Application of artificial neural networks for prediction of business indicators

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Abstract: *This paper examines the applicability of the neural networks in developing predictive models. A predictive model based on artificial neural networks has been proposed and training has been simulated by applying the Long Short-Term Memory Neural Network module and the time series method. Python programming language to simulate the neural network was used. The model uses the stochastic gradient descent and optimizes the mean square error. Business indicators for forecasting the results of the activity and the risk of bankruptcy of a company are forecasted and a comparison of the obtained forecast values with the actual ones is performed in order to assess the accuracy of the forecast of the developed model. As a result, it can be noted that business indicators can be successfully predicted through the Long Short-Term Memory Neural Network and the forecasted values are close to the actual ones.*
Keywords: *FORECASTING, MODEL, LONG SHORT-TERM MEMORY NEURAL NETWORK, BUSINESS INDICATORS, PYTHON*

INTRODUCTION

In modern conditions, one of the most important elements of the management process is the analysis of the indicators reflecting the business activities of the company.

The aim is to establish the patterns and trends in the development of business processes and to assess the direction and degree of influence of the factors that determine them in order to limit the negative and enhance the positive effects. The analysis helps to forecast and design the directions of the future policy of the company by identifying the past trends.

The first approach to analyzing business ratios to predict corporate failure and insolvency was developed by W. Beaver in 1966. Later, various models were developed based on analyzes of groups of companies studied by predefined qualitative characteristics.

The multivariate model for predicting corporate bankruptcy, known as Altman's Z-Score [1], is one of the most widely used models.

Another model, by G. Springate, was developed based on testing of 40 companies, with assets averaging $ 2.5 million. In the process of its creation, out of 19 business coefficients considered representative, only 4 coefficients remain in the final version of the model.

The DuPont model [2] is used for planning, analysis and control of the company's performance and is used in corporate financial management due to the ability to explore the company's potential to generate profit, reinvest it and increase turnover and sales. It is based on the analysis of ratios forming the coefficient Return on Equity (ROE).

Economic value added (EVA) is an analytical model created by the corporate consulting team of B. Stewart and J. Stern and is rapidly gaining popularity among the corporate financial community due to the innovative way of determining the real profitability of the company [3]. The EVA model evaluates the enterprise on the basis of the economic approach and is oriented towards its future and not towards the past. EVA measures the added value created by a particular investment [3, 4].

According to V. Kasarova [5], the application of different models for bankruptcy risk assessment on the same Bulgarian company gives different, in some cases contradictory results, as the models are developed in the conditions of a specific economy in a certain period of time and do not comply with current conditions.

The models do not take into account industry differences, which adversely affects their flexibility and adaptability and leads to excessive optimism or excessive pessimism in some cases. The models can be used as an additional analytical tool and must be appropriately adapted to the specific conjunctural and economic conditions [6, 3].

From the literature sources and the practical activity are known fuzzy models, application of neural networks, econometric analysis and others, to evaluate the business indicators reflecting the activity of the company.

In fuzzy models [7], the analysis and forecasting of financial condition indicators includes 3 stages:

The first stage - "blurring" of the input information, transforming the estimates of traditional indicators into fuzzy values based on expert assessments, modeling and simulation (using Matlab, Fuzzy, Toolbox, etc.).

Second stage - defining the rules according to which the defined fuzzy linguistic variables (inputs) are associated with the output linguistic variable.

Third stage - conversion of the fuzzy estimates obtained at the output of the fuzzy system into exact values.

A common and proven method of blurring is the Geometric Center of Gravity (COG).

Neural networks are used as an additional method for analysis of business indicators. According to A. Chabaan [8], the application of neural networks allows to calculate the risk of failure, decision-making when choosing investment alternatives, assessment of the risk of insolvency of the issuer / borrower [9] and others.

Assessing financial status using artificial intelligence does not replace existing mathematical models, but complements them by allowing the correct assessment of input data, without whose exact values the end result makes no practical sense. According to S. Kabaivanov [9], for example, the process of assessing the risk of insolvency can be realized in two aspects:

On the one hand, obtaining an accurate numerical indicator, individual for each surveyed economic agent (for example, the probability of insolvency for a certain time horizon).

On the other hand, to determine the affiliation of the analyzed object to predefined groups (for example, risk groups with pre-defined boundaries).

FORECASTING THE INDICATORS

Forecasting economic processes and phenomena is a tool for successful and effective business management and has an important role in the management process, as it assists management in making adequate and timely decisions related to the activities of the enterprise.

The report presents a neural network simulation in order to predict the indicators for business analysis. The aim is, on the basis of training of the neural network with indicators from previous periods, to calculate forecast indicators for the next period (in the considered example the data for it are known, and to make comparisons of the actual and forecast values).

After making the forecast, the data from it should be compared with the real data for the respective period and the level of the error from the forecast should be determined. On this basis, conclusions are drawn about the applicability of the model.

Table 1 provides data on the indicators of a real operating enterprise for the period 2011–2019. The indicators from 2019 are taken as a benchmark for comparing the forecast with real data.

Table 1. *Indicators of financial condition*

Indicators	2011	2012	2013	2014	2015	2016	2017	2018	2019
Profitability of income	0.27	0.21	0.18	0.22	0.15	0.16	0.15	0.21	0.11
Return on equity	0.55	0.34	0.24	0.26	0.19	0.18	0.14	0.18	0.08
Return on assets	0.45	0.18	0.15	0.19	0.11	0.12	0.14	0.16	0.07
Revenue efficiency	0.70	0.77	0.80	0.78	0.84	0.82	0.83	0.77	0.88
Cost efficiency	1.42	1.29	1.25	1.27	1.18	1.22	1.20	1.30	1.14
Total liquidity	8.10	5.65	4.44	5.93	2.70	4.89	6.59	10.89	8.17
Quick liquidity	7.30	5.08	4.02	5.45	2.55	4.72	6.29	10.39	7.56
Inventory turnover	17.48	17.93	16.52	35.92	29.23	36.00	35.60	13.00	22.10
Financial autonomy	8.65	1.24	1.73	2.08	1.88	3.14	4.51	7.42	7.37
Financial dependence	0.12	0.81	0.58	0.49	0.53	0.32	0.22	0.13	0.14

The forecasting of the indicators through a neural network is carried out in three stages:

1. Neural network training with known data.
2. Forecasting the indicators.
3. Evaluation of the accuracy of the forecast from the neural network by comparing the predicted with the real values of the indicators.

The method of forecasting time series for training and forecasting [10, 11] has been applied. A separate neural network is created for each of the indicators studied. Each of the neural networks has 3 input parameters and one output.

The information is distributed in a training sample, using the so-called "time window", that covers 3 consecutive years [12], to which the data from the fourth year are compared. For example, for the first indicator in Table 1: the values [0.27; 0.21; 0.18], and at the output [0.22].

The distribution of information is shown in Table 1. The training is performed in 5 stages, and at each stage information is submitted to the neural network in the manner shown in Table 2.

Table 2. *Training sample for the rate of return on income*

Stage	Indicator values (from Table 1)	
	Input	Outcome
1	2011, 2012, 2013	2014
2	2012, 2013, 2014	2015
3	2013, 2014, 2015	2016
4	2014, 2015, 2016	2017
5	2015, 2016, 2017	2018

The neural network is not trained with data for 2019, as the data for it will be used to compare with the data predicted by the model and assess the accuracy of the model

Table 3. *Values of the indicators from the training of the neural network*

Indicators	Value 2019	Forecast 2019	Error (%)
Profitability of income	0.11	0.13	-12.50
Return on equity	0.08	0.10	-4.26
Return on assets	0.07	0.09	-5.26
Revenue efficiency	0.88	0.85	16.67
Cost efficiency	1.14	1.15	-3.57
Total liquidity	8.17	8.03	1.71
Quick liquidity	7.56	7.35	2.68
Inventory turnover	22.10	21.41	3.00
Financial autonomy	7.37	7.02	4.72
Financial dependence	0.14	0.28	-20.29

At the next stage (forecasting by neural network) information about the indicator for 2016, 2017, 2018 is submitted to the model, and the model generates as a result a forecast for the value of the indicator for 2019. Then the forecast value obtained from the model is compared with the real value of the indicator and determine the error of the model.

During the test, 10 neural networks were created, which were trained with samples for each indicator. The data are presented in Table 3.

The Python programming language and the LSTM (Long Short-Term Memory Neural Network model) module to simulate a neural network were used. The neural network architecture is LSTM. The model uses a stochastic gradient version and optimizes the mean square error (Mean Square Error).

The accuracy of the forecast for each indicator is determined as a percentage by the formula:

$$Error\ (\%) = \left(\frac{x_{2019} - x_{forec.}}{x_{\max} - x_{\min}} \right) \times 100 \quad (1)$$

where:

X_{2019} is the value of the indicator for 2019;

$X_{forec.}$ - the forecasted value of the indicator;

X_{max} and X_{min} - the maximum and minimum values of the indicator for the studied period (2011-2019).

When the value of the forecast exceeds the value for 2019, the error is negative, otherwise it is positive.

As a result, the following conclusions can be drawn:

The values of the indicators return on equity, liquidity, financial autonomy and turnover of inventories are predicted by the neural network with high accuracy - the error is within ± 5%.

The indicators turnover of inventories, financial dependence, revenue efficiency, profitability of revenues - the error is high over 20%. In order to reduce this error and increase the accuracy of the prediction in future research, it is appropriate to study a longer time interval so that the neural network can be better trained, as well as to experiment with other structures or neural network models.

BANKRUPTCY RISK ASSESSMENT

Altman's management model was created to predict the viability of industrial exchange companies within 2 years and works with the financial performance of large corporations. As a tool for improving the decision-making process was proposed by E. Tsvetanova, a modified model based on the management model of Altman, which supports the process of determining the viability of small and medium enterprises [13].

The model is adapted to the Bulgarian conditions on the basis of empirical information from Bulgarian enterprises in order to predict whether small and medium enterprises will reach a state of bankruptcy in a period of one to two years with a certain degree of accuracy [14].

Other authors, Avelova, Marchev and team also point to the need to propose weights of Z-score, adapted to the specific economic conditions in which enterprises operate in Bulgaria [15].

Based on a study conducted on Bulgarian companies to adapt Altman's model for assessing the risk of corporate bankruptcy for Bulgarian conditions, E. Tsvetanova [13] proposed a model for Z-score with weighting factors according to the following equation:

$Z=2{,}213X_1+0{,}243X_2+0{,}760X_3+2{,}821X_4,$

where the financial ratios are as follows:

X_1 - Earnings before interest and taxes (EBIT) on total assets. This ratio has the greatest weight

X_2 - Working capital to total assets. The ratio has the lowest correlation in the function and the lowest statistical significance.

According to E. Tsvetanova, the first two financial ratios coincide with those of Altman [1], as well as their statistical significance for the model.

The next two financial ratios are structural indicators based on data from the company's statement of financial position. They largely reflect the specific factors and practices applied in the country.

X_3 - Equity to total assets. The company's equity is compared to total assets, which shows its financial stability.

X_4 - Money to total assets. A financial ratio that measures the portion of assets held in cash and cash equivalents. It is second in importance after EBIT to total assets.

The results obtained in an empirical way by E. Tsvetanova show that at values of Z-score:

Z < 0.4 - the probability of bankruptcy is very high;

Z - between 0.4 and 1.5 - companies fall into the zone of medium high probability of bankruptcy;

Z > 1.5 - there is a very low probability of bankruptcy [16].

The report assesses the company's bankruptcy risk using a Z-score. For this purpose, values of the indicators X_1, X_2, X_3 and X_4 of the company were calculated on the basis of real data for 2018 and 2019. The weighting coefficients proposed by E. Tsvetanova [16] are applied (Table 4).

Table 4. Indicators for calculating the Z-score

Indicator	**Values**		**Z**	
	2019	2018	2015	2014
X_1	0,077	0,175	0,077	0,175
X_2	0,587	0,614	0,587	0,614
X_3	0,861	0,856	0,861	0,856
X_4	0,586	0,613	0,586	0,613
Z-score			2,613	2,770

$$Z = 2{,}213X_1 + 0{,}243X_2 + 0{,}760X_3 + 2{,}821X_4 \quad (3)$$

The obtained values for Z are high - 2,613 for 2015 and 2,770 for 2018 and show that there is no risk of bankruptcy for the company.

Based on information about the financial and economic indicators of the company for the period 2011-2018, training of the neural network was performed by the method of forecasting time series [10, 11].

For each of the studied indicators - X_1, X_2, X_3 and X_4 a separate neural network is created, with 3 input parameters and one output. The information is distributed in training samples, using the "time window" method, which covers 3 consecutive years.

After the training of the neural network, at the next stage information is submitted about the indicators X_1, X_2, X_3 and X_4 for 2016, 2017 and 2018 and as a result a forecast for 2019 is obtained.

With the indicators obtained from the forecast, Z is calculated for 2019 and the value is compared with the value of Z = 2,613 for 2019, which is a result of the calculation with real data. The actual and obtained from the forecast results and the deviation are presented in Table 5.

Table 5. Results of the forecast for 2015

Indicator	**Values 2019**	**Forecast data - 2019**	**Deviation (%)**
X_1	0,077	0,081	5,2
X_2	0,587	0,772	31,5
X_3	0,861	0,774	-1,10
X_4	0,586	0,509	-13,14
Z-score	2,613	2,394	-8,38

The deviation is calculated by the formula:

$$Deviation(\%) = \left(\frac{x_{forecast}}{x_{value\,2019}}\right) \times 100 - 100 \quad (2)$$

where:

$X_{forecast}$ - projected value of the indicator for 2019;

$X_{value\ 2019}$ - real value of the indicator for 2019

The data for the indicator Z-score is calculated with real data for 2018 and 2019 and the data forecast by the neural network for 2019 show that for the company for both studied periods there is a very low risk of bankruptcy - the value of The Z-score is well above 1.5.

For 2019, there is a decrease in the value of the indicator X_1 - about 2 times, which is mainly due to a decrease in profit - more than 2 times for the studied periods. The values of Z-score for the two periods differ minimum limits - the deviation is - 8.38%, which shows that the method of forecasting with neural networks with a "time window" - 2,968 for 2018 and 2,613 for 2019 can is used to make forecasts for future periods.

CONCLUSION

The application of neural networks and the Z-score model could serve as additional tools for forecasting and analyzing the financial indicators and the risk of bankruptcy of companies in order to assist management in drawing up plans and decisions for future development.

The study demonstrated the applicability of a neural network simulated with a "time window" to predict financial ratios. The application of the Z-SCORE model for assessing the risk of insolvency of a functioning company by means of the forecasted values of the indicators and with weighting coefficients proposed for Bulgarian enterprises has been tested.

The obtained predicted values of the indicators show high accuracy (compared to the real indicators) and the possibility to apply a neural network structure with a "time window" in order to forecast the financial indicators for future periods. On this basis, it is possible to make timely and adequate decisions by the company's management.

The obtained results outline as a direction for future research in the field of forecasting indicators for financial and economic analysis, creating more accurate and complete forecasting models - based on neural networks, by studying and simulating other structures of neural networks and / or other modeling approaches and methods.

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