Neural Network Models for Assessing the Financial Condition of Enterprises for Supply Chain

Maxim Alexandrovich Popov [1], Alexey Sergeevich Katasev [2], Amir Muratovich Akhmetvaleev [2], Dina Vladimirovna Kataseva [2]

[1]*Kazan Federal University*

[2]*Kazan National Research Technical University named after AN Tupolev*

ministermaxxx@gmail.com

***Abstract*— The paper deals with the task of assessing the financial condition of enterprises. To solve it, we prove the necessity of building a neural network model for supply chain. A set of financial ratios is defined as the input parameters of the model: the current liquidity ratio of the enterprise, the equity ratio, the equity turnover ratio, and the return on equity ratio. The output parameters were the types of the financial condition of enterprises: an unstable state (regression), a normal state (stable) and an absolutely stable state (progression). The volume of input data for building neural network models for assessing the financial condition of enterprises amounted to 210 records. The construction and evaluation of the effectiveness of neural network models are based on the analytical platform Deductor. There have been built 32 modifications of neural network models with different architectures and trained with different samples formed randomly from the source data. To assess the effectiveness of the models built, a technique has been developed, which includes the stages of testing neural networks, evaluating their accuracy and average classification error taking into account weighting factors assigned by an expert. The results of calculations of errors of the first and second type for each financial condition, as well as the average total classification error, are presented. The best model with a minimum average classification error, which is a single-layer perceptron with 10 hidden neurons, was chosen. The classification accuracy of the model was about 98%. The neural network model is adequate and can be effectively used to solve the problem of assessing the financial condition of enterprises.**

***Keywords*—** *mathematical modelling, financial condition of an enterprise, neural network model, Supply chain, classification accuracy.*

1. Introduction

Modern conditions in the economy dictate their own rules regarding the financial and economic activities of enterprises [1]. Each of them seeks to ensure a balance in the internal and external environment, for which it is necessary to form objective preconditions for the sustainability of all activities. For the favourable development of enterprises, managers need to be able to competently assess their financial condition being an important category which mainly indicates the efficiency of the processes in the financial and economic activities.

Ensuring the sustainability and progressiveness of the financial condition of a company is one of the most important tasks solved by its managers because the favourable development of an enterprise is a guarantee of its stability and well-being. Assessment of financial condition is a task which solving determines the success of an enterprise as a whole [2]. The solution to this problem is achieved by applying various methods and approaches [3]: theoretical, expert, mathematical, etc. In particular, the use of modern information technologies to assess the financial condition of the enterprise on the basis of intelligent models and algorithms can make it possible to solve this problem as efficiently as possible [4].

Thus, the task of assessing the financial condition of an enterprise with the use of intellectual modelling technologies that is relevant in modern conditions is the key to making correct and informed decisions.

2. Methods

Data mining methods consist of statistical methods [5, 6], as well as methods of machine learning [7–9]. The basis of statistical modelling methods is the principle of using averaged cumulative experience of observations or experiments. Statistical data are objects or signs that characterize historical data and can take on different values.

Statistical data mining is based on the consistent application of deterministic and probabilistic methods [10-15]. At the first stage, it is necessary to analyze the prepared data and present them in a convenient form for perception by means of tables and diagrams in a supply chain strategy. Next, we need to use probabilistic-statistical models for the analysis that will allow us to more accurately understand the essence of the phenomenon or process under study and ensure the development of their adequate mathematical model [12, 16-23].

Information practice shows that among the approaches of artificial intelligence, machine learning methods [13] are of great practical significance for solving analytics problems, in particular, assessing the financial condition of enterprises. Currently, the most effective is the method of neural network modelling [14, 15].

A neural network is a system that has an architecture which was similar to the structure of a nervous biological tissue consisting of neurons. The main function of any neuron is the formation of the output signal, depending on the signals arriving at its inputs.

The construction of a neural network in modelling processes consists of the following main stages [16]:
- preparation of a data set (training and test sets);
- the input of initial data into an analytical application for building a neural network model;
- setting the required characteristics of the neural network (structure and training parameters);
- control over the learning process;
- testing and assessment of the adequacy of the neural network model built.

In the task of assessing the financial condition of an enterprise, the efficiency of using neural network models is determined by the availability and quality of the initial data characterizing the subject area under consideration. Therefore, an important step is the preparation of the initial data for the building of neural network models [17].

The building of neural network models for assessing the financial state of an enterprise begins with the preparation of baseline data. In this paper, we consider the financial state indicators of a number of enterprises from the machine-building complex as the source data.

A set of financial ratios was defined as input data for the model, namely:
- K_1 - the current liquidity ratio of an enterprise;
- K_2 - the capital ratio;
- K_3 – the equity turnover ratio;
- K_4 - the return on equity ratio.

Quantitative data on these indicators were obtained from the annual accounting financial statements of enterprises for 2012-2018.

In addition to the input data, the output data are to be set for the building of neural network models; they are the following types of the financial status of enterprises:
- Unstable state (hereinafter referred to as "regression");
- Normal state (hereinafter referred to as "stable");
- Absolutely steady state (hereinafter referred to as "progression").

The values of their financial ratios are assigned to each specific type of financial condition of enterprises. Table 1 presents a fragment of the initial data obtained for building neural network models for assessing the financial condition of enterprises.

Table 1. A fragment of the source data for building models in order to assess the financial condition of enterprises

Item No	Input parameters				Output parameters		
	K_1	K_2	K_3	K_4	*Regression*	*Stable*	*Progression*
1	0.99	-0.02	2.15	0.39	1	0	0
2	1.24	0.19	1.69	0.37	1	0	0
3	0.87	-0.16	1.93	0.31	1	0	0
4	1.15	0.13	2.16	0.54	0	1	0
5	0.81	-0.24	1.75	0.26	1	0	0
6	0.5	-0.99	2.19	0.2	1	0	0
7	0.88	-0.35	1.59	0.4	1	0	0
8	0.77	-1.38	12.96	0.23	1	0	0
9	1.59	-1.24	7.91	0.14	0	1	0
10	1.48	-1.29	5.63	0.01	1	0	0
11	1.07	-1.74	5.99	-0.24	1	0	0
12	0.6	-2.39	14.72	-1.97	1	0	0
13	0.37	-4,1	-7.78	1.99	1	0	0
14	0.51	-2.85	-3.96	0.74	1	0	0

15	0.73	-0.38	3.52	0.01	1	0	0
16	0.8	-0.25	3.81	0.02	0	1	0
17	0.87	-0.15	4.77	0.04	1	0	0
18	0.83	-0.21	6.81	0.03	1	0	0
19	0.85	-0.17	7.73	0.55	0	1	0
20	0.94	-0.06	4.01	0.39	1	0	0
21	1.01	0.01	3.2	0.42	0	1	0
22	1.5	-0.13	2.48	0.01	0	1	0
23	1.73	-0.06	2.59	0.1	0	1	0
24	1.44	-0.09	2.44	0.05	0	1	0
25	1.35	-0,1	2.35	0.01	0	1	0

The total amount of initial data for building neural network models for assessing the financial condition of enterprises amounted to 210 records.

For the building of neural networks, the "Processing Wizard" - "Neural Network" tool is used, which is part of the Deductor analytical platform. Given the random nature of the partitioning of a training set directly into the training and test sets in the process of building neural network models, this process was repeated many times to obtain a stable result. In total, 32 modifications of neural network models with different architectures, trained in different training samples and formed randomly from the initial data, were obtained as a result of experiments. The quality of learning of neural networks is determined by the contingency table. At the same time, the evaluation of the generalization ability for all constructed models was made, as well as the calculation of the errors of the 1st and 2nd type for each model.

3. Results and Discussion

To assess the effectiveness of the neural network models built, a special technique consisting of the following main stages has been developed:

1) determining the cost of an erroneous classification when testing neural network models;
2) assessment of the accuracy of models;
3) establishment of weighting coefficients for classification errors;
4) calculation of classification accuracy with regard to the established error rates;
5) assessment of the average accuracy for each neural network model;
6) determining the criterion for choosing the best neural network model;
7) selection of the best model based on the established criteria.

Each of the financial conditions of enterprises is reviewed for the cost of an erroneous classification in comparison with other states. We begin the study of estimates of neural network models with the calculation of errors of the first type. The general formula for calculating the first type error values of each model built is as follows:

$$E_I = \frac{n_T}{N_T}, \quad (1)$$

Where E_I is the value of the 1st type error, n_T is the number of incorrectly classified positive examples, N_T is the total number of positive examples.

Let us introduce into consideration the value w_{ij} which is the error weight assigned by the expert, where i and j correspond to the specific financial conditions of the enterprise. Then for each of the states, the following forms are valid :

$$E_{Ip} = \frac{w_{pc} * n_{Tpc} + w_{pn} * n_{Tpn}}{N_{Tp}}, \quad (2)$$

$$E_{Ic} = \frac{w_{cp} * n_{Tcp} + w_{cn} * n_{Tcn}}{N_{Tc}}, \quad (3)$$

$$E_{In} = \frac{w_{np} * n_{Tnp} + w_{nc} * n_{Tnc}}{N_{Tn}}, \quad (4)$$

where E_{Ip}, E_{Ic}, E_{In} are errors of the 1st type for the financial states "Regression", "Stable", "Progression", respectively. w_{pc} is the weight of the error for incorrect classification of the "regression" state (actually classified as "stable"), w_{pn} - misclassification error weight for "regression" state (actually classified as a "progression"), n_{Tpc} and n_{Tpn} are numbers for incorrectly classified good examples of the "regression" state, w_{cp} is a misclassification error weight for "stable" state (actually classified as "regression"), w_{cn} is the error weight of the incorrect classification of the "stable" state (actually classified as "progression"), n_{Tcp} and n_{Tcn} are the numbers of incorrectly classified positive examples of the "Stable" state, w_{np} is the error weight of the incorrect classification of the "progression" state), W_{nc} is the error weight of the incorrect classification for the "progression" state (actually classified as" stable "), n_{Tnp} and n_{Tnc} are the numbers of incorrectly classified positive examples of the "Progression" state, N_{Tp}, N_{Tc} and N_{Tn} is the totals for positive examples of the states "Regression", "Stable" and "Progression", respectively.

To calculate errors of the second type, it is also necessary to compile similar schemes. Calculation of the values of this error is carried out according to the formula:

$$E_{II} = \frac{n_F}{N_F}, \quad (5)$$

Where E_{II} is the error value of the 2nd type, n_F is the number of incorrectly classified negative examples, N_F is the total number of negative examples.

For each of the financial states, the following modifications of the formula (5) are used:

$$E_{IIp} = \frac{w_{cp} * n_{Fcp} + w_{np} * n_{Fnp}}{N_{Fp}}, \quad (6)$$

$$E_{IIc} = \frac{w_{pc} * n_{Fpc} + w_{nc} * n_{Fnc}}{N_{Fc}}, \quad (7)$$

$$E_{IIn} = \frac{w_{pn} * n_{Fpn} + w_{cn} * n_{Fcn}}{N_{Fn}}, \quad (8)$$

where E_{IIp}, E_{IIc}, E_{IIn} are errors of the 2nd type for financial states "Regression", "Stable", "Progression", respectively, w_{cp} is an error weight for incorrect classification of the state "stable" (actually classified as "regression"), w_{np} is the error weight for an incorrect classification of the "progression" state (actually classified as "regression"), n_{Fcp} and n_{Fnp} are the numbers of incorrectly classified negative examples of the "Regression" state, w_{pc} is the error weight for the incorrect classification of the "regression" state (classified as "stable"), w_{nc} is the error weight for an incorrect classification of the state "progression" (actually classified as "stable"), n_{Fpc} and n_{Fnc} are the numbers of incorrectly classified negative examples for the state "Stable", w_{pn} is the error weight for an incorrect classification of the state "regression" (actually classified as " progression "), w_{cn} is the error weight of an incorrect classification for the "stable" state (actually classified as "progression"), n_{Fpn} and n_{Fcn} are the numbers of incorrectly classified negative examples of the "Progression" state, N_{Fp}, N_{Fc} and N_{Fn} is the total number of negative examples of financial conditions "Regression", "Stable" and "Progression", respectively.

The choice of the best neural network model is made on the basis of the criterion of the average error value minimum, integrating both types of classification errors for all types of financial states of enterprises. This criterion is calculated as the arithmetic average for the formula:

$$E = \frac{0{,}5(E_{Ip}+E_{IIp})+0{,}5(E_{Ic}+E_{IIc})+0{,}5(E_{In}+E_{IIn})}{3}, \quad (9)$$

Where E is the average value of the model error.

Table 2 presents the results of calculations using formulas (2) - (4) and (6) - (9).

Table 2. Calculation results for the neural network model errors for assessing the financial condition of a company

Model No	Type of financial condition						E %
	Regression		Stable		Progression		
	E_{Ip},%	E_{IIp},%	E_{Ic},%	E_{IIc},%	E_{In},%	E_{IIn},%	
1	0	4.91	4.5	10.73	19.86	0	6.67
2	0	1.13	1.93	5.85	7.5	0	2.74
3	1,3	7.17	7.21	0.49	9.17	0.86	4.37
4	0	0	0	5.85	7.5	0.1	2.24
5	0	0	0	6.83	7.5	0	2.39
6	2.61	0	0	6.83	7.5	0	2.82
7	0	0	0	5.85	7.5	0.1	2.24
8	2.61	0	0	6.83	7.5	0	2.82
9	0	1.51	2.57	5.85	7.5	0	2.91

10	1,3	1.13	1.93	6.34	7.5	0	3.03
11	0	0	0	5.85	7.5	0.1	2.24
12	2.61	0	0	6.83	7.5	0	2.82
13	2.61	0	0	6.83	7.5	0	2.82
14	0	4.53	1.93	0	9.17	0	2.61
15	1,3	0	3.14	6.34	7.5	3.45	3.62
16	8.48	1.13	1.93	9.02	7.5	0	4.68
17	5.87	0	0	8.05	7.5	0	3.57
18	7.17	0	0	8.78	7.5	0	3.91
19	0	0	0	5.85	7.5	0.1	2.24
20	0	0	0	5.85	7.5	0.1	2.24
21	0	0	0	5.85	7.5	0.1	2.24
22	1.96	1.13	5.86	6.59	7.5	4.31	4.56
23	1,3	1.13	5.86	10.24	12.5	4.31	5.89
24	0	0.1	0	5.85	7.5	0	2.24
25	0	0.1	0	5.85	7.5	0	2.24
26	2.61	0	0	5.85	7.5	0	2.66
27	0	0.1	0	5.85	7.5	0	2.24
28	0	1.13	1.93	8.78	11.25	0	3.85
29	0	0	0	5.85	7.5	0.1	2.24
30	0	0	0	8.78	11.25	0	3.34
31	0	3.4	0	0.98	9.17	0	2.26
32	0	0	0	5.85	7.5	0	2.23

According to the data from the table, it can be seen that the best neural network model by criterion (9) is model No. 32. This model is a single-layer perceptron with 10 hidden neurons and allows us to assess the financial status of enterprises with an average error not exceeding 2.23%. The accuracy of this model is about 98%, accordingly

It should be noted that if the criterion (9) is satisfied for several models at once, the choice of the best one would be made on the basis of an additional criterion - the minimum number of elements of the neural network model structure.

4. Summary

Evaluation of the financial condition of any enterprise is the most important area of its activities related to analysis, planning and forecasting. The use of neural network modelling technologies can provide a concrete understanding of the existing problems in this subject area. The neural network model obtained in this work is adequate, which allows us to state that it can be effectively used to solve the problem.

5. Conclusions

Thus, the constructed neural network model is an effective tool for solving the problem of assessing the financial condition of enterprises. The development and comparative assessment of the results obtained on the basis of other data mining methods, as well as the construction of intelligent decision support systems [18-20] for evaluating the financial condition of enterprises on their basis, are seen as a direction for prospective studies.

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