DOI: 10.55643/fcaptp.6.53.2023.4224

THE DIAGNOSTICS OF THE ENGINEERING ENTERPRISE'S FINANCIAL CONDITION BASED ON THE USE OF NEURAL NETWORK MODELING

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ABSTRACT

The purpose of the paper consists in diagnosing the level of the financial condition of the engineering enterprise using the neural network approach and providing a forecast of its level for the future. The paper emphasizes the importance of diagnosing the financial condition of Ukrainian enterprises under modern conditions. Methods of traditional financial analysis are considered. The necessity of using modelling to improve the quality and accuracy of the analysis is emphasized. An analysis of existing models for assessing the financial condition and bankruptcy of enterprises is carried out. Different types of models developed by domestic and foreign authors are considered: models built on the basis of multivariate discriminant analysis, based on fuzzy logic methods, and others. The use of neural network modelling for assessing the financial condition is substantiated. A neural network model of financial state diagnostics is built based on the financial data of an engineering enterprise. To decrease the domain of input data, the use of the "centre of gravity" method is proposed, with the help of which the number of input variables of the model is reduced to five. A model based on a multilayer perceptron is built with the help of a powerful neural network modelling tool (SSN). The neural network was trained by the backpropagation method. An assessment of the financial condition of the engineering enterprise PJSC NKMZ is made with the help of the model for 10 future periods. The proposed method of diagnosing the financial state allows the management of the engineering enterprise to predict the onset of a crisis state and develop a financial recovery plan.

Keywords: financial condition, bankruptcy, multivariate discriminant analysis, integral indicator, fuzzy logic, neural network model

JEL Classification: G17

Received: 24/10/2023
Accepted: 07/12/2023
Published: 31/12/2023

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INTRODUCTION

The transformation of the national economy of Ukraine into an open economy creates a fundamentally different external environment for domestic enterprises. Therefore, there is a need to adapt all enterprise systems to constantly changing conditions. So, the management of each economic entity should aim at finding such administration options that are able to predict possible financial situations and implement effective management decisions in a timely manner that direct the enterprise activities to achieve the assigned goal under the conditions of a changing external environment.

Any modern enterprise is considered from the point of view of a systemic approach, when all elements of its economic and production system are interconnected, therefore, influencing the financial aspect of the enterprise, it is possible to influence its functioning as a whole.

There is a need for regular monitoring of the financial state of the enterprise for its effective functioning. Ignorance of the owner of the enterprise about the real state of affairs creates a threat of financial instability, loss of expected profits, as well as an increased level of probability of bankruptcy. It is the timely obtaining of information about the financial condition of the management object that gives a chance to avoid possible problems and prepare for the consequences. Financial diagnosis helps to obtain such information.

The need for diagnostics of the financial state of the enterprise is caused by the need for effective management of the financial resources of business entities. The main content of the diagnostics is a comprehensive systematic study of the financial condition of the enterprise, as well as the factors affecting it.

A manufacturing enterprise is a complex system with various connections between its elements. Such a system not only provides its existence but is also an integral part of the entire economic system of the country. The parameters describing the financial condition of the enterprise are quite numerous, and they are also interconnected with each other. Therefore, there is a need to develop an effective methodology for assessing financial condition.

Conducting a timely and regular assessment of the level of the enterprise's financial condition is very important for the effectiveness of its economic activities. An accurate assessment of the level of financial stability allows the management of enterprises to implement the necessary management measures to preserve it. Such an assessment is useful not only directly for the management of the enterprise but also for suppliers of material resources, as it gives an understanding of whether the partner is solvent. There is also a benefit for representatives of the banking system and credit institutions aiming to assess the creditworthiness of business entities, for investors – for the purpose of assessing the profitability of future investments, and other participants of the market system (Philosophov et al., 2008).

The search for effective methods of assessing the financial condition is always topical among the directions of scientific research (Rohma et al., 2021). Under modern socio-economic conditions, which are constantly changing, the requirements for methods of assessing the financial condition of enterprises are also increasing. The methods of traditional financial and economic analysis have lost their relevance, as most of them are based on outdated information and do not take into account the realities of today's market economy, and its turbulent nature. Also, traditional methods do not take into account exactly how to assess the obtained results. Such methods offer a rather large number of financial coefficients that often duplicate each other.

It should also be emphasized that papers on traditional financial analysis (Poddierohin, 2011) are based on taking into account the current state of the business entity, without the possibility of forecasting its level in the future. Researching the prospects of future development is very important for every enterprise, especially under modern socio-economic conditions. By receiving the results of the analysis, which contain a forecast of the level of the financial condition, it is possible, if necessary, to take timely measures that will contribute to improving its level for the future.

The constructed financial coefficients do not take into account the affiliation of the enterprise to a certain industry, though the capital structure may differ significantly depending on the industry in which the enterprise operates. So, for example, the capital structure of a manufacturing enterprise and an enterprise engaged in trading operations differ in the ratio of the value of fixed assets and current assets in the structure of the balance sheet of enterprises. Business entities engaged in production activities have a much larger share of fixed assets in the balance sheet structure than commercial entities; therefore, when developing methods for assessing the financial condition of such enterprises, it is advisable to take this feature into account.

Currently, there is a need to develop an effective methodology for assessing the financial condition of engineering enterprises, since the engineering industry occupies a leading place among the branches of the national economy and is an investment-attractive industry, despite the fact that in recent years there has been a gradual reduction in production volumes. The volume of trade in engineering products is constantly increasing in the world market (Ukrpromzovnishekspertyza, 2021). The EU states are the leaders in the volume of production of engineering products. According to the Export Strategy for the Engineering Sector for 2019-2023 (Eksportna stratehiia dlia sektuori mashynobuduvannia, 2019), "the industrial production sector, despite the growth of the service economy, continues to occupy a dominant position worldwide: it accounts for approximately 16 per cent of global GDP and 13 per cent of employment". Until 2014, 60% of exports of the engineering industry of Ukraine went to the russian market. High competition in the European market and problems with the lack of certified laboratories in the domestic market make it difficult for domestic enterprises to enter the markets of the European Union. A low level of financing is one of the main obstacles to the development of exports. In order to fulfil new orders, it is necessary to increase the amount of working capital and the volume of purchases of modern fixed assets. To solve such tasks, it is necessary to increase the level of profitability of engineering enterprises, attract new sources of investment, etc. One of the tools for achieving such goals consists not only of an accurate assessment of the current financial condition of engineering enterprises but also of forecasting its level for the future. Therefore, at the moment, it is very important not only to develop effective methods for assessing the financial condition that take into account the realities of the modern national economy but also those that take into account the industry specifics of the enterprise.

DOI: 10.55643/fcaptp.6.53.2023.4224

LITERATURE REVIEW

The diagnostics of the enterprise's financial state is one of the most important conditions for its successful functioning. Diagnostic is an effective tool that allows the prevention of financial crises and ensures an appropriate level of financial and economic condition. Most of the subjects of the national economy have an unsatisfactory capital structure. The information about the financial condition, received in a proper time, allows the management to restore the profitability and solvency of the enterprise, to increase its financial potential. Such information can be obtained using new progressive methods of diagnosing the financial condition.

The constant provision of the company management with up-to-date information about the current financial state of the company is a tool for overcoming crisis phenomena.

A lot of papers by domestic and foreign scientists are devoted to the development of methods and models of financial condition diagnostics. Domestic economists L.A. Lakhtionova (2001), A.M. Poddierohin (2011), T. G. Ben, S. B. Dovbnia N.V. (Ben, 2002) and others made a significant contribution to the development of theoretical and metrological approaches to assessing the financial condition of Ukrainian enterprises.

Different papers have different approaches to defining the concept of the financial condition of the enterprise. So, for example, A.M. Poddierohin (2011) defines the financial condition of the enterprise as "... a complex concept that is the result of the interaction of all elements of the system of financial relations of the enterprise, is determined by a set of production and economic factors and is characterized by a system of indicators that reflect the availability, placement and use of financial resources". O.I. Pavlenko (2010) emphasizes that the financial condition "...is the real (at a fixed moment in time) and potential financial capacity of the enterprise".

In the economic literature, not only the definitions of the concept of "financial condition" differ, but also the approaches to its assessment are different. There are four groups of financial analysis methods: transformative, qualitative, coefficient and integral (Yelisieieva, Reshetniak, 2007).

With the help of transformational methods, a more convenient format of financial reporting is formed for further calculations. For example, aggregation of balance sheet items. This method cannot be used as an independent tool for assessing the financial condition; it is a preparatory stage before conducting an assessment.

Qualitative methods include methods of horizontal and vertical analysis of financial statements, analysis of balance sheet liquidity, as well as questionnaire schemes.

The vertical analysis is used to research the changes in the structure of assets and liabilities of the enterprise, to compare the obtained structure with an ideal template. The use of this method is complicated by the difference in the structure of the balance sheet of enterprises belonging to different sectors of the economy, for example, trade enterprises and those engaged in production activities. Therefore, the choice of a standard for each individual enterprise is a problematic point of analysis.

Using the horizontal analysis of financial reporting, it is possible not only to research the trends of the enterprise development but also to make their forecast for the future. However, as a rule, the conclusion is made on two reporting dates, the current and the previous time period. Therefore, this approach has a number of limitations: for a more detailed assessment of the obtained changes, it is necessary to analyze additional data; the change of some indicators results from the action of many factors that are not taken into account when conducting such an analysis, therefore, without taking them into account, it is impossible to make a high-quality forecast.

The most common method in financial practice is coefficient analysis. However, its use also has a number of limitations, which complicates the analysis: a rather large number of coefficients offered for the assessment, lack of a clear mechanism for interpreting calculations, and normalized values of the coefficients used for the analysis can vary greatly depending on the sector of the national economy, to which the business entity belongs. At the same time, coefficient analysis is the most convenient to use, and it should be developed and improved. The tool of mathematical modelling allows for modernizing such analysis methods.

The financial condition diagnostics using mathematical models allows for the expansion of the scope of traditional methods of analysis, partially eliminating their shortcomings. Models built by means of discriminant analysis methods are one example of the use of mathematical modelling. A conclusion about the level of the financial condition of enterprises is made based on the calculation of the value of the integral indicator and its comparison with the critical value.

Western economists use the method of discriminant analysis to build mathematical models for predicting the bankruptcy of enterprises. These are the models of Altman (1968), Springate (1978), Lees and Taffler (Taffler, 1983), Fulmer (1984), Zmijewski (1984), etc. developed for American and European enterprises. They differ in the set of factors used to calculate the integral indicator and the weighting coefficients of the multifactor model.

Altman's Z-model (Altman, 1968) is more widely used in Western practice. Nevertheless, this model has a number of disadvantages. The model was built in the 60s of the last century. Of course, during this time the economy has undergone significant changes, so it is not appropriate to compare the financial condition of enterprises belonging to different centuries. Also, Altman selected five coefficients out of 22 that were subjected to investigation. This choice was not sufficiently justified. Moreover, the model built on the financial data of US enterprises showed a significant error when it was applied to determine the level of bankruptcy of economic entities of other countries.

British economist Taffler (1983) proposed a four-factor model for predicting corporate bankruptcy. He proposed to divide all enterprises, analyzed with the use of this model, into two classes: with a slight probability of bankruptcy and with a high probability of bankruptcy. In practice, it is very difficult to determine what a high probability of bankruptcy is.

In the 80s of the last century, Fulmer's model (1984), developed for commercial and auditing companies, gained wide popularity. This model is nine-factor, which makes it possible to provide a more comprehensive assessment of the financial condition of enterprises. However, when building the model, the multicollinearity of the factors was not investigated. It is clear that this reduces the quality of the built model.

The Lis model (1972) is widely known, but when using it to assess the financial condition of domestic enterprises, an inflated level of the integral indicator is observed. The profit from sales in this model has the largest weighting factor, while the factor reflecting the ratio of equity and debt capital is the lowest one. That is, the model almost does not take into account tax regimes. This factor has a very strong influence on the level of financial stability of economic entities under the conditions of the domestic economy.

French economist J. Depalyan (1988) developed the credit-men method for assessing the financial condition of enterprises. This method is quite promising because it allows comparing the indicators of the company activity with the average values of the industry.

The well-known financial analyst U. Beaver (1966) proposed a five-factor model that makes it possible to use the indicator of profitability of assets and draw conclusions about the timing of the company's bankruptcy. It is necessary to note that the difficulty of interpreting the final value and the use of outdated data are the shortcomings of the model.

A three-factor model (CA Score) (Klebanova, 2015) was developed on the basis of J.Lego's discriminant analysis method. Its construction was based on financial data of industrial enterprises of the city of Quebec. For this reason, it is not suitable for calculating the level of financial status of domestic enterprises.

Ukrainian scientist O. Tereshchenko (2006) developed a six-factor discriminant model of bankruptcy diagnosis. The great advantage of this model is that it is built on the financial data of Ukrainian enterprises engaged in various types of economic activity (of different branches). However, the uncertainty interval of the financial state is quite wide, and there is no in-depth classification of conditions, which complicates further analysis.

Another domestic researcher, O. Matviychuk, proposed a multifactorial mathematical model for assessing the threat of bankruptcy. The author analyzed previous models and, when developing his model, took into account the specifics of the functioning of domestic enterprises under the conditions of a transformational economy.

In Ukraine, the procedure for assessing the financial condition of an enterprise is regulated at the legislative level (Ministry of Finance of Ukraine, 2016). In accordance with the multi-criteria model of financial crisis identification (MFU methodology), the method of multi-factor discriminant analysis is also used to construct an integral indicator for assessing the financial condition of the beneficiary. It is proposed to calculate such an indicator and compare it with the limit values. The peculiarity of this calculation is that, depending on the type of economic activity, as well as the size of the enterprise (group 1 - large and medium, group 2 - small), a mathematical model and a limit value for determining the class of financial condition is proposed. The financial condition of the enterprise is assigned to one of five classes depending on the interval to which the calculated value of the integral indicator belongs.

In addition to models based on the use of the method of multivariate discriminant analysis to assess the probability of bankruptcy, logit models are used (Sammut, 2011). The absence of problems with the interpretation of the resulting indicator is a significant advantage of this assessment method. This indicator determines the nominal value of the probability of bankruptcy and can take values only in the interval from 0 to 1.

DOI: 10.55643/fcaptp.6.53.2023.4224

All the models listed above are quantitative. Increasingly, qualitative models are used to assess the financial condition of economic entities. The Argenti model (A-calculation) (Klebanova, 2015) is an example of such an assessment method. The aggregate indicator is calculated on the basis of several factors that cause bankruptcy. Each factor is assigned a number of points. As a result, management actions that may lead to the company's bankruptcy in the future are assessed. This approach has advantages compared to quantitative methods of assessment because not only financial but also managerial, socio-psychological, judicial, etc. factors are among the ones that can affect the level of probability of bankruptcy of the enterprise in the future. However, the method has a significant drawback: since experts must be involved to assess the factors, the subjectivity of the assessment may occur.

Thus, in the scientific research of both domestic and foreign scientists, a large number of models and methods for assessing the financial condition of an enterprise and the probability of bankruptcy are proposed. However, in modern domestic realities, the possibility of applying such models is complicated. First, there are no statistical data on Ukrainian enterprises that have been officially declared bankrupt. Second, none of the models takes into account all the factors that lead to bankruptcy. Third, in Ukraine, the legal framework for the bankruptcy of business entities is not perfect, it needs to be refined. Fourth, the peculiarities of the national economy need to use the financial data exclusively of Ukrainian enterprises when building such models.

Many authors emphasize that most of the models that exist for assessing the level of financial condition and the threat of bankruptcy are related to classification problems, i.e. they assign a business entity to a certain class. However, the financial condition of the enterprise is often rather difficult to unambiguously assess, to assign to a clearly defined class. This problem is solved by methods of fuzzy logic.

The use of fuzzy logic methods involves the construction of linguistic variables and terms corresponding to them. On their basis, Membership functions are formed on their basis and image recognition is carried out according to the established rules. In practice, such a situation may occur that the values of the integral indicators of the financial condition (used during the implementation of the fuzzy logic method) in the dynamics may take jump-like values. In this case, the empirical values will differ significantly from the obtained theoretical ones, and the use of economic and mathematical methods becomes inappropriate.

In such cases, it is advisable to use the catastrophe method (Klebanova et al., 2015), which makes it possible to provide an adequate assessment of the financial condition of the enterprise in the event of a sharp change in the dynamics of financial and economic indicators. When using this method, capsoid and umbilical catastrophes are considered. Capsoid catastrophes occur when one variable has an unsteady relationship with others, and umbilical catastrophes occur when two variables have an unsteady relationship with others. The possibility of the occurrence of catastrophes is estimated by constructing systems of equations of elementary catastrophes. If the coefficient of determination of the equation of one of the catastrophes turns out to be greater than the corresponding coefficient of the equation of stable connections, then it is concluded that the occurrence of a catastrophe is possible. Next, models of sustainable and unsustainable development are built by building predictive models. If the actual parameters of the models are in the bifurcation set, then the threat of a catastrophe is most likely.

Artificial intelligence methods show the effectiveness of their use in assessing the financial condition and probability of bankruptcy. The assessment of possible financial crises is carried out on the basis of the construction of neural networks with the help of developed software. The accuracy of the obtained estimates is much higher than that with the use of other models and methods.

AIMS AND OBJECTIVES

The purpose of the paper is to substantiate the feasibility of conducting a diagnosis of the level of the financial condition of an engineering enterprise using a neural network approach and to provide a forecast of its level for the future.

To achieve the purpose, the following task is set and solved:

- substantiation of the feasibility of using a neural network approach to modelling the assessment of the financial state of enterprises;
- construction of a neural network model for assessing the financial condition of an engineering enterprise;
- conducting an analysis of the results obtained through the use of a neural network;
- calculation of the level of financial status of the engineering enterprise for new cases.

METHODS

The following research methods are used: the method of analyzing scientific sources, the method of information search, the method of analytical review, and the method of analyzing regulatory documentation on the topic of assessing the financial condition of economic entities. A neural network is used to diagnose the financial condition of an engineering enterprise.

An analysis and generalization of the experience of developed countries in assessing the financial condition and probability of bankruptcy of enterprises is carried out. The application of the method of analysis of scientific sources makes it possible to search and systematize scientific materials and identify areas for further analysis. The method of information search is used for the purpose of finding and selecting information on the practical experience of assessing the financial condition of enterprises in developed countries, regulatory documents and modern research. The method of analysis of normative documentation related to the subject of the study allowed for carrying out a retrospective search of normative legal acts related to the field of research. The method makes it possible to find all normative legal acts that regulate the assessment of the financial condition of economic entities in developed countries and in Ukraine for a certain historical period concerning one direction. Also, the method allows one to expand the range of document searches for certain search directions.

Identification of the type of financial condition of enterprises is based on the calculation of groups of indicators of solvency, financial stability, capital turnover, profitability and business activity. Since the number of such indicators is rather large, in each of the selected groups of indicators, it is necessary to choose a "representative" indicator that contains the main information load, which is characteristic of the indicators of the group. It is suggested to use the "centre of gravity" method (Klebanova et al., 2015) to solve this problem. The choice of this method is determined by the following: this method does not impose restrictions on the number of indicators in the group (allows working with one-, two-, multi-element clusters); allows one to obtain a set of weakly correlated features (that is, excludes duplication of information); makes it possible to single out representative indicators of groups that have a strong correlation with signs (indicators) belonging to the same group.

The proposed indicator of filter algorithm includes the following main stages: formation of the initial data matrix, standardization of indicator values, calculation of the distance matrix, and formation of a set of indicators-"representatives" of groups.

The above algorithm is used to form a system of indicators-"representatives" of groups of financial ratios that analyze solvency, financial stability, capital turnover, profitability and business activity of an engineering enterprise.

The "representative" indicators are selected in each group of the analyzed financial ratios with the use of the given methodology: quick liquidity ratio (group of solvency indicators); financial risk ratio (group of financial stability indicators); capital turnover ratio (a group of capital turnover indicators); profitability of total assets (a group of profitability indicators); equity turnover ratio (a group of indicators of business activity).

The method of backpropagation of the error (Back Propagation) is used to train the neural network. A multi-layer perceptron is chosen as the best model for forecasting the financial state of the enterprise. The Statistica Neural Networks (SNN) package is used to build a neural network. It combines a convenient interface and wide options for choosing different types of neural networks. SNN consists of automatic neural network search tools, which allow one to choose the best network for further analysis from many ones built automatically. This software product contains state-of-the-art powerful and optimized network learning algorithms, and user control tools over parameters that affect network quality, such as activation and error functions, and network complexity.

RESULTS

The financial condition of the enterprise is at the centre of financial diagnostics. It is formed under the influence of factors of the external and internal environment. Many scientists propose to use only accounting reporting data when conducting a diagnostic of the financial condition; others propose to use a wider list of sources of information that comprehensively characterizes the financial and economic activity of the enterprise.

However, the enterprise, as an object of diagnostics, is a complex, highly organized, dynamic system; therefore, when researching the financial condition, it is necessary to take into account all factors and types of activities that have an impact on the final result. So, there is a need to use an expanded set of indicators that are displayed in accounting reports, management and operational accounting data.

DOI: 10.55643/fcaptp.6.53.2023.4224

European integration conditions require our country to develop all branches of the national economy. Particular attention is paid to the state of the engineering industry because labour productivity in other sectors of the national economy depends on its effective functioning.

The engineering industry in Ukraine is a leading and quite powerful sector of industry, which, according to the State Statistics Service of Ukraine, covers almost 4.5 thousand enterprises, employing 342 thousand people (State Office of Statistics of Ukraine, 2017).

However, recently there have been negative trends in the development of the industry. There is a reduction in the number of large and medium-sized engineering enterprises; the number of small ones has increased over the last decade (State Office of Statistics of Ukraine, 2022).

In addition, in nowadays unsteady economic conditions, there is a need to conduct a qualitative assessment of the level of the financial condition of engineering enterprises and forecast its future level. Domestic industrial enterprises face the problem of determining future income and expenses, uncertainty in business partners, in the national legislative framework, and, therefore, the uncertainty of the prospects of the enterprise. The development of effective diagnostic methods and tools makes it possible not only to assess the level of the company's financial condition in the current period but also to forecast its level for the future.

In order to develop effective management solutions, the management of the enterprise must anticipate possible negative situations, and influence them, directing its economic activity in the necessary direction.

Before building a neural network model, one needs to calculate financial indicators that will be used as input data for building a neural network. Based on the financial statements of the large engineering enterprise PJSC "Novokramatorsk Engineering Plant (PJSC NKMZ) for the years 2000-2020, groups of indicators of solvency, financial stability, capital turnover, profitability and business activity are calculated.

The number of indicators in each direction of financial analysis is quite large. Using the "centre of gravity" method (Klebanova et al., 2015), it is possible to choose a "representative" indicator in each group, which carries the main informational load that is characteristic of other indicators of its group.

The "centre of gravity" method consists of several stages. In the first stage, a matrix of input data is built, containing the values of the calculated financial ratios of the engineering enterprise for a number of years. Then the values of financial ratios are standardized. At the last stage, a matrix of distances is built. Euclidean distance is considered a measure of similarity of features. The next stage determines the sum of the distances of each indicator to others in its group. The representative in each group is the indicator that carries the main information load and can be used to identify the type of financial condition.

The "representative" indicators of PJSC NKMZ are selected with the use of the "centre of gravity" method as input indicators for conducting neural network modelling: quick liquidity ratio (group of solvency indicators); financial risk ratio (group of financial stability indicators); capital turnover ratio (a group of capital turnover indicators); profitability of total assets (a group of profitability indicators); equity turnover ratio (a group of indicators of business activity).

The process of building a neural network is quite complex because it is based on significant calculations and numerous computational experiments. In order to simplify the process and reduce the time of such calculations, modern software packages implementing the appropriate technologies are used e.g., such software products as Statistica Neural Networks, NeuroShell, NeuroSolutions and others (Klebanova et al., 2018).

The Statistica Neural Networks (SNN) package was used to build a neural network model for diagnosing the financial state of the engineering enterprise. Such a package contains modern methods of training neural networks, allows the construction of complex networks with different architectures, allows the user to control the selection of the activation function, allows selective training of different fragments of networks, and also contains a powerful Network Wizard tool, which allows the user to independently make decisions on the choice of network structure and select its parameters.

The tools of the SNN program allow you to split the initial data sample into three classes: educational, with the help of which a neural network is built; verified, which is used as a knowledge base for adjusting weights; and the test, which is applied to the input of the constructed neural network and is a means of checking the flexibility of the model to new data. The division of the initial data sample into three groups is carried out randomly, while the number of observations in the samples is specified directly or by default.

It is possible to build several neural network models by using the SNN package, train them and test them by applying various methods. As a result, you can choose the best model that gives the smallest error when testing it. The program has an Intelligent Problem Solver for this.

The input data for building the model are the "representative" indicators, calculated based on the financial statements of PJSC NKMZ. Using the SNN package, 21 neural network models are built (Table 1).

Table 1. Characterization of the quality of the neural network models that are selected for forecasting the assessment of the financial condition of PJSC NKMZ. Note: KM- (K-Means) – K-means algorithm; KN (K-Nearest Neighbour) – the K-nearest neighbourhood algorithm for determining the deviations (radii) of radial elements; PI (Pseudo-Invert) – least-squares optimization algorithm for a linear layer; BP – (Back Propagation) – error back propagation method; CG (Conjugate Gradient Descent) – method of descent on conjugate gradients.

Neural network model No.	Conventional designation of the network type	Number of input variables	Number of el. on the 1st hidden layer	Number of el. on the 2nd hidden layer	The size of the error for the training sample	The size of the error for the control sample	The size of the error for the tested sample	The quality of the forecasting results on the training sample	The quality of the forecasting results on the control sample	The quality of the forecasting results on the tested sample	Conventional notation of model training methods *
1	RBF	1	4	-	260.5609	0	0	1	0	0	KM, KN, PI
2	RBF	1	1	-	260.5598	0	0	1	0	0	KM, KN, PI
3	RBF	1	2	-	260.5588	0	0	1	0	0	KM, KN, PI
4	MLP	1	13	-	251.8562	0	0	1	0	0	BP0b
5	Linear	2	-	-	251.4344	0	0	1	0	0	PI
6	Linear	4	-	-	251.4344	0	0	1	0	0	PI
7	Linear	1	-	-	251.4344	0	0	1	0	0	PI
8	Linear	3	-	-	251.4344	0	0	1	0	0	PI
9	MLP	1	8	-	251.071	0	0	1	0	0	BP0b
10	MLP	1	13	-	250.7282	0	0	1	0	0	BP0b
11	MLP	5	4	-	0.465664	0.4687	0.4719067	0	0	0	BP0b
12	Linear	1	-	-	0.4343879	0.4516	0.4602771	0.6	0.7272727	0.6666	PI
13	Linear	2	-	-	0.2946665	0.4243	0.407391	0.9	0.9090909	0.8888	PI
14	Linear	3	-	-	0.2916238	0.4207	0.4009967	0.9	0.9090909	0.8888	PI
15	RBF	3	1	-	0.4245658	0.3962	0.3687923	0.5	0.7272727	0.6666	KM, KN, PI
16	MLP	2	1	-	0.2761606	0.3757	0.3369586	1	0.9090909	1	BP50, CG50
17	RBF	3	1	-	0.4399655	0.3621	0.3664763	0.4	0.9090909	0.8888	KM, KN, PI
18	Linear	4	-	-	0.2730227	0.2913	0.3026483	0.9	1	0.8888	PI
19	MLP	5	8	-	0.09257	0.2285	0.05967	1	0.9090909	1	BP50, CG12b
20	MLP	5	8	-	0.1142356	0.2159	0.07365	1	0.9090909	1	BP50, CG7b
21	MLP	4	7	-	0.008026	0.0707	0.001546	1	1	1	BP50

The smallest error is a multi-level perceptron with 4 elements on the input layer (Inputs) and 7 elements on the hidden layer (Hidden) (Figure 1). This model has 4 variables in the input layer, i.e., one variable has been excluded to improve the prediction quality. A model from which the capital turnover ratio is excluded is chosen for qualitative forecasting of the level of the financial condition of PJSC NKMZ.

The BP perceptron training method – (Back Propagation) – the method of reverse error propagation – is an effective training model for multilayer complex networks. This method is based on a steep descent approach that reduces the network error during the process of determining the synaptic weights.

DOI: 10.55643/fcaptp.6.53.2023.4224

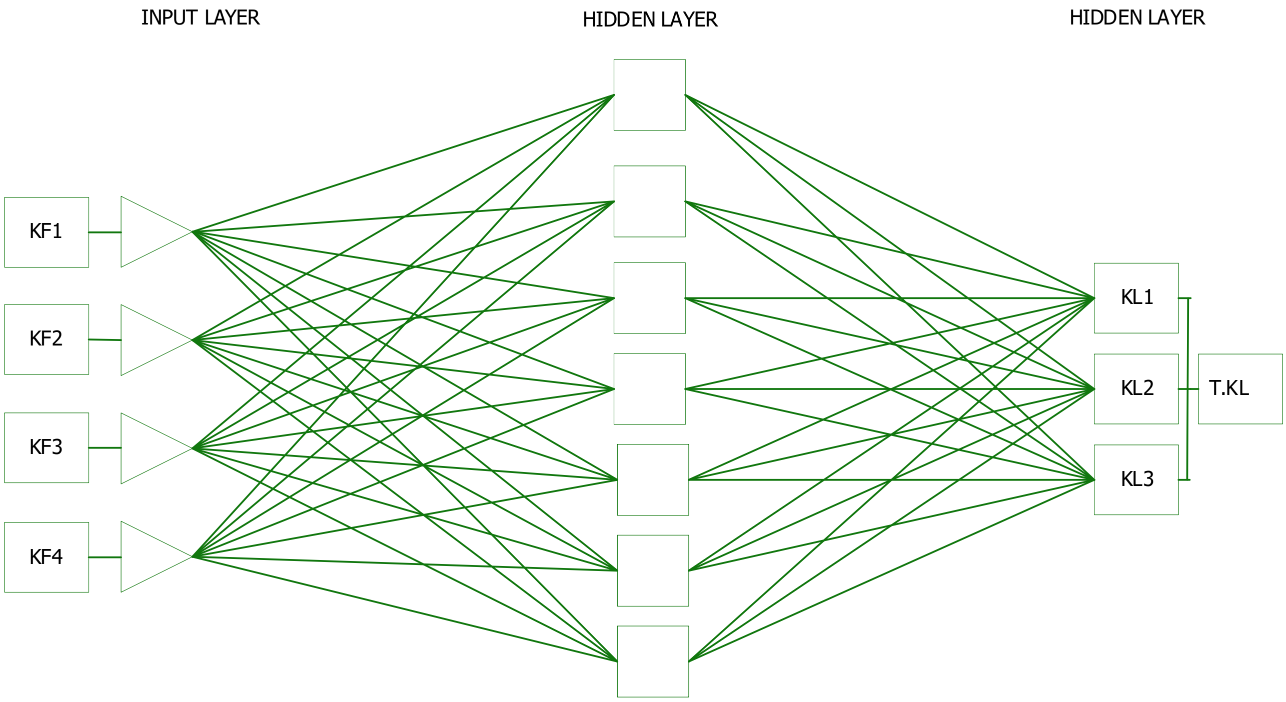

Figure 1. A view of the architecture of the multilayer perceptron model. Note: KF1 – quick liquidity ratio; KF2 – financial risk factor; KF3 – profitability of total assets; KF4 – equity turnover ratio; KL1 – unsteady financial condition; KL2 – normal financial condition; KL3 – steady financial condition; T. KL – class type by model.

The output data are the classes of the financial state of the enterprise: KL1 – Unsteady financial condition, KL2 – Normal financial condition, KL3 – Steady financial condition.

We analyze the statistics of the quality of recognizing the type of financial status of PJSC NKMZ (Table 2).

Table 2. Statistics of the quality of recognition of the multilayer perceptron.

Sample type	Training sample			Control sample			Test sample		
Class type	KL2	KL3	KL1	KL2	KL3	KL1	KL2	KL3	KL1
Total number of observations	4	3	3	0	3	5	0	3	2
Correctly classified	4	3	3	0	3	5	0	**3**	1
Incorrectly classified	0	0	0	0	0	0	0	0	**1**
Unclassified	0	0	0	0	0	0	0	0	0

According to the data in the Table, it can be seen that in the researched sample, 4 observations are assigned to the second class (normal financial condition), 3 observations – to the third class (steady financial condition) and 3 – to the first class (unsteady financial condition). In the control and the test sample, not a single observation is classified as a normal financial state.

One observation is misclassified in the test sample. Table 3 shows that one case was mistakenly assigned to the first class, but it belongs to the third.

Table 3. Analysis of the quality of recognition of a multilayer perceptron.

Sample type	Sample being trained			Control sample			Sample being tested		
Recognized class type	KL2	KL3	KL1	KL2	KL3	KL1	KL2	KL3	KL1
KL2	4	0	0	0	0	0	0	0	0
KL3	0	3	0	0	3	0	0	3	**1**
KL1	0	0	3	0	0	5	0	0	1

Using the built neural network model, it is possible to make a forecast of the level of the company's financial condition for the future. Table 4 presents the classification result using multilayer perceptron for new cases.

Table 4. Result of classification using multilayer perceptron for new cases.

Case No.	Quick liquidity coefficient (KF1)	Financial risk coefficient (KF2)	Return on aggregate assets (KF3)	Equity turnover coefficient (KF4)	Class type by model (T.KL)
1	-0.2	0.4	1.13	0.658	Steady financial condition
2	-0.3	0.5	1.5	0.758	Steady financial condition
3	-0.147	0.4578	1.758	0.857	Steady financial condition
4	0.582	-0.258	-0.956	0.358	Unsteady financial condition
5	1.187	1.548	0.842	-0.127	Steady financial condition
6	-0.4	0.5	1.7	1.3	Normal financial condition
7	-0.117	0.376	0.540	0.116	Steady financial condition
8	-0.3034	0.477	3.346	2.346	Normal financial condition
9	-0.2285	0.516	0.741	0.424	Steady financial condition
10	-0.6504	0.577	0.946	0.663	Steady financial condition

The given task refers to classification tasks, i.e., the constructed neural network allows classifying the financial condition of the engineering enterprise, depending on the entered input financial coefficients, which will be calculated in the future based on the financial statements of the enterprise. That is, using the data obtained with the help of the use of a neural network, it is possible to quickly and accurately classify the level of the company's financial condition for the reporting period.

A neural network is a tool that makes it possible to classify correctly the financial condition of an engineering enterprise. An accurately determined level of financial condition will help the management of the enterprise to assess trends in its functioning, determine the causes of the condition, and ways of development, and timely develop a financial recovery plan in case of diagnosing an unsteady condition.

DISCUSSION

The method of assessing the financial condition has already developed in world practice. The differences consist only in the predominance of certain methods of analysis and in the sequence of their application. Developments by domestic authors very often do not take into account the transitional state of the national economy and also do not meet the conditions of comprehensiveness of the assessment. The methodological recommendations proposed by the Ministries and departments also do not meet the conditions of the completeness of the analysis, modern complex conditions.

Analyzing such a common method of financial analysis as coefficient analysis, it is possible to highlight a number of its shortcomings. This method is grounded on the calculation of financial coefficients, which are calculated based on the data of the financial statements of enterprises, and the comparison of the calculated indicators with their critical values. However, the proposed limit values of financial coefficients cannot be applied to assess the financial condition of enterprises of various branches of the national economy. Since the capital structure of national enterprises has its own characteristics depending on their branch affiliation, the branching aspect must be taken into account when developing the assessment methodology.

In addition, there is a close relationship between financial coefficients, and the calculated indicators are static in nature. Many authors (Klebanova, Guryanova, Gvozdytskyi, 2018; Yelisieieva, Reshetniak, 2007) emphasize the imperfection of the method of coefficient analysis. Therefore, domestic and foreign economists suggest moving from the use of traditional methods of financial analysis to the use of modelling when assessing the financial condition of an enterprise.

Calculations of integral indicators and their comparison with critical values are proposed. On the one hand, this speeds up the analysis, on the other hand, we face the same problems as when applying the coefficient analysis method. All calculated

DOI: 10.55643/fcaptp.6.53.2023.4224

critical values, with which integral indicators are compared, are calculated either without taking into account the conditions of the national economy or without taking into account the sectoral specificities of business entities. Therefore, the critical values used in the economic literature in the process of calculating the integral indicator do not provide an objective assessment of the financial condition of the enterprise.

Thus, a comprehensive study of such a methodological problem, which takes into account the realities of the national economy, and the peculiarities of the functioning of economic entities under conditions of imperfect market relations, currently does not exist.

Therefore, in order to take into consideration all, the specified conditions, it is proposed to use neural network modelling for comprehensive diagnostics of the financial condition of engineering enterprises. This technique has undoubted advantages: firstly, in order to determine the financial condition of the engineering enterprise, it is not necessary to apply a boundary indicator that should take into account the branch affiliation of the organization, secondly, to build such a model, it is not necessary to determine the level of the financial condition class in previous time periods (as when building a predictive model based on statistical methods).

Thus, the proposed model for diagnosing the financial condition of an engineering enterprise based on the use of neural network modelling has great potential for application in modern economic conditions, as it is self-training and easily adapts to changes.

The presented model of financial status diagnostics has its limitations. Since the data for training the neural network model are calculated on the basis of the financial statements of an individual enterprise, in this case PJSC NKMZ, the diagnostic results can be applied only to this enterprise.

CONCLUSIONS

The created model for diagnosing the level of the financial condition of an engineering enterprise using neural networks is flexible and easily adaptable to the changing conditions of the external economic environment. Its application at the enterprise allows for enhancing the efficiency of its functioning due to timely information on the level of financial condition and prompt correction of current management actions in the direction of its improvement. Moreover, the assessment made with the help of the model for several new periods enables the enterprise to predict the deterioration of the situation in the future and to take the necessary measures to improve the financial situation.

The global task of the economy aiming at European integration is the preservation of the engineering industry since the products it manufactures are the basis for the functioning of other branches of the national economy. Therefore, the use of the presented model for diagnosing the financial condition allows the management of the engineering enterprise not only to assess the current level of the financial condition of the enterprise but also to predict its level for the future. This is very important because the current conditions of the national economy are constantly changing. Therefore, methods and models that enable the management of engineering enterprises to conduct timely and high-quality diagnostics of the financial condition are now in great demand. The use of the proposed neural network model allows predicting the onset of a critical state, applying all the necessary means to save the enterprise in advance.

The calculated level of the financial state of PJSC NKMZ for ten new cases allows the enterprise management to adjust its financial strategies and form a financial recovery plan, which makes it possible to reduce the level of financial threats that may cause its condition to deteriorate in the future.

In the future, it would be useful to build neural network models for financial state diagnostics for several large enterprises in the engineering industry of Ukraine and compare the results of the obtained estimates. It is possible to form a sample of these enterprises, which are representatives of the following sub-sectors: heavy engineering; general mechanical engineering; medium mechanical engineering; precision engineering; production of metal products and blanks; and repair of machines and equipment. It is advisable to use a neural network to classify the levels of financial conditions of the selected enterprises in the sub-branches of mechanical engineering and compare the results.

ADDITIONAL INFORMATION

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Validation: *Oksana Zakharova*
Investigation: *Tetiana Reshetnyak, Oksana Zakharova, Viktoriia Shashko, Inna Fomichenko*
Visualization: *Oksana Zakharova*
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DOI: 10.55643/fcaptp.6.53.2023.4224

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ДІАГНОСТИКА ФІНАНСОВОГО СТАНУ МАШИНОБУДІВНОГО ПІДПРИЄМСТВА НА ОСНОВІ ВИКОРИСТАННЯ НЕЙРОМЕРЕЖЕВОГО МОДЕЛЮВАННЯ

Метою роботи є проведення діагностики рівня фінансового стану машинобудівного підприємства за допомогою застосування нейромережевого підходу та надання прогнозу його рівня на майбутнє. У статті підкреслено важливість проведення діагностики фінансового стану підприємств України в сучасних умовах. Розглянуто методи традиційного фінансового аналізу. Підкреслено необхідність використання моделювання для підвищення якості й точності аналізу. Проведено аналіз існуючих моделей оцінки фінансового стану та банкрутства підприємств. Розглянуті різні типи моделей, що були розроблені вітчизняними й закордонними авторами: моделі, побудовані на основі багатофакторного дискримінантного аналізу, на базі методів нечіткої логіки та інші. Обґрунтовано використання нейромережевого моделювання для оцінки фінансового стану. Побудовано нейромережеву модель діагностики фінансового стану на основі фінансових даних машинобудівного підприємства. Для скорочення простору вхідних даних було запропоновано використання методу «центру тяжіння», за допомогою якого кількість вхідних змінних моделі було зменшено до п'яти. За допомогою потужного інструменту проведення нейромережевого моделювання (SSN) була побудована модель на базі багатошарового персептрону. Нейромережа була навчена методом Back Propagation. За допомогою моделі зроблено оцінку фінансового стану машинобудівного підприємства ПрАТ НКМЗ на 10 майбутніх періодів. Запропонований метод діагностики фінансового стану дозволить керівництву машинобудівного підприємства передбачити настання кризового стану та розробити план фінансового оздоровлення.

Ключові слова: фінансовий стан, банкрутство, багатофакторний дискримінантний аналіз, інтегральний показник, нечітка логіка, нейромережева модель

JEL Класифікація: G17