PREDICTING OF THE DEVELOPMENT OF THE ENTERPRISE BY USING NEURAL NETWORK TOOLS

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Abstract:
This research focused on prediction of the state of the enterprise and the artificial neural network is selected as a prediction tool. The prediction performed through the use of the financial key indicators. In this paper we analysed the dynamics of the of financial indicators of the company of Luhansk region "Luganskteplovoz", Ukraine and for solving of financial state of enterprise we used the software Statistica Neural Networks.

Keywords: prediction, artificial neural network, development of the enterprise, model of forecasting, financial indicators

The knowledge of the dynamics of enterprise development allows at any given time to identify the critical state and apply the proactive control actions.At the same time enterprises are faced with two problems is the incompleteness of the data or, on the contrary, significant amounts of information. The state of the enterprise depends on many factors, such as, the current financial and economic indicators, inflation, exchange rate, cooperation with suppliers and customers, competition policy. This paper discusses the possibility of using the neural network method for assessing the state of the enterprise and forecasting its future development on key financial parameters.

The possibility of using a neural network in predicting follows directly from its ability to compile and release the hidden dependencies between the input and output data. An artificial neural network is regarded as a converter which is capable for the certain combination of inputs x to issue respective output signals y realizing a function y=f(x). The specific form of the conversion is determined by the architecture of the neural network and the characteristics of neural elements, controls and synchronization of information flow between neurons [Haykin, S.,1999].

The results of neural network modeling are well approximated by the actual data and show the minimum error. This allows to conclude that the modeled neural network is sensitive to variations of the input parameters therefore it can be used to predict economic performance of enterprises in future periods. This neural network will allow company management to take informed decisions about business enterprises.

Neural network tools for prediction

The developed automated technology of management of development of enterprise will use the accumulated base for quick and adequate reaction to unexpected events. This is a creating an expert system. One of the modern mathematical methods, which to some extent meet all the specific requirements, is a method of artificial neural networks.

It need to display the nonlinear dependencies between the many factors, including indicators of the financial condition of the company [Sharapov, Kaydanovych, 2012].

The basis of the decision of a task of constructing a model of intellectual development of the automated control systems of the enterprise will be put artificial neural network. This approach to the construction of a neural network allows taking into account the background of the observed processes and gather information to form the right strategy for the management of the enterprise development. [Lavrukhin, 2015].

The operating principle of neuron is: input signals (xn) pass through transfer function and generate the results. In addition, all neurons are interconnected and are certain segments that form of the artificial neural network. [Cherednichenko, Shura, 2015]

The input interlayer receives the information from the environment and transmits it to the next level, where it is analyzed and processed. Then processed information becomes the output, forming the various states. The transfer of information from one neuron to another is an important aspect of neural networks. [Cherednichenko, Shura, 2015]

We should reflect the nonlinear dependencies between the many factors for effective diagnosis of the enterprise. The mathematical apparatus of artificial neural networks makes it possible to consider the specified feature and effectively replace classical discriminant model [Sharapov, Kaydanovych, 2012]

The ukrainian and foreign authors proposed the approaches for forecasting of trends of development of the enterprise using economic and mathematical models to fuzzy logic. The company addresses the following tasks using artificial neural networks: management of prices and production, planning of costs, determination of dependencies between costs of advertising, sales, price of competition, price of product, the choice of optimal financial, pricing, marketing strategies from the perspective of maximizing profit or sales volume, determination of factors influencing the parameters of the company, forecasting of consumer behavior when changing marketing policy, finding the optimal strategy of advertising, determination of most promising segments of the product for consumers, management of various processes, monitoring of manufacturing processes with continuous adjustable of control parameters, technical diagnostics, assessment of creditworthiness, financial time series prediction, forecasting of stock prices; medical diagnostics; linguistic analysis [Kean, J., 1992].

There is a possibility to use the programs that are based on artificial neural networks. The application program MATLAB allows solving tasks of technical computing. The software package GeneHunter uses genetic algorithms to solve optimization problems. NeuroShell Trader system is used for predicting and finding of effective trading strategies in financial markets. NeuroShell Classifier software used for solving pattern recognition (situations) and referring them to a particular category [Berestyuk, Yarmolyuk, 2014]. The software package Statistica Neural Networks used for solving regression and time series prediction. ExcelNeuralPackage implements the concept of neural networks and the possibility of solving a broad range of financial, economic, statistical and management tasks.

A mathematical basis of models of artificial neural network is oncoming proliferation. It is based on a combination of layer of neurons Kohonen (the self-organizing map). Its objective is to select the common characteristic in the test object through their clustering [Jacko, Dovgun, Litvinchuk, 2014].

The first phase of construction of forecasting models of the company made the choice of necessary factors, the transformation, the formation of these case studies and the presenting them to the input layer. The set of independent variables on the basis of which we make the opinion on the company, has a set of the most informative indicators of financial and economic activity [Berestyuk, Yarmolyuk, 2014]. There are a lot of factors in contemporary financial analysis, but it is advisable to choose the most important ones.

The artificial neural networks enable to include in the model as much as possible informative indicators. This network does not require for its operation prerequisites of stationary of the process under study or the absence of multicollinearity of input. [Sharapov, Kaydanovych, 2012]

The task the selection of the most significant independent factors faces during constructing of the model, given the extent of the impact on performance indicators. From a mathematical point of view, this problem is reduced to an optimum compaction of information on financial condition, that initial information display minimal number of parameters at a given level of accuracy.

The neural network consists of competitive layer, which is represented in this case the Kohonen self-organizing map, and output layer is the original stars of Grossberh. Kohonen self-organizing map learns "without a teacher" and it did not need the desired feedback of network for the correct settings synaptic weights. The search for hidden dependencies is performed in the structure of the of financial indicators the company, it is due to the implementation of the procedure [Jacko, Dovgun, Litvinchuk, 2014]. This process of learning of network provides a two-dimensional displaying multi-input vectors, making them clustering.

After the formation of all examples for supplying of inputs to the neural network with the aim of training is necessary to choose the structure of Kohonen maps. The number of parameters of each neuron of the layer of Kohonen equals to parameters in the input examples that in our model is equal to ten elements.

The advantage of methods based on neural networks is no need in mathematical model specification while neural networks allows to consider the impact of factors influencing the results. Neural networks appropriate to use a where there is a great amount of data. In this case, the nonlinear interaction between the factors taken into account automatically. It is expedient to use neural networks in tasks with incomplete information as well as the tasks, which are characterized intuitive solution.

The main difference this approach to modeling of financial indicators is to solve the tasks of prediction by recognizing template pattern in the structure of financial indicators and assigning recognizable pattern to clusters that characterize the different classes of change of the index.

The model of development is determined by view of business opportunities, the company's indicators (initial conditions) [Zhi-Yuan Li, 2015] and external factors:

$$An=F\ (O;\ DR;\ FE),$$

An - the company's development results,
O - business opportunities,
DR - index of the firm,
FE - external factors.

The ability of neural networks to the prediction follows from its ability to compile and release hidden dependencies between the input and output data [Burda, A., Kuszmowska, B., Hippe, Z., 2007]. After training, the network can predict the future state of the company based on several previous states [Honkela, T., Lagus, S.K., Kohonen, T., 1996, Kramer, M.A.,1991].

The construction of a neural network is performed in the following order. We select and optimize the indicators by identifying the cyclicity and determining the trend. Then we choose the structure of the neural network and the algorithm of the network' training. Finally, we are implementing the training of the neural network and its testing, during which we determine the quality of forecasting. The last step is the trial forecasting of the state of our company.

The model of the state of the company is constructed using Statistica Neural Networks package (StatSoft Inc.), which combines the user-friendly interface and a wide choice of different types of neural networks.

In this case the inputs of the of the neural network is fed the set of parameters on which can successfully predict the state of the enterprise. The output is a forecast of the state for the next time.

We used the following financial ratios as inputs: x1 - coverage ratio, x2 - quick ratio, x3 - cash ratio, x4 - the debt to equity ratio, x5 - the coefficient of ensuring current assets own funds, x6 - the debt ratio, x7 - assets turnover ratio, x8 - days sales outstanding, x9 - creditor days ratio, showing the intensity of the impact of threats. The output variable is the result of the financial condition (y - the coefficient of financial independence). These particular financial ratios have been widely used as inputs, even for neural networks and other nonlinear models.

Let us now discuss why the particular indicators have been chosen. The equity-to-asset ratio (y) is used to assess a company's financial leverage. A higher ratio shows that the company is more sustainable and less risky. Coverage ratios (x1) are a useful way to help gauge such risks [Back, B., Laitinen, T., Sere, K., 1996]. Coverage ratios are comparisons designed to measure a company's ability to pay its liabilities; analyze a company's ability to service its debt and other obligations. The better the ability of the enterprise to fulfill its obligations to its lenders. The trend of coverage ratios is studied to ascertain the change in a company's financial position. The quick ratio (x2) is a liquidity ratio that measures the ability of a company to pay its current liabilities when they come due with only quick assets. It shows how well a company can quickly convert its assets into cash in order to pay off its current liabilities. It also shows the level of quick assets to current liabilities. Higher quick ratios are more favorable for companies because it shows there are more quick assets than current liabilities. The cash ratio (x3) is useful for determining the amount of cash available to pay for a borrower's interest expense. The ratio is used to determine whether a business can meet its short-term obligations. A low cash ratio may be an indicator of financial difficulty. The debt to equity ratio (x4) shows the percentage of company financing that comes from creditors and investors. A higher debt to equity ratio indicates that more creditor financing (bank loans) is used than investor financing (shareholders). A lower debt to equity ratio usually implies a more financially stable business. Companies with a higher debt to equity ratio are considered more risky to creditors and investors than companies with a lower ratio. The coefficient of availability of internal funds (x5) disclose whether the enterprise has enough of its resources, which are necessary to its financial stability. Debt ratio (x6) is a solvency ratio that measures a firm's total liabilities as a percentage of its total assets. The debt ratio shows a company's ability to pay off its liabilities with its assets. The higher this ratio, the more leveraged the company is, implying greater financial risk. The Asset Turnover ratio (x7) can be used as an indicator of the efficiency with which a company is deploying its assets in generating revenue. The ratio shows how efficiently a company can use its assets to generate sales. Higher turnover ratios mean the company is using its assets more efficiently. Lower ratios mean that the company isn't using its assets efficiently and most likely have management or production problems. The days sales outstanding calculation (x8) shows the liquidity and efficiency of a company's collections department. This ratio measures the number of days it takes a company to convert its sales into cash. A lower ratio is more favorable because it means companies collect cash earlier from customers and can use this cash for other operations. A higher ratio indicates a company with poor collection procedures and customers who are unable or unwilling to pay for their purchases. The creditor cays ratio (x9) shows the average number of days your business takes to pay suppliers. Any downward trend in the Creditor Days ratio means that an increasing amount of cash is needed to finance the business [Danich, V., Parkhomenko, N., 2013].

All the ratios show a major problem for businesses and we can evaluate the state of the company. In this work we introduce a novel set of indicators that can be used as the financial ratios and lead to significant improvement in prediction accuracy.

To scroll through the neural network models in the Neural Networks' packet Statistica we apply the Intelligent Problem Solver. This module allows to see quite a number of possible models, conduct their training and testing different methods to automatically select the best. The model of prediction of the financial state is based on the neural network of Multi Lauer Perseptron (MLP). The separation the original data is performed into groups at random, min hidden units are 4, max hidden units are 13. The error of this network is minimal of twenty automatically constructed networks. Figure 1 shows the architecture of the model.

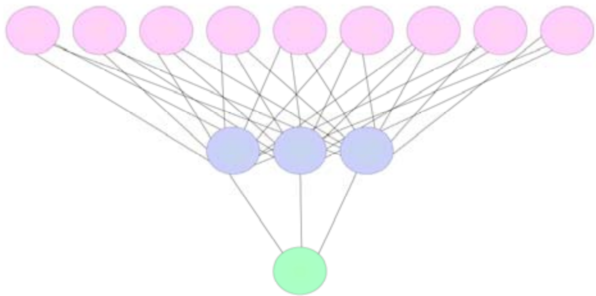

Figure 1. The architecture of the neural network with an input group of neurons, one hidden layer neurons and one output neuron

During the constructing of the model we chose as the optimal architecture of multilayer perceptron with nine inputs and three hidden layers. Using this model, we can make a prediction the state of the company.

Forecasting of financial indicators by using Neural Networks

We present the results of experiments on forecasting changes in financial indicators using economic and mathematical models constructed on Neural Networks.

The object of research was chosen the dynamics of the of financial indicators the company of Luhansk region "Luganskteplovoz" (Ukraine). This company produces railway locomotives and rolling stock. The initial of time series were converted to the input vector, each of which contains data for the last seven years.

In research was formed forecasting model of the enterprise, based on a set of financial indicators of liquidity, solvency and business activity: y - the equity-to-asset ratio, x1 - coverage ratio, x2 - quick ratio, x3 - cash ratio, x4 - the debt to equity ratio, x5 - the coefficient of ensuring current assets own funds, x6 - the debt ratio, x7 - assets turnover ratio, x8 - days sales outstanding, x9 - creditor days ratio.

During research we was constructed the range of economic and mathematical models based on neural networks of different configurations to determine the most appropriate set of explanatory variables. As a result of using of neural network is possible to receive the specific predictions about the financial situation of the company, depending on the values of key financial indicators.

By using STATISTICA Neural Networks we construct a neural network for solving the tasks of regression analysis and forecasting [Grigorieva, Fayzullina, Kulikova, 2014]. The purpose of research is to construct a mathematical neyromodel, which for a new set of input data would be give out response Y with a precision better than 5%. This model should reflect the connection between indicators of economic activity of the enterprise Y, X1-X9 (inputs of model) and financial independence of the company Y (output of model). Later it can be used to predict the development of the enterprise in the future periods.

For training the network we take a sample of the data for the years 2009-2015, formed on the basis of financial statements (see Table 1)

Table 1

Benchmark data

N	Y	X1	X2	X3	X4	X5	X6	X7	X8	X9
1	-0,018	0,625	0,249	0,009	-0,017	-0,03	-54,169	1,188	64	112
2	-0,022	0,734	0,278	0,004	-0,021	-0,44	-27,59	1,286	34	52
3	0,432	0,76	0,57	0,033	1,312	-0,24	2,312	1,91	37	120
4	0,381	0,893	0,48	0,084	1,626	-0,107	2,626	1,197	71	108
5	0,395	1,154	0,754	0,018	1,53	0,154	2,58	1,717	66	50
6	0,61	0,72	0,352	0,005	0,589	-0,541	1,64	1,048	6	74
7	0,426	0,557	0,307	0,013	0,426	-0,761	2,346	0,32	77	164

We give the surface of the dependencies Y = f (X1 ... X4), where y - the equity-to-asset ratio, x1 - coverage ratio, x2 - quick ratio, x3 - cash ratio, x4 - the debt to equity ratio (figure 2).

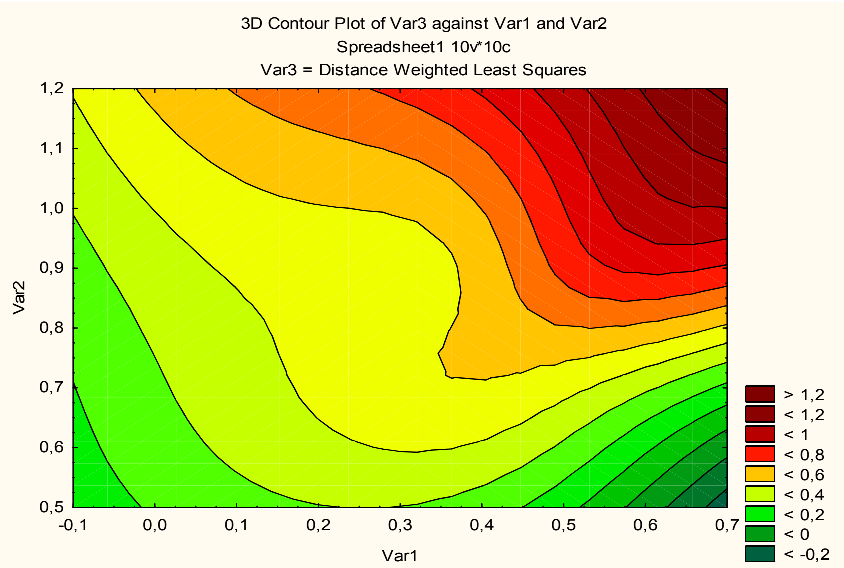

Figure 2a. Surfaces Y = f(X1,X2)

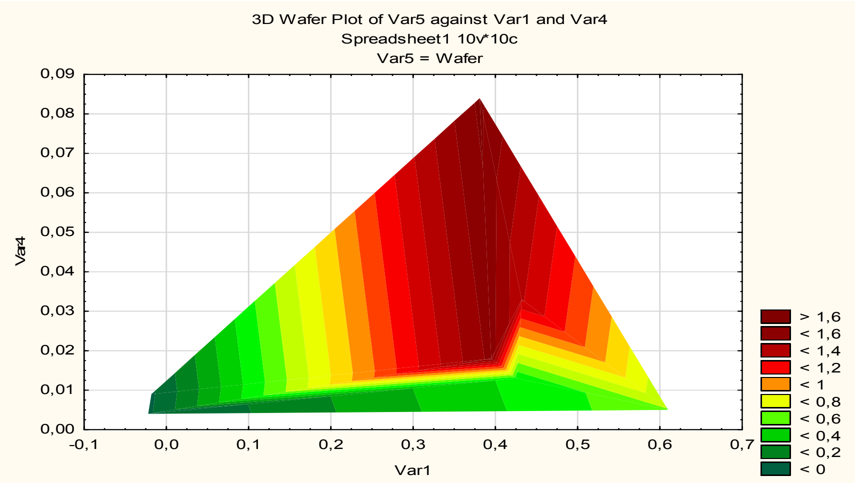

Figure 2b. Y = f(X3, X4)

The graph 1 (a) shows the relation between (y) equity-to-asset ratio of the company and coverage ratio (x1) and quick ratio (x2). As it is evident from the graph 1 (b) there is a slight correlation between (y) equity-to-asset ratio of the company and the cash ratio (x3) and the debt to equity ratio (x4). The fact of the non linearity of the task is not in doubt. By type of surfaces, shown in Figure 1, it is difficult to assume the form of dependencies, moreover, that is not taken into account all factors. To construct a model we use the module Statistica Nonlinear Estimation. Previously we will analyze the importance of independent factors Y, X1-X9 and the degree of their influence on the output parameter Y, and define the form of the functional dependence Y = f (Y, X1, X2, ..., Xn). We construct a neural network, which itself will select the adequate function that best approximates the original data.

We construct a neural network, which itself will select the adequate function that best approximates input data [Lawrence, J.,1994]. The next step is training the network on the test set. Here, is first necessary divide the input data (Y, X1-X9) and output (Y) and to assess the significance of the inputs, as not all factors X have a significant effect on the studied parameters Y. The proportion of the influence of some factors may be so small that their ignore will not lead to substantial deviations of the investigated object. Then we define network configuration. STATISTICA Neural Networks allows you to simplify this process by using the procedures of Intelligent Problem Solver, which will automatically reduce dimension of the projected network, selecting the most significant factors and independently and will search the neural network analyzing the different typologies of network.

The objective of the algorithm of search is to select several configurations of neural network and the best choice from the perspective of minimum error at the output of the network and its high productivity (Table 2).

Table 2

The resulting neural network

Summary of active networks (Spreadsheet1)										
Net name	Training perf	Test perf	Validation perf	Training error	Test error	Validation error	Training algorithm	Error function	Hidden activation	Output activation
MLP 9-9-1	0,988764	0,00	0,00	0,000864	0,083046	0,001358	BFGS 0	SOS	Sine	Logistic
MLP 9-4-1	0,999999	0,00	0,00	0,000000	0,000001	0,000001	BFGS 16	SOS	Exponential	Tanh
MLP 9-8-1	0,929414	0,00	0,00	0,005970	0,001273	0,000684	BFGS 5	SOS	Sine	Tanh
MLP 9-13-1	0,999984	0,00	0,00	0,000002	0,061080	0,013336	BFGS 0	SOS	Exponential	Logistic
MLP 9-10-1	0,925503	0,00	0,00	0,004726	0,000002	0,015548	BFGS 6	SOS	Exponential	Sine

Analyzing net-names we can make a conclusion that neural network MLP 9-4-1 is more reliable. The test error is minimal for this network. In the absence of some of the information we can use the neural network MLP 9-13-1, the prediction error is 0,000002. Both the neural networks are exponential dependence.

We turn to the neural forecast. Making use of the trained and tested neural network. The calculation of prediction is presented in Table 3.

Table 3

Predictions spreadsheet for Var1 (Spreadsheet1) Samples: Train

Var2 Input x1	Var3 Input x2	Var4 Input x3	Var5 Input x4	Var6 Input x5	Var7 Input x6	Var8 Input x7	Var9 Input x8	Var10 Input x9	Var1 Target y
0,6250	0,2490	0,0090	-0,017	-0,030	-54,16	1,1880	64,000	112,00	-0,018
0,7340	0,2780	0,0040	-0,021	-0,440	-27,59	1,2860	34,000	52,00	-0,022
0,8930	0,4800	0,0840	1,626	-0,107	2,6260	1,1970	71,00	108,0	0,381
1,154	0,7540	0,0180	1,5300	0,1540	2,5800	1,7170	66,000	50,00	0,3950
0,7200	0,3520	0,0050	0,5890	-0,541	1,6400	1,048	6,000	74,00	0,610

Table 3 gives a prediction of the financial key indicators between 2016 and 2020 years. The coverage ratios grow therefore the company is not able to pay current bills. The quick ratio shows that liquid assets do not cover short-term liabilities, and thus there is a risk losing its financial solvency in

2016-2020 years. The company is not able to pay immediately the obligation in 2016-2020, as the cash ratio is less than 0.2. The debt to equity ratio in 2016-2017 shows that the company loses his financial independence, and the financial situation is becoming extremely unstable. The coefficient of ensuring current assets own funds shows that the own capital decreases and the risk of loss of financial stability increases (2016-2017); the state of the company will stabilize in 2019. According to the forecast of the debt ratio in 2016-2017 we can see the high depending on the debt capital. Dynamics of the assets turnover ratio shows the fluctuations in sales volumes during 2016-2020 as well as a dynamic days sales outstanding. The results of neural network modeling are well approximated by the actual data and the total square error is 3%. This allows to conclude that the modeled neural network is sensitive to variations of the input parameters therefore it can be used to predict economic performance of mechanical engineering enterprises in future periods. According to the results forecast in the company over the next 4 years it is expected to improve the financial state of the majority of financial indicators. If we compare financial independence of the company, we can find out that they become much higher every new year. The financial state of "Luganskteplovoz" will be better only in 2019-2020.

Conclusions

For a successful evaluation of the company and predicting of the future development proposed the use of neural network technology. By using Statistica Neural Networks package we constructed the model for evaluating and predicting the state of the engineering enterprise on data of the enterprise "Luganskteplovoz".

A result of research the obtaining neural network allows to quickly install the complex dependencies between the results of financial and economic activities and the state of the enterprise, reflecting the level of risk in future periods.

The main advantages of using the resulting neural model to predict the development of the enterprise in contrast to the available models include the following.

We used a small set of indicators reflecting the main areas of business, namely asset management, equity, credit status, sales management, investment attractiveness and more. The resulting neural model can be trained in those cases where the unknown patterns of development of the situation and the relationship between the input and output data. The neural network has the ability to adapt to the environmental change and change in real time. These neural networks can be used to analyze the financial stability of enterprises and diagnostics of bankruptcy as with the analytic purposes and for decision-making on investments.

The use of this model allows us not only assess the financial state of the enterprise, but also to predict its level of development, depending on the values of financial indicators.

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