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RESEARCH OF FINANCIAL OBJECTS WITH USING OF ARTIFICIAL INTELLIGENCE APPARATUS

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Анотація

Штучний інтелект здатний обробляти великі обсяги інформації і виконувати рутинні дії, його впровадження дозволяє компаніям виключити «людський фактор», скоротити число аналітиків і менеджерів і протистояти шахрайству. Переваги штучного інтелекту численні і їх важко ігнорувати. У той же час, багато компаній, як і раніше, побоюються витрат часу і коштів, які будуть потрібні для застосування штучного інтелекту, а також можливих проблем із впровадженням штучного інтелекту в фінансові послуги. Проте, не можна вічно ухилятися від технічного прогресу, і якщо не зіткнутися з ним зараз, це може коштувати дорожче в довгостроковій перспективі. Штучний інтелект забезпечує більш швидку і точну оцінку потенційного позичальника при менших витратах, а також враховує широкий круг чинників, що призводить до прийняття більш обґрунтованого рішення на основі отриманих даних. Кредитний скоринг, що надається штучним інтелектом, заснований на більш складних і глибинних алгоритмах в порівнянні з тими, які використовуються в традиційних системах. Це допомагає кредиторам розрізняти заявників з високим ризиком неповернення коштів і тих, хто подав кредитну заявку, але не має великої кредитної історії. Об'єктивність є ще однією перевагою механізму зі штучним інтелектом.

Abstract

Artificial intelligence is capable to process large amounts of information and performing routine actions, its implementation allows companies to eliminate the "human factor", reduce the number of analysts and managers and resist fraud. The benefits of artificial intelligence are numerous and hard to ignore. At the same time, many companies remain cautious, fearing the time and expense it will take to deploy AI, and the potential challenges to integrating AI into financial services. However, you cannot shy away from technical progress forever, and if you do not face it now, it can cost more in the long run. Artificial intelligence provides a faster and more accurate assessment of a potential borrower at a lower cost, and also takes into account a wider range of factors, which leads to a more informed decision based on the obtained data. Credit scoring provided by artificial intelligence is based on more sophisticated and in-depth algorithms than those used in traditional systems. This helps lenders distinguish between applicants with a high risk of default and those who have applied for a loan but do not have an extensive credit history. Objectivity is another advantage of the AI engine.

Ключові слова: штучний інтелект, фінансовий стан підприємства, СППР, нечітка логіка, генетичні алгоритми, нейронні мережі.

Keywords: artificial intelligence, financial condition of the enterprise, DSS, fuzzy logic, genetic algorithms, neural networks.

Today, the production sphere makes high demands on the formalization of tasks to support effective decision-making. These problems arise when analyzing the financial condition of enterprises, investment design, tenders and more. The decision must be reasoned, objective, as errors in the conclusions can lead to loss or loss of profit. Given the diversity of financial processes, the multiplicity of financial stability indicators, it can be argued that this task is complex, and to solve it requires the creation of an automated expert system or decision support system with large-scale involvement of economic and mathematical methods and modern information technology.

There are now a large number of indicators for assessing financial and economic activities to determine and analyze the financial condition of the enterprise. Many methods have been developed to assess the financial condition of the enterprise. In the practice of financial analysis, a number of indicators are well known that characterize certain aspects of the current financial condition. These include indicators of liquidity, profitability, stability, capital turnover, profitability and more. Some standards are known for a number of indicators, which characterize their value positively or negatively. For example, when the company's own funds exceed half of all liabilities, i.e. the coefficient of autonomy is more than 0.5, then its value is considered "good" (respectively, when it is less than 0.5 - "bad"). But in most cases, the indicators assessed in the analysis, it is impossible to unambiguously normalize. This is due to the specifics of the economy, the current characteristics of existing enterprises, the state of the economic environment in which they operate.

There are methods that evaluate enterprises on a point system, in particular [1]. However, it is impossible to speak unequivocally about the optimality of such a technique, because the scoring system is designed largely conditionally, is not accurate, and a limited number of indicators are used for analysis.

There are also many models of anti-crisis planning of the enterprise, including the Forest model to assess the financial condition, Altman's assessment of the bankruptcy probability, the financial condition of the enterprise assessment on Beaver's indicators, etc. [2]. The disadvantage of these models is that they do not provide the financial condition of the enterprise comprehensive assessment, and therefore may be quite significant deviations from the forecast data from the real ones. It should also be noted that these models do not take into account the specifics of the Ukrainian market, because there is a difference in inflation and cycle phases, a different tax climate that needs to be adjusted.

Thus, in order to obtain a more objective the financial and economic condition of the enterprise assessment, it is necessary to create an effective assessment methodology.

Also relevant is the issue of calculation automation and the financial condition of the enterprise (FCE) evaluation [3]. To do this, the authors propose to use decision support systems (DSS), which allow for a more accurate and in-depth the financial condition of the enterprise analysis, speed up the decision-making process, reduce its risk.

DSS refers to human-machine systems that allow decision-makers to use objective and subjective data and knowledge to solve poorly structured problems. One of these is the central problem of financial management – the FCE assessment.

DSS fully searches for possible solutions and compares their options. Whereas the identification of goals, problems and the formation of criteria, as well as the choice of the final decision are left to the decision maker.

DSS allows you to analyze and suggest options for decision making. The decision-maker is responsible for making the decision, so he must anticipate all its possible consequences. If she has doubts or new factors that can be entered into the system and get a refined solution, the DSS re-performs the necessary calculations and offers a new solution.

A number of decision-making procedures automation with the help of DSS allowed to solve the following tasks on a computer:

1. Generate possible solutions;

2. Analyze the decision consequences;

3. To ensure the operation of the system with input data coming from other systems.

4. Display the set of input data on the set of output by formalizing the decision-making process on the basis of the appropriate mathematical apparatus.

Therefore, for the implementation of these problems there is a need to choose the optimal mathematical apparatus, taking into account the specifics of solving a particular financial problem. A common and effective approach to the identification of various objects in the DSS construction is the use of fuzzy logic, neural networks, genetic algorithms theories.

Using DSS is very important when conducting a financial analysis due to the need to make the most appropriate decision that can affect the profitability of the project. It is often necessary to make decisions with conflicting data with a high level of so-called "noise". This should be taken into account when creating financial support decision support systems. One way out of such a difficult situation is to use fuzzy logic.

Fuzzy logic is the most important feature of human thinking, it characterizes a person's ability to summarize information and highlight its main features necessary for making appropriate management decisions. Using fuzzy logic is effective where it is not possible to clearly formalize the input parameters, where the conclusions of experts made in verbal form prevail [4]. Based on this theory, methods of constructing computer fuzzy systems significantly expand the application of computers field. Recently, fuzzy control is one of the most active and effective research areas on the application of fuzzy set theory. Fuzzy management is particularly useful when technological processes are too complex to analyze using conventional quantitative methods, or when available sources of information are interpreted qualitatively, inaccurately, or indefinitely. It is experimentally proven that fuzzy control gives better results compared to those obtained with conventional control algorithms.

Using fuzzy sets to formalize DSS eliminates the need to consider all possible combinations of object evaluation parameters. This significantly simplifies the work of experts, and therefore make the development of such DSS cheaper. In addition, when identifying objects with many evaluation parameters, the number of which is several tens, rational decision-making taking into account all combinations of parameters becomes simply impossible, because the need to search at least n^k combinations (n = 2), where n is the number of terms, and k – is the number of evaluation parameters.

Thus, we propose to use the fuzzy sets apparatus to analyze the financial condition of the enterprise. Today, this branch of mathematics is developing rapidly, and the use of fuzzy sets in decision-making systems already has considerable economic benefits. The emergence of full-fledged statistics will return to the use of probabilities in risk analysis and at the same time improve the quality of fuzzy classification of financial parameters.

Consider the formation of input/output DSS parameters sets for the FCE evaluation. The set of evaluation parameters X should provide the formation of the following complex parameters: the set of quantitative indicators $Z=f(Y_1 ... Y_4)$ and qualitative $Y_5=f(x_1 ... x_4)$.

Quantitative characteristics are determined on the basis of indicators groups number, in particular: financial stability $Y_1 = f(x_1 ... x_4)$ (x_1 - coefficient of independence, x_2 - coefficient of dependence, x_3 - coefficient of financial risk, x_4 - coefficient of maneuverability); liquidity and solvency $Y_2 = f(x_5 ... x_9)$ (x_5 - monetary solvency ratio, x_6 - estimated solvency ratio, x_7 - liquidity solvency ratio, x_8 - critical liquidity ratio, x_9 - share of net working capital in current assets); business activity $Y_3 = f(x_{10} ... x_{18})$ (x_{10} - asset turnover ratio, x_{11} - receivables turnover ratio, x_{12} - accounts payable turnover ratio, x_{13} - inventory turnover ratio, x_{14} - fixed assets turnover ratio, x_{15} - turnover ratio, x_{16} - maturity of receivables;

x_{17} - maturity of accounts payable, x_{18} - duration of inventory turnover); profitability $Y_4 = f(x_{19} ... x_{22})$ (x_{19} - return on costs, x_{20} - return on sales, x_{21} - return on all assets, x_{22} - return on equity).

In turn, these estimated quantitative parameters are calculated based on the primary input parameters obtained from the financial statements.

The generalized qualitative indicator is a function $Y_5 = f(x_{23} ... x_{25})$ (x_{23} - professional abilities of the head of the enterprise, x_{24} - the level of motivation, x_{25} - advertising policy and experience of the firm).

In turn, these evaluative quality parameters are calculated using the primary input parameters obtained from experts.

Define the set of output parameters $O = \{O_1,..,O_s\}$.

Consider each of these O_j, $j = \overline{1,S}$ (S = 5) solutions: O_1 - excellent FCE; O_2 - normal FCE; O_3 - satisfactory FCE; O_4 - critical FCE; O_5 - unsatisfactory FCE.

For the estimation parameters x_1, ..., x_{25} we will use a single scale of linguistic terms: H - low, C - medium, B - high.

We construct membership functions with unregulated values a, a_1, a_2, c, c_1, d, d_1, b for each parameter separately (table 1).

Table 1.

Values of parameters a ... b for quantitative parameters x_1 ... x_{22}

x	**a**	**b**	**c**	**d_1**	**c_1**	**d**
x_1	0	1,0	0,3	0,6	0,4	0,7
x_2	0	1,0	0,3	0,6	0,4	0,7
x_3	0	4,0	0,7	2	1,0	2,5
x_4	-2	2,0	0,2	0,5	0,3	0,7
x_5	0	3,0	1,0	1,6	1,2	1,8
x_6	0	3,0	1,2	1,8	1,4	2,0
x_7	0	3,0	1,0	1,6	1,2	1,8
x_8	0	1,0	0,2	0,6	0,3	0,7
x_9	-3	1,0	0,2	0,5	0,3	0,6
x_{10}	0	4,0	1,0	2,5	1,5	3
x_{11}	0	12,0	3,0	7,0	4,0	8,0
x_{12}	0	12,0	3,0	7,0	4,0	8,0
x_{13}	0	10,0	2,0	6,0	3,0	7,0
x_{14}	0	3,0	0,8	2,0	1,0	2,2
x_{15}	0	2,0	0,5	1,2	0,7	1,5
x_{16}	0	1,0	0,2	0,4	0,25	0,5
x_{17}	0	1,0	0,2	0,4	0,25	0,5
x_{18}	0	1,0	0,2	0,4	0,25	0,5
x_{19}	-1	2,0	0,7	1,0	0,8	1,2
x_{20}	-1	1,0	0,35	0,55	0,45	0,65
x_{21}	-1	1,0	0,2	0,4	0,3	0,5
x_{22}	-1	2,0	0,7	1,0	0,8	1,2

For each linguistic term we define the membership function, based on the variants of functions given in [5]. The specificity of the selected quantitative parameters is that when these parameters change in a certain interval, the value of the function does not change, and outside this interval there is a nonlinear dependence. Thus, we obtain the membership functions of three fuzzy terms for the quantitative parameters x_1, ..., x_{22}, which are shown in Figs. 1.

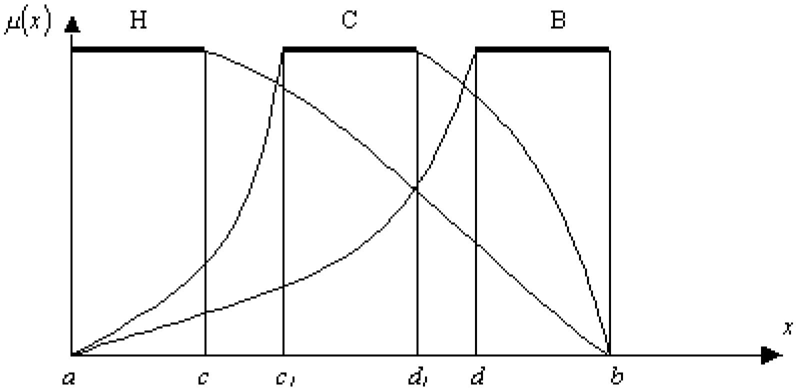

Fig. 1. Belonging functions of three fuzzy terms for quantitative parameters x_1 ... x_{22}

$$\mu^{н}(x)=\begin{cases}1, & x\in[a,c),\\ \left(\dfrac{b-x}{b-c}\right)^{0,8}, & x\in[c,b],\end{cases}\quad \mu^{c}(x)=\begin{cases}\left(\dfrac{x-a}{c_1-a}\right)^{1,2}, & x\in[a,c_1],\\ 1, & x\in(c_1,d_1),\\ \left(\dfrac{b-x}{b-d_1}\right)^{0,8}, & x\in[d_1,b],\end{cases}$$

$$\mu^{в}(x)=\begin{cases}\left(\dfrac{x-a}{d-a}\right)^{1,2}, & x\in[a,d],\\ 1, & x\in(d,b].\end{cases}$$

In these functions we take k = 1,2, l = 0,8 which bring them closer to the functional dependencies selected from real data and expert estimates. In particular, most indicators are growing faster than falling. Thus, if with the growth of the indicator its belonging to the middle level increases faster, then with the fall - belonging to the high level occurs at a slower rate.

Belonging functions for qualitative parameters are shown in Fig.2.

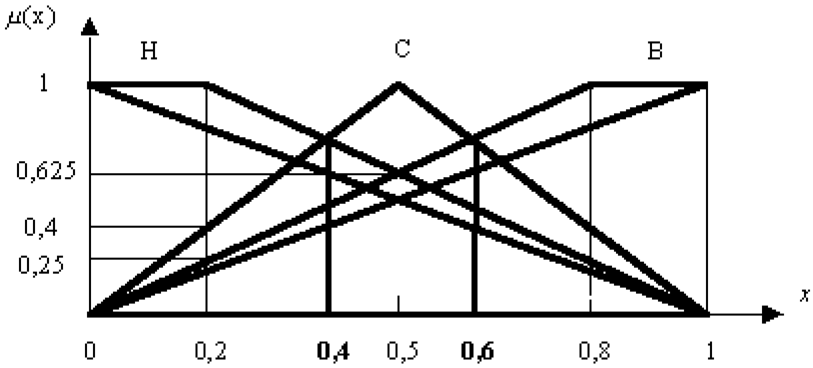

Fig. 2. Functions of belonging of qualitative parameters at t = 3

The whole values set of membership functions for t = 3 is summarized in table 2.

Table 2.

Values of membership functions for t = 3

Therm	$\mu^{н}(x)$	$\mu^{c}(x)$	$\mu^{в}(x)$
H	1	0,4	0,25
C	0,625	1	0,625
B	0,25	0,4	1

Using the information provided by banking experts in the field of financial management, we will compile appropriate knowledge matrices to assess the quantitative and qualitative characteristics of the FCE, as well as its final assessment (tables 3-5).

Table 3.

Knowledge matrix for quantitative indicators x_1 ... x_{22}

x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}	x_{11}	x_{12}	x_{13}	x_{14}	x_{15}	x_{16}	x_{17}	x_{18}	x_{19}	x_{20}	x_{21}	x_{22}	**Z**
H	B	B	H	H	H	H	H	H	H	B	B	H	H	C	C	B	B	H	H	H	H	**H**
H	B	C	B	H	H	H	C	C	H	C	C	H	C	C	B	B	C	H	H	H	H	
H	B	C	H	H	C	C	H H	H H	H	H	C	H	H	C	B	C	C	H	H	H	C	
H	B	B	B	C	H	H	C	C	H	H	H	H	H	H	C	B	B	C	H	C C	H	
H	B	C	B	C	C	H	C	C	H	C	C	H	C	C	B	B	C	C	H	H	H	
H	B	B	H	H	C	H	H H	H H	C	B	C	C	H	C	B	C	C	H	H	H	C	
C	C	C	B	C	H	H	C	H	C	B	C	C	C	C	C	C	C	C	C	C	C	**C**
C	H	C	H	C	C	B	H	H	C	H	C	C	H	C	C	C	H	C	C	C	C	
C	C	H	B	C	C	C	H	H	C	C	C	C	C	C	H	C	B	C	H	C	B	
C	B	C	H	C	C	C	B	B	C	H	C	C	H	C	C	C	H	C	C	B	C	
B	C	H	B	C	C	B	C	C	C	C	C	C	C	C	H	C	H	C	B	C	B	
C	H	C	C	C	C	B	C	C	C	B	C	C	C	C	H	C	H	C	C	B	B	
B	H	H	C	B	B	B	B	B	B	B	B	B	B	B	H	H	H	B	B	B	B	**B**
B	H	C	C	B	C	B	C	C	B	C	B	B	C	B	H	H	C	B	C	B	B	
B	H	C	C	C	C	B	C	C	B	C	B	B	C	B	C	H	H	B	B	B	C	
B	H	H	H	B	C	B	C	C	B	B	B	B	B	B	H	H	C	B	C	B	B	
B	H	C	B	C	B	B	C	C	B	B	C	B	B	C	H	C	C	B	C	B	C	
C	C	H	H	C	C	B	C	C	B	C	B	B	C	B	H	H	C	B	C	B	B	
C	C	H	B	C	B	C	C	C	B	B	C	B	B	C	H	C	H	B	B	B	C	

Table 4.

Knowledge matrix for qualitative indicators x_{23} ... x_{25}

x_{23}	x_{24}	x_{25}	Y_5
H	H	H	H
H	C	H	
C	H	H	
H	H	C	
H	C	C	C
C	H	C	
C	C	H	
C	C	C	
C	B	C	
C	C	B	
B	C	C	
C	B	B	B
B	C	B	
B	B	C	
B	B	B	

Table 5.

Knowledge matrix for the FCE assessment

Z	Y_5	O
B	B	O_1
C	B	O_2
B	C	
C	C	O_3
C	H	O_4
H	C	
H	H	O_5

Using the method given in [6], we describe these matrices of knowledge by logical equations that connect the membership functions of the variables Z, Y_5 and O_j.

In addition to traditional statistical methods, neural networks are used in financial analysis to formalize the decision support system.

Many mathematical models of a neuron can be created on the simple neuron construction concept basis. The so-called summing function combines all the input signals coming from the sending neurons. The value of such a union is a weighted sum, where the scales are synaptic powers. Excitatory synapses have a positive weight, and inhibitory synapses have a negative weight. To express the lower level of neuronal activation, compensation (offset) is added to the weighted amount.

The so-called activation function calculates the output signal of the neuron by the level of activity. The activation function is usually sigmoid. Other possible types of activation functions are linear and radially symmetric function.

Mathematically, neural networks can be considered as a class of statistical modeling methods, which in turn can be divided into three classes: estimation of probability density, classification and regression.

DSS can be fully implemented on a neural network. In contrast to the traditional use of such NM to solve only the problems of pattern recognition and formation, in DSS on the basis of neural networks coordinated tasks are solved: pattern recognition and formation; obtaining and storing knowledge (empirically found natural connections of images and influences on the object of control); evaluation of qualitative characteristics of images; decision-making.

DSS features based on neural networks are:

– redundancy of neurons in the network, necessary for the adaptation of the control system to the ever-changing living conditions that change, the object of control. As a result, for the practical implementation of the control system it is necessary to create large neural networks (for comparison, the human brain contains ~ 1011 neurons).

– neural networks consists of specific neurons that are closer analogues of a biological neuron and adapted to solve decision support problems.

The transfer functions of all neurons can change, and the scales are network parameters and cannot change. The DSS neural network selects those signals that have the maximum level. Further, those issuers that have the maximum signal level should be considered as data for processing by the genetic algorithm of the system.

Genetic algorithms are another interesting method of constructing a formalized DSS. They were developed based on the observation of processes that constantly occur in nature.

The main difficulties in applying classical methods for optimizing nonlinear functions are related to the problems of local extremum or "dimension curse". Attempts to overcome these problems have led to the creation of genetic algorithms theory that grow the optimal solution by crossing the original variants with subsequent selection by some criteria.

There are two main advantages of genetic algorithms over classical optimization techniques [7]:

1. The genetic algorithm has no significant mathematical requirements for the types of objective functions and constraints. The researcher should not simplify the model of the object, losing its adequacy. A variety of objective functions and types of constraints (linear and nonlinear) defined on discrete, continuous, and mixed universal sets can be used.

2. When using classical methods, the global optimum can be found only if the problem has the convexity property. At the same time, the evolutionary operations of genetic algorithms make it possible to effectively find the global optimum.

Genetic algorithms allow solving problems of forecasting, classification, finding the best solutions to problems. The specificity of the financial analysis tasks is the large arrays of expert data using, which determines the feasibility of using genetic algorithms to identify economic objects in the DSS construction. The use of genetic algorithms leads to a significant reduction in the time to find the optimal solution. A possible application of genetic algorithms is the models establishment that solves the problem of compiling different schedules, forecasting economic processes, designing complex systems and more.

CONCLUSIONS. Thus, when building decision support systems based on fuzzy sets, neural networks and genetic algorithms, we can conclude that the use of these technologies is a promising direction in the development of support systems and decision making. The possibilities of using such systems in the economy are unlimited at this stage of economic development and science and technology. Already today, there are neural network-based decision-making systems used by company financial managers to reduce risk when planning companies' financial activities. However, these systems have not yet been widely used in Ukraine. This is due to the imperfection of the financial market. But this does not mean that such systems will not find a worthy application in the domestic market.

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