehicles of 5.90%. The automotive industry accounts for 47% of total industrial production and 13% of gross domestic product. In 2017, almost 155 000 people worked in this sector. The automotive industry has a share of 35% in industrial exports. In 2018, the automotive industry recorded an annual increase in sales of more than 14%. Net profit reached a level of more than 630 million €, which represents an annual growth of almost 3.50%. In the industry ranking, the engineering industry in 2019 accounted for almost 15.20% after the automotive industry (32.40%). Electrical industry accounted 9.20%.

The engineering industry include SK NACE 25 - Manufacture of metal products except machinery and equipment, SK NACE 28 - Manufacture of machinery and equipment, SK NACE 29 - Manufacture of motor vehicles, trailers and semi-trailers and SK NACE 30 - Manufacture of other transport equipment. Due to the nature of production, part of the group of SK NACE 25 – Manufacture of metal products except machinery and equipment belong more to the metallurgical industry. According to Jencova (2018) the most competitive during the period 2008-2019 from the branch of engineering industry is SK NACE 28 – Manufacture of machinery and equipment. According to the Statistical Office of the Slovak Republic, 708.50 thousand people were employed in industry. The engineering industry registered 2 100 companies, where were employed almost 104.20 thousand people. In 2018, companies in the engineering industry recorded an annual increase in sales of 12.80%. Total revenues amounted to more than 40.80 billion €. Compared to 2017, this is more than double an annual increase. The profit of engineering companies in 2018 was 989 million €, which represents an annual growth of 9.20%. By contrast, in 2017 there was a decrease of profit by 3.50%. In 2018, labor productivity recorded a significant increase of 11%. The average monthly wage in the sector in 2018 was 1 325 €, which represents an increase of more than 7.50%. Up to 80% of production is exported. Compared to 2017, almost 14% more goods and products were exported. Thus, exports amounted to 32.70 billion €. Table 2 shows financial indicators of the engineering industry for the year 2018.

Table 2. Median of financial indicators of the engineering industry for the year 2018

Financial indicators	SK NACE 28	SK NACE 29	SK NACE 30
ROA – return on assets	3.88 %	2.21%	0.00%
ROE – return on equity	9.23%	5.97%	-0.44%
ROS – return on sales	4.21%	2.53%	0.17%
TI – total indebtedness	56.76%	57.88%	50.83%
TL – total liquidity	1.61	1.65	1.85
CL – current liquidity	1.29	1.24	1.05
Share of EBITDA in sales	7.24%	5.18%	0.63%
Inventory turnover	8.13 days	10.34 days	50.13 days
Receivables turnover	62.89 days	47.16 days	132.64 days
Short-term trade receivables turnover	42.56 days	32.32 days	45.90 days
Share of value added in sales	25.10%	19.60%	30.27%
Turnover of assets	1.16	1.34	0.78

Source: own processing according to Statistical Office of the Slovak Republic

3. MATERIALS AND METHODS

SPSS software, which includes neural networks (MLP – Multi Layer Percepton), was used to calculate the prediction. To enter into the calculation were used financial indicators of non-financial corporations in the electrical and engineering industry. Financial ratios were calculated on the basis of absolute indicators, which were obtained from the financial statements of non-financial corporations, which are available in the Register of Financial Statements of the Slovak Republic. In the electrical industry, the total sample consists of 754 non-financial corporations and in the engineering industry 233 non-financial corporations. Financial ratios for the electrical industry are calculated for the year 2017 and for the engineering industry for the year 2018.

At the input of the neural network for the electrical industry is 11 financial indicators:

- Maturity of Short-term Trade Liabilities - x_1
- Return on Sales (ROS) - x_2
- Return on Investment (ROI) - x_3
- Current Liquidity (CL) - x_4
- Turnover of Assets (TA) - x_5
- Total Indebtedness (TI) - x_6
- Share of Value Added in Sales - x_7
- Financial Leverage (FL) - x_8
- Return on Equity (ROE) - x_9
- Liabilities / EBITDA (L/E) - x_{10}
- Net Working Capital / Assets (NWC / A) - x_{11}

For the neural network for the engineering industry, 11 financial indicators are input:

- Return on Assets (ROA),
- Return on Sales (ROS),
- Financial Leverage (FL),
- Personnel Costs / Sales (PC / S),
- Total Assets Turnover Ratio (TATR),
- Total Indebtedness (TI),
- Total Liquidity (TL),
- Net Working Capital / Assets (NWC / A),

– Current Liquidity (CL),
– Current Assets Turnover Ratio (CATR),
– Debt-Equity Ratio (DER).

In modifying neural network for electrical and engineering industry were dropped financial indicators of indebtedness (Financial Leverage, Total Indebtedness, Liabilities / EBITDA), so the input was 8 financial indicators. Neural networks were assembled with one or two hidden layers. The output of the neural network was an indication of the bankruptcy of the company, which is 0 (the company is not in bankrupt) or 1 (the company is in bankrupt). We defined bankruptcy as the ratio of equity to debt. If this ratio was less than 6%, the enterprise had a default of 1 for the variable bankruptcy, otherwise it was assigned a value of 0.

4. RESULTS AND DISCUSSION

In the analysis of two sectors (electrical and engineering industry), the network had one or two hidden layers, two groups of financial ratios (11 - 8) were used, with the intention of finding optimal models in 8 cases. First, we will deal with the electrical industry and 11 financial indicators at the input. The distribution of data (enterprises) into the training and test set was 70:30. Table 3 shows the distribution of the data set for the training and test set for the electrical industry.

Table 3. Case Processing Summary - Electrical Industry

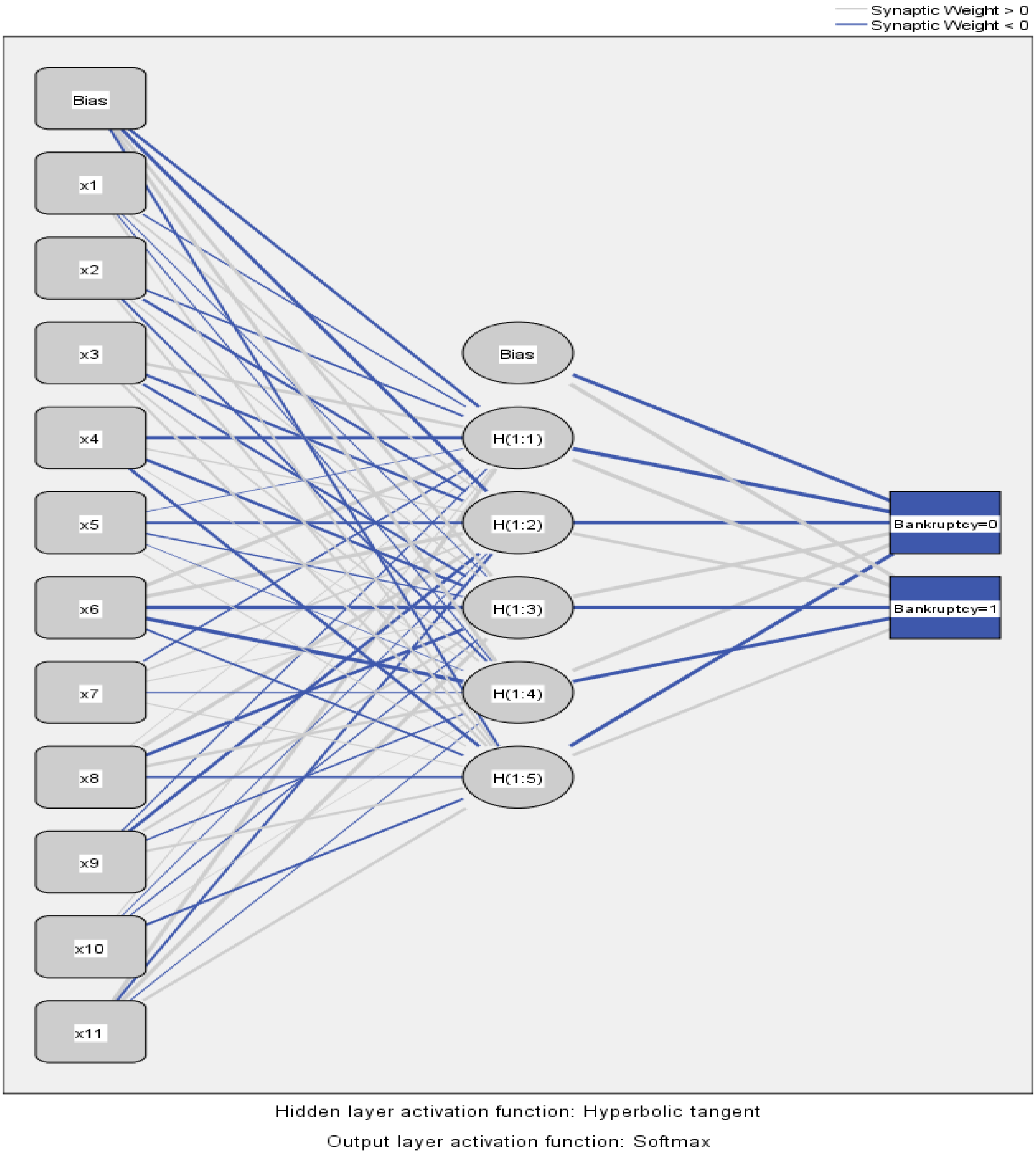
		N	*Percent*
Sample	Training	513	68.30%
	Testing	238	31.70%
Valid		751	100,00%
Excluded		3	
Total		754	

Source: own processing

MLP module SPSS find an optimal solution for electrical industry, one hidden layer and 11 financial indicators, that shown in Figure 1. The hidden layer has 5 neurons.

Figure 1 illustrates the connections of individual neurons shown by lines of different thickness and color. Links with a blue line mean, that the weight between the given variables is a value less than 0, and conversions with a gray line mean, that the weight at this point has a value greater than 0. If the line is thicker, the weight values are numbers from 0 and conversely, thinner lines indicate values closer to 0. Specific values of synaptic weights between individual neurons in the case of electrical industry, one hidden layer and 11 financial indicators are given in Table 4.

Figure 1. Network topology for one hidden layer (Electrical industry, 11 financial indicators)



Source: own processing

Table 4. The values of weights between neurons (Electrical industry, 11 financial indicators, 1 hidden layer)

Parameter Estimates

Predictor		Predicted									
		Hidden Layer 1								Output Layer	
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	Bankruptcy=0	Bankruptcy=1
Input Layer	(Bias)	,722	-,398	-,563	-,137	,205	,315	-,336	,382		
	x1	,169	,349	,579	,207	,515	,429	,305	-,527		
	x2	,097	,359	-,168	-,053	-,109	-,095	-,126	-,004		
	x3	,129	-,210	-,506	-,381	-,013	-,252	,014	,368		
	x4	,131	-,155	,756	,166	-,071	,200	-,251	,044		
	x5	,272	,255	-,040	-,267	,199	-,002	-,039	-,173		
	x6	-,054	,983	2,059	,465	,180	,209	-,350	-1,221		
	x7	-,059	-,217	-,040	,136	-,021	,041	,208	-,119		
	x8	-,070	,351	,739	-,140	,261	,436	-,714	-,073		
	x9	-,835	-,118	,981	-,112	-,180	,783	-,574	,304		
	x10	-,168	-,214	,100	,352	-,454	,007	-,042	,075		
	x11	-,166	-,806	-,706	-,288	,519	-,563	,600	,863		
Hidden Layer 1	(Bias)									-,134	1,156
	H(1:1)									,427	-,374
	H(1:2)									-,163	,112
	H(1:3)									-,690	,759
	H(1:4)									,277	-,320
	H(1:5)									,186	-,210
	H(1:6)									,648	-,753
	H(1:7)									-,249	,243
	H(1:8)									,321	-,370

Source: own processing

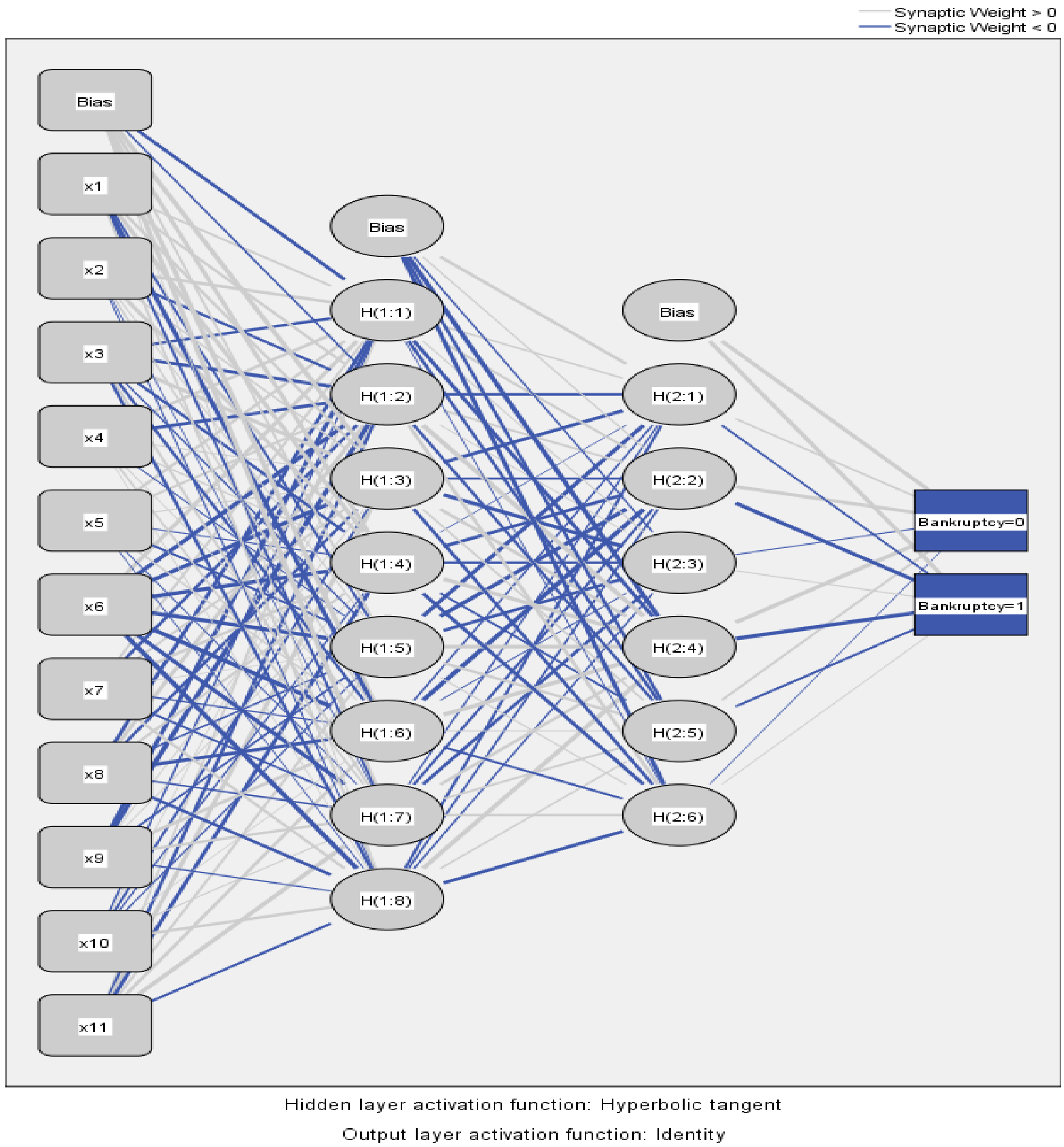
For clarity, we will present the network topology for electrical industry, two hidden layers and 11 financial indicators (Figure 2). It can be seen from the figure, that the first hidden layer has 8 neurons and the second hidden layer has 6 neurons.

The output variable Bankruptcy was defined using the ratio of equity to debt. If this ratio was less than 6%, the company had the number 1 bankruptcy variable (company is in bankrupt), otherwise it was assigned the value 0 (company is not in bankrupt). We therefore decided to dropped the debt indicators from the input data in the next approximation:

- Total Indebtedness - x_6
- Financial Leverage - x_8
- Liabilities / EBITDA - x_{10}

An analysis is performed for the electrical industry with 11 indicators and 8 indicators, respectively, with one or two hidden layers (Table 5). Similarly, the analysis is performed for the engineering industry (Table 6). In the following, we will no longer deal with network topology or synaptic weights. Only the final table is given, in which the results of the success of estimates of optimal models for individual options are presented.

Figure 2. Network topology for two hidden layers (Electrical industry, 11 financial indicators)



Source: own processing

Table 5. Model Success (Electrical industry)

Sample		*11 indicators, 1 hidden layer*			*11 indicators, 2 hidden layers*			*8 indicators, 1 hidden layer*			*8 indicators, 2 hidden layers*		
		Predicted			*Predicted*			*Predicted*			*Predicted*		
		0	1	Correct	0	1	Correct	0	1	Correct	0	1	Correct
Training	0	418	0	100,0%	418	0	100,0%	407	10	97,6%	409	8	98,1%
	1	2	93	97,9%	1	94	98,9%	44	53	54,6%	39	58	59,8%
	Overall	81,9%	18,1%	**99,6%**	81,7%	18,3%	**99,8%**	87,7%	12,3%	**89,5%**	87,2%	12,8%	**90,9%**
Testing	0	196	1	99,5%	196	1	99,5%	191	7	96,5%	191	7	96,5%
	1	2	39	95,1%	3	38	92,7%	17	23	57,5%	15	25	62,5%
	Overall	83,2%	16,8%	**98,7%**	83,6%	16,4%	**98,3%**	87,4%	12,6%	**89,9%**	86,6%	13,4%	**90,8%**

Source: own processing

A comparison of the success of the models in Table 5 shows, that models without debt ratios are less successful. It does not appear, that models with two hidden layers are more successful than models with one hidden layer. Table 6 shows the success of models for the engineering industry. Models for the engineering industry are more successful than models for the electrical industry. A 100 percent success rate was recorded for the test set. For the training set, models without debt ratios are less successful.

Table 6. Model Success (Engineering industry)

Sample		*11 indicators, 1 hidden layer*			*11 indicators, 2 hidden layers*			*8 indicators, 1 hidden layer*			*8 indicators, 2 hidden layers*		
		Predicted			*Predicted*			*Predicted*			*Predicted*		
		0	1	Correct	0	1	Correct	0	1	Correct	0	1	Correct
Training	0	144	0	100,0%	144	0	100,0%	140	4	97,2%	142	2	98,6%
	1	0	17	100,0%	0	17	100,0%	7	10	58,8%	9	8	47,1%
	Overall	89,4%	10,6%	**100,0%**	89,4%	10,6%	**100,0%**	91,3%	8,7%	**93,2%**	93,8%	6,2%	**93,2%**
Testing	0	67	0	100,0%	67	0	100,0%	67	0	100,0%	67	0	100,0%
	1	0	5	100,0%	0	5	100,0%	0	5	100,0%	0	5	100,0%
	Overall	93,1%	6,9%	**100,0%**	93,1%	6,9%	**100,0%**	93,1%	6,9%	**100,0%**	93,1%	6,9%	**100,0%**

Source: own processing

CONCLUSIONS

Neural networks are a versatile and powerful tool for modeling complex systems. Many financial institutions use neural networks to estimate the risk assessment of borrowers and forecasts of bonds and share prices. Multiple neural network (MLP - Multi Layer Percepton) with algorithm of back propagation of error is the most widely used in practice. We used this network to predict the bankruptcy of companies in the electrical (SK NACE 26 and SK NACE 27) and engineering (SK NACE 25, SK NACE 28, SK NACE 29 and SK NACE 30) industries. The paper presents an analysis for the electrical industry with 11 and 8 indicators, respectively, with one or two hidden layers. Similarly, the analysis is performed in the engineering industry. In the following, the paper did not deal with network topology. 8 models were found for prediction in both industries depending on the number of input neurons (variables - financial ratios) and the number of hidden layers. All models were highly successful on the training and test set. It cannot be said, that models with two hidden layers were more successful than models with one hidden layer. However, models in which debt ratios were also included were more successful. This procedure for predicting corporate bankruptcy is highly effective.

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