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Illia Chikov

PhD in Economics, Senior Lecturer of the Department of Computer Science and Economic Cybernetics, Vinnytsia National Agrarian University, Vinnytsia, Ukraine;

ORCID: [0000-0002-2128-5506](https://orcid.org/0000-0002-2128-5506)

Oliha Khaietska

Candidate of Economy Sciences, Associate Professor, Head of the Department of Economics and Entrepreneurship, Vinnytsia National Agrarian University, Vinnytsia, Ukraine;

ORCID: [0000-0002-0262-1455](https://orcid.org/0000-0002-0262-1455)

Yuliia Okhota

PhD in Economics, Assistant of the Department of Administrative Management and Alternative Energy Sources, Vinnytsia National Agrarian University, Vinnytsia, Ukraine;

ORCID: [0000-0001-9943-2206](https://orcid.org/0000-0001-9943-2206)

Denys Titov

PhD in Economics, Senior Lecturer of the Department of Finance, Banking and Insurance, Vinnytsia National Agrarian University, Vinnytsia, Ukraine;

ORCID: [0000-0002-0112-6663](https://orcid.org/0000-0002-0112-6663)

Vyacheslav Prygotsky

Candidate of Legal Sciences, Associate Professor of the Department of Law, Vinnytsia University of Finance and Economics, Vinnytsia, Ukraine;

ORCID: [0000-0002-0790-0541](https://orcid.org/0000-0002-0790-0541)

Vitalii Nitsenko

D.Sc. in Economics, Professor of the Department of Entrepreneurship and Marketing, Ivano-Frankivsk National Technical Oil and Gas University, Ivano-Frankivsk, Ukraine;

e-mail: vitaliinitsenko@gmail.com

ORCID: [0000-0002-2185-0341](https://orcid.org/0000-0002-2185-0341)

(Corresponding author)

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MODELING OF THE SYNTHETIC INDICATOR OF COMPETITIVENESS OF AGRICULTURAL ENTERPRISES: A METHODOLOGICAL APPROACH TO THE USE OF NEURAL NETWORK TOOLS

ABSTRACT

The article is devoted to the development of a methodical approach to modelling a synthetic indicator of the competitiveness of agricultural enterprises using the tools of neural networks.

The authors used general scientific and special research methods, such as monographic, logical-theoretical, statistical and economic-mathematical, visualization, system analysis, taxonomy and neural network modelling, generalization, logical abstraction and conclusion generation. The study was based on materials from the State Statistics Service of Ukraine, scientific developments of foreign and domestic scientists on the defined topic, and financial statements of the agricultural enterprises of Vinnytsia region LLC «Ahrokompleks «Zelena dolyna», PJSC «Dashkivtsi», LLC «Selyshchanske», PE «Dary sadiv», PE «Fortuna» the main type of economic activity of which according to Classification of economic activities 01.11 – cultivation of cereals (except rice), legumes and oilseeds.

The article develops and presents a non-classical approach to the assessment of the competitiveness of agricultural enterprises has been developed, which is based on the principles of neural network modelling. It allows to obtain a well-founded quantitative indicator, which can be easily interpreted into a linguistic evaluation on a three-level scale of competitiveness and used for comparison, monitoring and making sound decisions on improving the competitiveness of agricultural enterprises.

The non-classical approach complements traditional methods of competitiveness assessment, expanding their capabilities and eliminating certain limitations. The use of neural network modelling in competitiveness assessment allows to take into account complex and non-linear relationships between different factors and indicators, which contributes to an increase in the objectivity and accuracy of competitiveness assessment, which in turn allows enterprises to make better decisions and improve their strategies to achieve success in the market.

The results of the study can be used to support strategic decision-making in the agricultural sector, identify priority development directions, and improve the competitive strategies of enterprises and the functioning of business processes.

Keywords: agricultural enterprises, synthetic indicator, competitiveness, neural networks, latent trait, modeling, linguistic assessment, Harrington scale

JEL Classification: C02, C53, C81, D24, O13

INTRODUCTION

In order for a company to be competitive, it must have an effective development strategy, a perfect production organization, highly qualified personnel, as well as the ability to quickly adapt to changes in the market and respond to new trends and challenges. Competitiveness is the main characteristic that reflects the compliance of economic entities with the requirements of the competitive environment, as well as their ability to

quickly respond and adapt to changes in the market situation. Information about a company's own level of competitiveness is important for awareness of the company's strengths and weaknesses in comparison with other market participants. This allows the management to focus on the company's readiness to expand sales markets, make decisions on optimizing business processes, develop programs for the implementation of innovative measures, etc. This implies the need for regular diagnostics of the competitiveness of an economic entity to form a "portrait" of the competitive advantages of the enterprise and competitors at a specific point in time.

LITERATURE REVIEW

Competitiveness is a multifaceted concept that can be viewed from different aspects. In particular, as an independent economic category, a market mechanism, an indicator of performance, an instrument of state policy, a factor of economic growth and a way to improve the quality of life, etc. This led to the fact that this problem was studied by scientists from different points of view. Thus, scientists (Kaletnik et al., 2020; Honcharuk et al., 2023; Tokarchuk et al., 2021; Sitkovska et al., 2019; Hranovska, 2016; Sumets et al., 2022a, 2022b; Lupenko et al., 2022a) have thoroughly investigated the issue of conducting effective entrepreneurial activity in the agricultural sector.

Scholars (Yankovyi, 2013; Khalimon, 2016; Matviichuk, 2010; Shved and Bila, 2017; Sakhno et al., 2023) pay considerable attention to the study of diagnostic issues of the level of efficiency of enterprises. Some researchers (Matviichuk, 2010; Honcharuk, 2020; Kharynovych-Yavorska, 2017; Yasynska and Ivchenkova, 2019; Semenets-Orlova et al., 2020; Demianchuk, 2022; Lupenko et al., 2022b) have studied the use of artificial intelligence methods in modelling the functioning of business processes.

To solve multidimensional problems, including the assessment of the level of competitiveness of enterprises, neural network modelling methods are often used (Honcharuk, 2020; Yasynska, and Ivchenkova, 2019; Yankovyi et al., 2019; Sazonets et al., 2020). According to the research of scientists (Soloviov, 2016), the method of neural network modelling allows for the creation of models of various architectures for forecasting performance indicators of agricultural production management at different levels of management. Also, as scientists (Matviichuk, 2010; Dvigun et al., 2022a, 2022b; Kvasha et al., 2019) note, the main advantages and features of using neural network modelling tools to build models for assessing the efficiency of economic systems are adaptability, flexibility and the ability to process large amounts of information.

Thus, the adaptability of models developed on the basis of neural network tools means that they can quickly react to unpredictable conditions and adapt to new data. Such models can independently change their internal parameters and structure to account for changes in input data caused by changes in the environment. That is, they are able to "learn" and adapt to the conditions of the external environment. This indicates that the model can be updated and improved over time, taking into account new factors affecting the competitiveness of the enterprise. This allows the model to work effectively in rapidly changing and uncertain conditions.

The flexibility of neural network models lies in their ability to adapt to different requirements and conditions, including different types of data, tasks, and contexts (Shteingauz et al., 2021; Andreichenko et al., 2021). The flexibility of the model is determined by its ability to work with different input parameters (including text and numerical information, images, and sound), change its architecture and parameters according to the needs of the task, and use different types of data for forecasting or modelling. This allows the model to assess the competitiveness of agricultural enterprises from different aspects of their functioning and take into account a wide range of factors, such as market trends, the activity of competitors, changes in consumer tastes, etc.

No less important feature of neural network models is their ability to efficiently process large amounts of data, which can be difficult to process using traditional methods (Kalina et al., 2022; Svyrydenko and Revin, 2022a, 2022b). This provides them with the ability to analyze information, make predictions, and model complex economic processes. Using such models allows to obtain a more complete understanding of the subject area, including the competitiveness of an enterprise based on a wide range of data.

The study of different aspects of competitiveness reflects its complexity and wide range of impact on different spheres of the economy and society. Highlighting the nature of competitiveness from different perspectives and researching its factors contributes to understanding its complexity and importance. The scientific works of scientists who study competitiveness in different spheres provide valuable conclusions and recommendations for achieving a high level of competitiveness in the agricultural sector and other sectors of the economy.

The results of the scientific work of Ukrainian scientists indicate significant progress in the field of research on effective entrepreneurial activity in the agricultural sector and diagnostics of the level of competitiveness of agricultural enterprises.

However, the issue of the application of neural network tools for assessing the competitiveness of agricultural enterprises is insufficiently researched and requires further research and development.

AIMS AND OBJECTIVES

The purpose of the article is to develop a methodological approach to modelling a synthetic indicator of the competitiveness of agricultural enterprises using neural network tools. To achieve the set goal, a number of tasks were formulated and solved, including:

- analyzing scientific works in the subject area and systematizing data in the field of evaluating the competitiveness of agricultural enterprises;
- describing the algorithm for using the tools of neural networks in modelling the indicator of the competitiveness of agricultural enterprises;
- providing a system of partial indicators of the competitiveness of agricultural enterprises and forming a structural model for assessing the competitiveness of agricultural enterprises according to the "input-output" principle;
- based on the described algorithm, a neural network model for assessing the competitiveness of agricultural enterprises was developed; based on the developed algorithm, the competitiveness of the studied agricultural enterprises in the Vinnytsia region was diagnosed;
- linguistic interpretation of the obtained data was carried out according to a three-level scale of competitiveness;
- formulated proposals and recommendations for the use of the developed methodological approach in practical situations.

METHODS

The authors used general scientific and special research methods, such as: monographic (in the analysis of scientific literature on the selected topic); logical-theoretical (in the formulation of scientific problems, development of hypotheses and their justification); statistical and economic-mathematical (in the processing of statistical data); visualization (for a visual demonstration of the results of the study); system analysis (in the formation of methodological foundations for assessing the competitiveness of agricultural enterprises); taxonomy and neural network modeling (in the development of a neural network model of the synthetic indicator of competitiveness of agricultural enterprises); generalization, logical abstraction and conclusion generation (in the formation of recommendations and conclusions based on the results of the study).

The information base of the study included materials from the State Statistics Service of Ukraine, scientific developments of foreign and domestic scientists on the defined topic, and financial statements of the investigated enterprise.

The subject-object base of the study was the entrepreneurial activity of agricultural enterprises in the Vinnytsia region LLC «Ahrokompleks «Zelena dolyna»», PJSC «Dashkivtsi», LLC «Selyshchanske», PE «Dary sadiv», PE «Fortuna» the main type of economic activity of which according to Classification of economic activities 01.11 – the cultivation of cereals (except rice), legumes and oilseeds.

RESULTS

The provision of food security at both the national and global levels depends on the functioning of the agricultural sector (Khaietska, 2022; Hutorov et al., 2021). The agricultural sector of the Ukrainian economy, despite the difficult conditions in which the country found itself (economic and political crises, variability of the external environment, the COVID-19 pandemic, and the military aggression from russia), continues to demonstrate a high level of operational stability (Zakharchuk et al., 2019; Koblianska et al., 2022; Chikov et al., 2022). According to the State Statistics Service of Ukraine, in 2021 the agricultural sector generated 10.63% of Ukraine's GDP, which amounts to 580.52 billion UAH (Figure 1) (State Statistics Service of Ukraine, 2021). This is the highest indicator among the components of GDP by the production method and confirms the thesis that the agricultural sector is one of the most important elements of the Ukrainian economy, capable of ensuring the country's stable economic development.

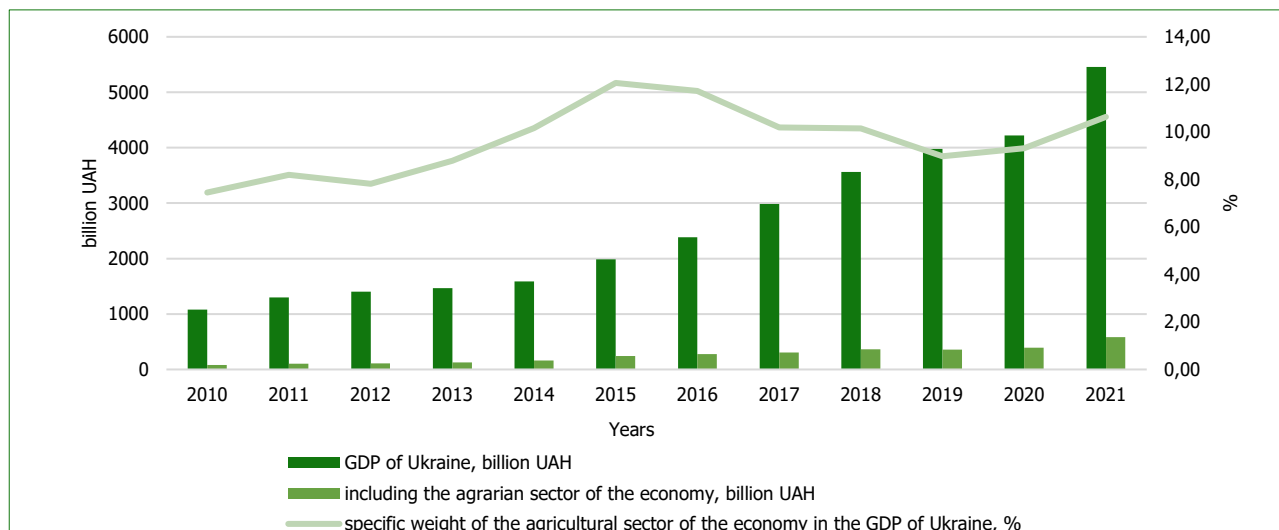


Figure 1. GDP dynamics and the share of the agricultural sector of the economy in the GDP of Ukraine, 2010-2021, % (Source: State Statistics Service of Ukraine, 2021)

In a world where international trade and global exchange are already commonplace, agricultural enterprises must be ready to compete not only in the domestic market but also on the international stage. This means that agricultural producers must improve their technologies, increase productivity, and also care about the quality and efficiency of production.

The diagnosis of the competitiveness of agricultural enterprises is becoming an integral part of the process of integrating the latter into the international field of relations. By analyzing financial indicators, productivity, resource utilization, and compliance with quality standards, agricultural enterprises can identify areas for improvement and optimization of their activities. Diagnosis helps to identify threats and opportunities that may affect their competitiveness in the future.

The diagnosis of the competitiveness of agricultural enterprises requires an assessment of various aspects of the system's functioning, including its capacity, resources, strategic management, innovative potential, etc. The assessment of complex systems in this context means creating a model that reflects the interaction of different components of the enterprise and allows to determine its level of competitiveness.

The greatest difficulty in assessing the competitiveness of agricultural enterprises is that their activities have a number of specific properties that do not allow the use of evaluation methods that are usually applied to enterprises of other types of activity. These features include external risks that enterprises are unable to control, such as climatic conditions, volatility of prices for seed material, fertilizers, pesticides, variability of prices for the sale of agricultural products, etc.

Assessment of the competitiveness of an enterprise is an extremely complex and multifaceted task that requires a deep assessment of a wide range of indicators that characterize different aspects of its activities and the interpretation of the results obtained. In general, the problem of diagnosing competitiveness lies in the lack of a single generally accepted methodical approach for its assessment. This is explained by a number of features: firstly, the approach to assessing competitiveness may differ depending on the size or specifics of the economic entity's activity, which entails both the formation of a radically different set of descriptive indicators and a change in the mathematical apparatus for processing these indicators; secondly, the approach to the assessment of competitiveness may differ depending on the object of research, for example, the assessment of competitiveness may be carried out in relation to products, enterprises, divisions, industries, etc.; thirdly, the sectoral features of the functioning of enterprises are taken into account. In this regard, a wide system of methods for assessing the competitiveness of enterprises has been developed, but none of them has been specifically adapted to assess the competitiveness of agricultural enterprises. Thus, some methods use complex mathematical models, with subjective assessments and limits of indicators, while in others, the interpretation of the resulting indicators largely depends on the expert's assessments, which makes it difficult to implement them in real conditions and raises doubts about the objectivity of the assessment results.

Regardless of whether the analysis is carried out of the entire economic system in general or of its individual component, the problem of determining a certain (synthetic) indicator that could characterize the level of its competitiveness depends on the processing of a significant array of indicators. Thus, the assessment of the competitiveness of agricultural enterprises is conditioned by the processing of not only generalizing indicators but also those that characterize individual component systems according to certain properties and aspects. In other words, a problem arises in the development of a

method of aggregation of evaluation indicators in accordance with the object of the study, while at the same time not violating the integrity of their connections with each other.

Complex systems, which are characterized by multidimensionality, non-linearity and the interaction of many factors, are often difficult to analyze without the use of models. Models allow for a deeper analysis of systems, including the interaction of various structural components; to reveal and study the properties, dynamics and behavior of these systems; understand how changes in some elements of the system can affect other components, as well as identify potential problems or relationships that may not be visible at first glance (Palamarchuk et al., 2021; Kryzhaniv's'kyi et al., 2020). In this context, modelling is a key tool for analyzing and predicting complex systems.

Evaluation of economic processes in modern changing conditions is impossible without the use of mathematical modelling methods and digital technologies (Chikov et al., 2022). Modelling is a complex and multi-criterion process of building a model of the studied subject area, which consists in creating simplified representations of real systems or processes that allow understanding their functioning, and interrelationships and predicting their behaviour under various development scenarios. It is worth noting that modelling the researched processes using economic and mathematical methods requires the researcher to have a clear idea of the structure of the model of the subject area.

When modelling the assessment of a subject area, researchers face a number of problems. First, it is difficult to determine a sufficient number of indicators to take into account all aspects of the enterprise's activity; secondly, there is a need and complexity of taking into account heterogeneous units of indicator values; thirdly, there is a moment of uncertainty associated with the problem of interpreting the results obtained.

All of the aforementioned problems force researchers to work on the development and implementation of new, more complex economic-mathematical models for the evaluation of socio-economic systems. This means developing models that would be able to adequately assess the efficiency of a company's operation, take into account the variety of values of indicators, and provide a clear interpretation of the results obtained.

The peculiarity of the competitiveness indicator is that it cannot be formed as an independent indicator for the characterization of the efficiency of the functioning of an economic entity, but only in relation to a specific object of market relations. Taking into account this peculiarity, the assessment of competitiveness involves the fixation of the results of the competitive struggle of the enterprise in the form of competitive advantages in comparison with competitors.

According to the position of scientists (Yankovyi, 2013; Khalimon, 2016; Horák et al., 2023) the indicator of competitiveness of an enterprise should be considered as a latent (hidden) characteristic of an enterprise, which does not have a single measure. Latent characteristics appear on the "surface" of economic phenomena in the form of a set of symptom factors - individual group indicators and/or partial indicators, which reflect different aspects of complex economic systems.

The feature of building models with latent variables is that the model is built on the hypothesis that some output latent variable I_i is an aggregated measure of a set of partial variables $\{x_1, x_2, \dots, x_n\}$ i.e. $I_i = \{x_1, x_2, \dots, x_n\}$ (Chikov, 2021; Qawaqzeha et al., 2023).

Thus, considering the competitiveness of an enterprise as a latent indicator, that is, a generalized indicator of a set of indicators at a lower level of the hierarchy, we propose to assess the level of competitiveness of agricultural enterprises using a synthetic indicator of enterprise competitiveness (SIEC).

As noted by Honcharuk (2020) and Perevozova et al. (2023) the analysis of the environment of functioning of economic systems in the absence of an adequate mathematical model requires the use of artificial intelligence methods. Taking into account the above, we propose to build a model of the competitiveness indicator using the synthesis of approaches of functional modelling, taxonomy methods and tools of neural networks. The specified indicator is the result of aggregation of indicators of a lower level of the hierarchy, which, in turn, are synthesized indicators of previously normalized partial criteria that characterize the efficiency of entrepreneurial activity. The proposed indicator shows the current level of financial and economic activity of the enterprise, which serves as a starting point for determining the vector of development of its activity.

To form a system of competitiveness indicators, it is advisable to use a system of fuzzy derivation of a hierarchical structure according to the "input-output" principle, in which the output from one set of data is the input for another – a higher level of the hierarchy (Figure 2).

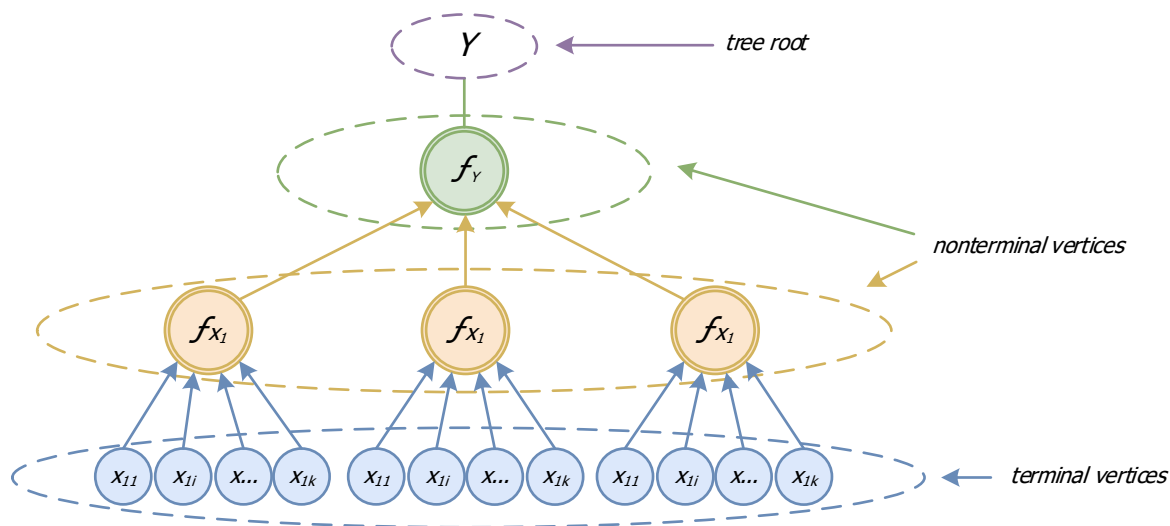


Figure 2. Hierarchical tree of logical inference.

To perform an analytical interpretation of a hierarchical model, we will use the principle of modularity of functional networks (subnetworks). It allows us to interpret the hierarchical model as a stream graph, in which each node of this graph can have a similar tree-like representation that corresponds to the hierarchical levels of detail of the labour processes. Accordingly, the model for assessing the competitiveness of an enterprise will be characterized by the following system of equations (Matviichuk, 2010) (1):

$$\begin{cases} X_1 = f_{X_1}(x_{11}, x_{1i}, \dots, x_{1k}) \\ X_2 = f_{X_2}(x_{21}, x_{2i}, \dots, x_{2k}) \\ \dots \\ X_n = f_{X_n}(x_{n1}, x_{ni}, \dots, x_{nk}) \\ Y = f_Y(X_1, X_2, \dots, X_n) \end{cases} \quad (1)$$

where X_n – group indicators of enterprise competitiveness (GIES); f_{x_n} – convolution function of partial criteria for the competitiveness of an enterprise x_{nk} ; Y – an overall indicator of the competitiveness of an enterprise; f_Y – convolution function of the overall competitiveness indicator of an enterprise.

We propose to model the synthetic indicator of the competitiveness of agricultural enterprises through a system of group indicators: G_{PC} – group property status indicator; G_L – group liquidity indicator; G_{FS} – group indicator of financial stability; G_{BA} – group indicator of business activity; G_P – group profitability indicator.

Based on the set of above-formed criteria, a direct assessment of the level of competitiveness of the studied enterprise is carried out. The model for assessing the competitiveness of an enterprise will have the following form (2):

$$I_{ec} = f_{I_{ec}}(G_{PC}, G_L, G_{FS}, G_{BA}, G_P) \quad (2)$$

where I_{ec} – a general integrated indicator of enterprise competitiveness.

Based on the above-formed systems of indicators and the structure of the hierarchical tree of logical inference, it is possible to present our own structure of the model for assessing the competitiveness of an enterprise (Figure 3).

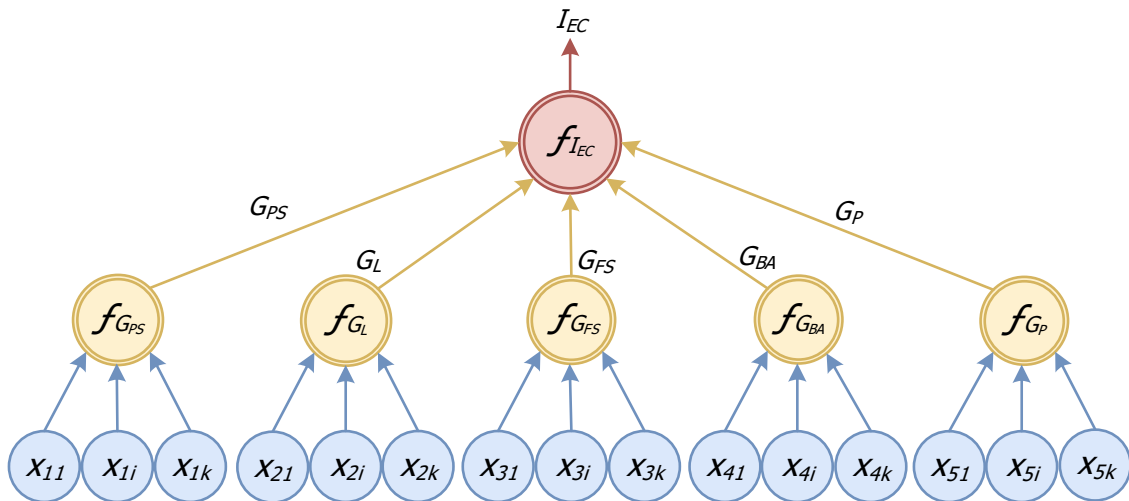


Figure 3. Structural model for assessing the competitiveness of agricultural enterprises.

The analytical model for assessing the competitiveness of agricultural enterprises, in turn, will have the following form (Chikov, 2021) (3):

$$\left\{ \begin{array}{l} G_{PC} = f_{G_{PC}}(x_{11}, \dots, x_{1k}) \\ G_L = f_{G_L}(x_{21}, \dots, x_{2k}) \\ G_{FS} = f_{G_{FS}}(\dots) \\ G_{BA} = f_{G_{BA}}(\dots) \\ G_P = f_{G_P}(x_{n1}, \dots, x_{nk}) \\ I_{ec} = f_{I_{ec}}(G_{PC}, G_L, G_{FS}, G_{BA}, G_P), \end{array} \right. \quad (3)$$

where G_i – group integral indicators of competitiveness of an agricultural enterprise; x_{nk} – partial performance criteria of the agricultural enterprise; f_{G_i} – the convolution function of partial criteria of an agricultural enterprise x_{nk} ; I_{ec} – a synthetic indicator of the competitiveness of an agricultural enterprise; $f_{I_{ec}}$ – the convolution function of the synthetic indicator of the competitiveness of an agricultural enterprise.

To build a model for calculating the integrated indicator of the competitiveness of agricultural enterprises, an approach similar to artificial neural network modelling (ANN) was chosen. Artificial neural networks are a set of mathematical tools that are based on simplified models of biological neural structures, with the help of which complex functional dependencies are implemented (Kriegeskorte et al., 2019; Gaman et al., 2022; Dankevych et al., 2023).

The most common type of neural network is a perceptron (Figure 4).

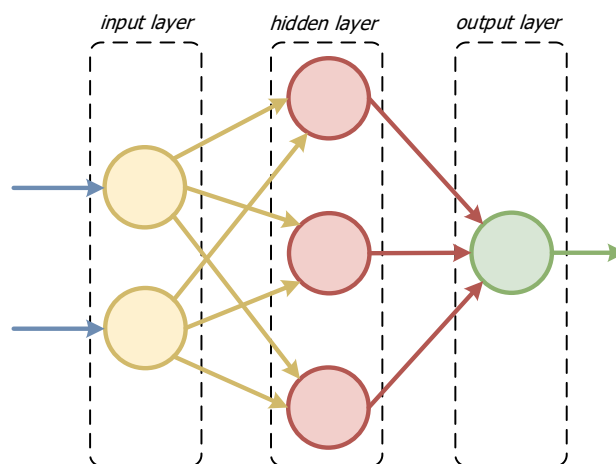


Figure 4. Perceptron-type neural network.

As can be seen from Figure 4, all neurons in a perceptron neural network are combined into layers – input, hidden and output layers of neurons. The input layer of neurons serves to receive input data, in the neurons of the hidden layer, the processing of input layer data occurs, and the last layer – the output, serves to output the results of the neural network.

Let's consider the general structure of a neural network in more detail (Figure 5). This neural network consists of three input neurons, one hidden neuron, and an output layer.

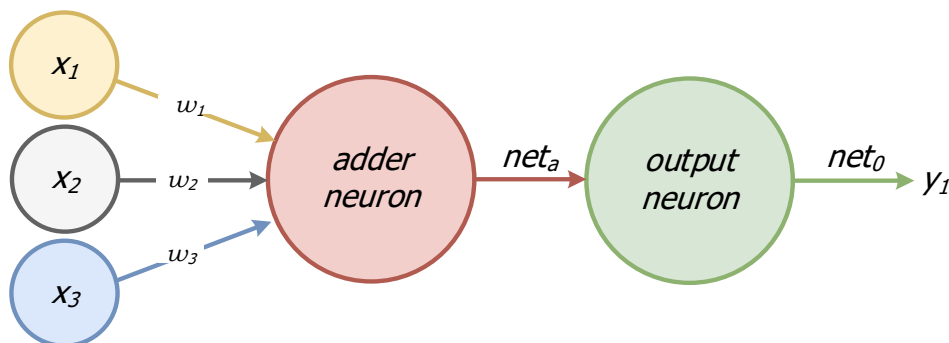


Figure 5. The basic structure of a neural network.

All neuron inputs have weighting coefficients – w_i , which are formed based on the input and output indicators x_i and y_i respectively. The adder neuron is calculated as a weighted sum of input data (4):

$$net_a = x_1 * w_1 + \dots + (x_i * w_i) \longrightarrow net_a = \sum_{i=1}^n x_i w_i \quad (4)$$

where net_a – the result of the adder neuron.

Processing in the output neuron, in turn, looks like this (5):

$$net_o = \psi(net_a) \quad (5)$$

where net_o – the result of the functional transformation of the adder neuron $\psi(\dots)$.

In the context of this scientific work, we will consider the issue of weighting factors in more detail. It is a well-known fact that not all partial criteria have the same effect on the resulting indicator, and if factor indicators are processed without their preliminary "weighting", an incorrect, in terms of economic justification, evaluation of the studied system will be obtained. This is explained by the fact that the partial criteria that make up the information base for calculating the synthetic indicator will affect the latter with the same force, that is, their influence will be balanced ($w_i = \frac{1}{n_i}$), which in socio-economic systems is not always a reflection of the real situation. Of course, there are cases where a balanced impact can occur, but on the condition that there is theoretical and experimental confirmation that the system is capable of functioning under the same impact of factor indicators.

Thus, understanding that the evaluation of the efficiency of the functioning of complex socio-economic systems is based on the definition of a certain generalizing indicator by processing a large number of partial criteria and that these indicators cannot have the same level of impact on the resulting indicator, the task arises of neutralizing the fact of their equilibrium action by introducing hierarchy coefficients (weights), which allow to distribute descriptive criteria by the level of strength of the impact of partial criteria on the integral indicator. In fact, we are talking about "weighing" the indicators.

Consider the concept of "weighting" indicators in the context of neural network modelling. Suppose there are three input neurons, each of which transmits a specific piece of information – a partial criterion. According to the number of input neurons, the same number of weight coefficients is formed, i.e. three. Based on the input indicators and their weight coefficients, the input information is "weighted" in the neuron (Figure 6).

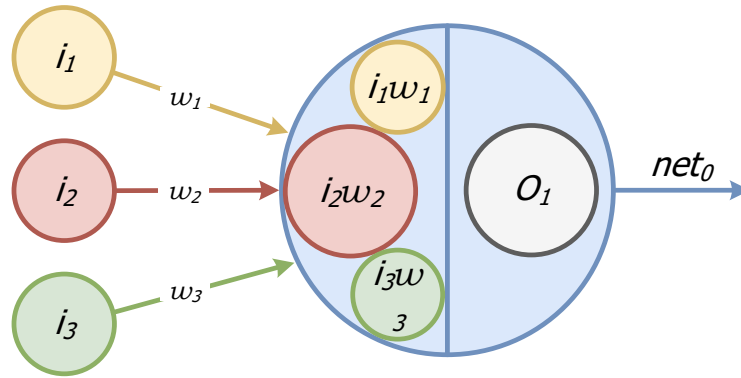


Figure 6. The principle of "weighting" indicators.

If the weight coefficient of a neuron that transmits information is greater than the rest, then such information will be dominant in the next neuron. Thus, the "weighting" process forms a vision of the level of importance of the indicators in the input data array.

It is worth paying special attention to the activation function of neurons. A fundamentally important step in modelling, which distinguishes the mathematical toolkit of neural networks from others, is the transformation of the output signal of the adder through the activation function to the result y_i , which is the desired output signal of the neural network.

The general model of neural activation can be represented by the expression (Jianli Feng et al., 2019) (6):

$$y = f_{activation}[\sum_{i=1}^n x_i w_i] \implies y = \psi[\sum_{i=1}^n x_i w_i], \quad (6)$$

A linear activation function is proposed for use as a neuron activation function in a model for assessing the competitiveness of agricultural enterprises. It allows to obtain the resulting signal in a wide range of values (depending on the input data). It is advisable to use it in regression tasks, i.e. when the output of the neural network is a continuous numerical value – $x_i \in R$. For example, forecasting a certain price, calculating the probable profit, determining the financial risk, calculating the integral indicator, etc., i.e. there will be any specific value that is the result of the task.

The equation of this function is given by the expression (7):

$$\psi(x) = x; x \in (-\infty; +\infty) \quad (7)$$

The output of this activation function will be proportional to the input argument, i.e., the output of the neuron *output* will be equal to the output of the neuron *adder_n* (8):

$$output_n = adder_n \quad (8)$$

It is worth noting that a linear activation function is not recommended to be applied to more than one layer of a neural network, otherwise, the non-linearity will be lost. If all layers use a linear activation function, then the output of the network will be a linear combination of the inputs, which limits the power and flexibility of the model in solving complex tasks.

It should be noted that the evaluation of an economic system is usually based on a system of indicators with different data measurements. In this case, all input indicators must be brought to a single type – to normalize the indicators, which will improve the accuracy of the calculation.

In economic theory, there are two types of indicators: indicator-stimulator, the growth of which leads to an improvement in the state of the system, and indicator-disincentives, the growth of which leads to a deterioration in the state of the system. For the indicator-stimulator, normalized indicators are determined by the min-max method, which is presented below (Vdovenko, et al., 2021; Koliadenko et al., 2021) (9):

$$z_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (9)$$

where z_i – normalized indicator; x_i – initial input value; x_{min} – the minimum value of the i indicator of the studied sample; x_{max} – the maximum value of the i indicator of the studied sample.

The calculation of normalized indicator disincentives is carried out using the inverse min-max method (Vdovenko, et al., 2021; Koliadenko et al., 2021) (10):

$$z_i = \frac{x_{max} - x_i}{x_{max} - x_{min}} \quad (10)$$

It is worth noting that the mathematical apparatus for normalization of indicators transforms the initial values into a dimensionless form in the range of $z_i \in [0; 1]$. In such situations, it is possible that the normalized indicator will be equal to zero, which can cause an error in further calculations, therefore, to avoid this case, we suggest using modified normalization methods. Normalized indicators in this case will be in the range of $z_i \in [1; 2]$ (Chikov, 2021) (11, 12):

$$z_i = 2 * \frac{x_i - x_{min}}{x_{max} - x_{min}} - 1, z_i \in S_{i,k}, \quad (11)$$

$$z_i = 2 * \frac{x_{max} - x_i}{x_{max} - x_{min}} - 1, z_i \in D_{i,k} \quad (12)$$

From a methodological point of view, it is advisable to form two subsets of indicators before normalization – a subset of indicator stimulators and a subset of indicator disincentives. This will make it possible to optimize the normalization process by parallel transmission of entire arrays of learned sorted values to the normalization block, which will make it possible to significantly reduce the data processing time (13):

$$\begin{aligned} NX_{x_i} &= \{S_{i,k} \cup D_{i,k}\} \\ S_{i,k} &= \{i_k \mid k = \overline{1, m}\} \\ D_{i,k} &= \{i_k \mid k = \overline{1, n}\} \end{aligned} \quad (13)$$

where NX_{x_i} – set of standardized indicators x_i ; $S_{i,k}$ – a subset of the standardized i indicator-stimulator of the k group; $D_{i,k}$ – a subset of the standardized i indicator-disincentives of the k group.

As mentioned above, group integral indicators are the result of a functional convolution of partial criteria of the enterprise activity. To determine the group integral indicators G_i , it is necessary, first, to normalize the array of input data; secondly, to perform a "convolution" of indicators into a single indicator.

Solving the issue of input data normalization, we suggest integrating the normalization neuron into the hidden layer of the neural network model. The normalization model of input indicators will have the form of a simple single-layer neural network of the perceptron type, which consists of input, hidden (normalization layer) and output layers (Figure 7).

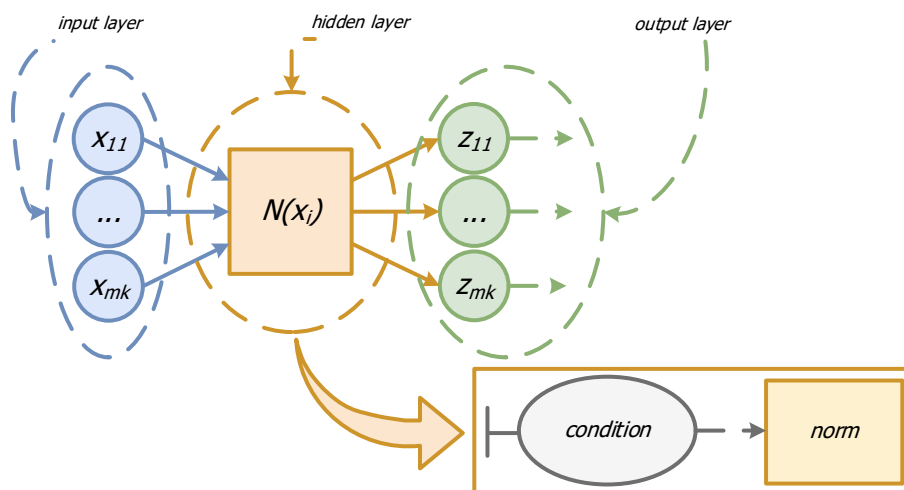


Figure 7. Indicator normalization model. * Note: * - the normalization model is shown in the example of the first group of input indicators

In classical methods, where data normalization is performed before it is fed into a neural network, in the proposed unconventional approach, the normalization model is integrated directly into the hidden layer of the network. This significantly reduces the time required to process input data and contributes to more efficient use of resources during model training and prediction.

The input layer of the neural network model stores the primary data x_i necessary for calculating the enterprise competitiveness indicator, they pass through the normalization neuron $N(x_i)$ in the hidden layer, and the normalized data z_i is obtained at the output.

This, the proposed non-classical integration of the normalization model serves to bring the input indicators, which have different units of measurement, to the dimensionless form of the indicators, thereby rejecting the fact of the dominance of some indicators over others, increasing the accuracy of the calculation.

As shown in the figure, structurally, the normalization neuron consists of two blocks: condition i norm. First of all, it is worth paying attention to block conditions. As mentioned above, there are two types of indicators – stimulators and disincentives, therefore, before normalization, this block determines the type of the input indicator.

After defining the type of indicators, the indicators are directly normalized in the block norm. The logical model of the normalization neuron can be analytically represented as follows (14):

$$\begin{bmatrix} x_{11} \\ \dots \\ x_{mk} \end{bmatrix} \rightarrow x_i^\uparrow \vee x_i^\downarrow \rightarrow \begin{bmatrix} \frac{x_i - x_{min}}{x_{max} - x_{min}} \uparrow \vee \frac{x_{max} - x_i}{x_{max} - x_{min}} \downarrow \\ \dots \\ \dots \end{bmatrix} = \begin{bmatrix} z_{11} \\ \dots \\ z_{mk} \end{bmatrix} \quad (14)$$

where, $x_i^\uparrow, x_i^\downarrow$ – input data (indicator-stimulator and indicator-disincentives).

The next component of the neural network is the processing of normalized indicators, and the definition of group indicators – G_i . The method of functional convolution of processing neurons makes it possible to aggregate a large number of indicators without reducing the accuracy of the calculations, which undoubtedly has a positive impact on the variability of the input indicators.

The calculation model is shown in Figure 8.

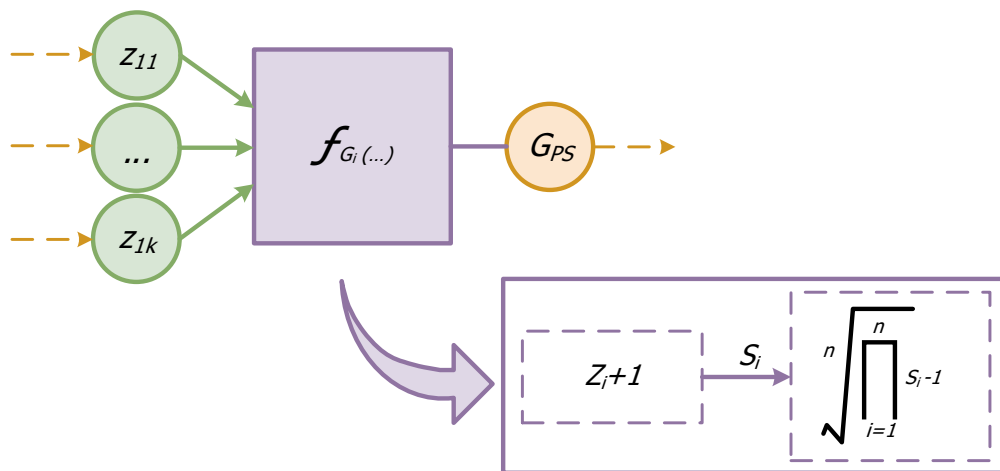


Figure 8. Model of the calculation of GII with normalization neuron*. Note: * the model is depicted on the example of the calculation of the group indicator of property status G_{PS}

As in the previous model, the processing neuron is proposed to be divided into two blocks:

1. the first block performs pre-processing of normalized data $s_j = z_j + 1$. This ensures that zero values of partial normalized indicators do not lead to calculation errors in the future. It is worth noting that this action is valid if normalization was performed using formulas (9) and (10). When using the modified approach (11) and (12), this step is ignored;
2. in the second block, a functional convolution of previously calculated indicators is performed, thereby determining the group indicators G_i (15):

$$G_i = \sqrt[n]{\prod_{i=1}^n s_i} - 1 \quad (15)$$

After the calculation of the group indicators, their weight coefficients are determined. Fishburn's method was selected for the calculation of the weight coefficients, which is one of the ranking methods. According to the tools of this method, ranking is based on statistical characteristics, which increases the accuracy of forecasting and excludes the factor of subjectivity compared to other methods of determining the weights of indicators, where expert assessment methods are used. The method allows to determine the weight coefficients if certain information is known about the studied indicators.

To determine the level of weighting of group indicators G_i , each group of indicators $x_i (i = \overline{1, m})$ is assigned a certain rating (rank) $r_i (i = \overline{1, m})$ in accordance with the magnitude of the values of the indicators themselves. An element assigned rank "1" has the highest significance, and conversely, an element assigned rank m – has the lowest level of impact. Next, the studied elements are arranged in order of decreasing rank by building a descending arithmetic progression and determining the weight coefficients according to the following system of equations (16):

$$\begin{cases} x_1 > x_2 > \dots > x_i > \dots > x_n \\ w_i = \frac{2(n-i+1)}{n(n+1)}, i = \overline{1, n} \end{cases} \quad (16)$$

where w_i – the weight of the studied element, n – the number of studied elements, i – the rank of the individual researched element.

The general algorithm for calculating the weighting coefficients is presented in Table 1.

Table 1. Algorithm for determining the weights of GII groups by Fishburn's method. (Source: Zachosova, 2019)														
Step number	Description of the steps of "weighting" indicators	Analytical interpretation												
Step 1	Ranking of the investigated indicators	<table border="1"> <tr><td>G_i</td><td>Rank</td></tr> <tr><td>G_1</td><td>a_1</td></tr> <tr><td>G_2</td><td>a_2</td></tr> <tr><td>...</td><td>...</td></tr> <tr><td>G_i</td><td>a_i</td></tr> <tr><td>G_n</td><td>n</td></tr> </table>	G_i	Rank	G_1	a_1	G_2	a_2	G_i	a_i	G_n	n
G_i	Rank													
G_1	a_1													
G_2	a_2													
...	...													
G_i	a_i													
G_n	n													
Step 2	Construction of a decreasing arithmetic progression	$G_1 > G_2 > \dots > G_i > G_n$												
Step 3	Determining the weights of indicators	<table border="1"> <tr><td>G_i</td><td>w_i</td></tr> <tr><td>G_1</td><td>w_{K_1}</td></tr> <tr><td>G_2</td><td>w_{K_2}</td></tr> <tr><td>...</td><td>...</td></tr> <tr><td>G_i</td><td>w_{K_i}</td></tr> <tr><td>G_n</td><td>w_{K_n}</td></tr> </table>	G_i	w_i	G_1	w_{K_1}	G_2	w_{K_2}	G_i	w_{K_i}	G_n	w_{K_n}
G_i	w_i													
G_1	w_{K_1}													
G_2	w_{K_2}													
...	...													
G_i	w_{K_i}													
G_n	w_{K_n}													

The final step is to define the synthetic indicator of enterprise competitiveness (SIEC). Figure 9 shows the module of the neural network model for determining the competitiveness indicator of agricultural enterprises.

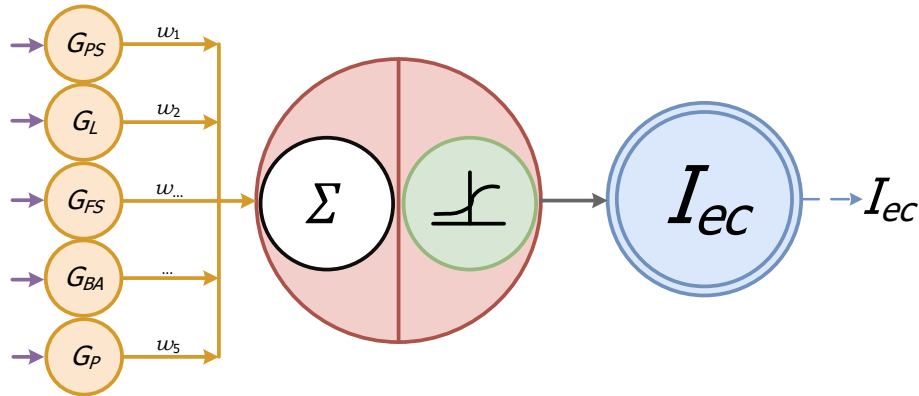


Figure 9. Neural network for assessing the competitiveness of agricultural enterprises.

The input layer of the model consists of G_i group integral indicators and their weighting coefficients w_i . The model for determining the synthetic indicator of competitiveness will be presented as follows (17):

$$I_{ec} = \psi_{linear}[\sum_{i=1}^n G_i w_i], I_{ec} \in [0; 1] \quad (17)$$

where I_{ec} – SIEC; $\psi_{linear}(\dots)$ – linear activation function; G_i – group integral indicators; w_i – weighting coefficients of group integral indicators of i group.

To summarize the above, the neural network model for determining the overall integrated indicator of competitiveness of agricultural enterprises is shown in Figure 10.

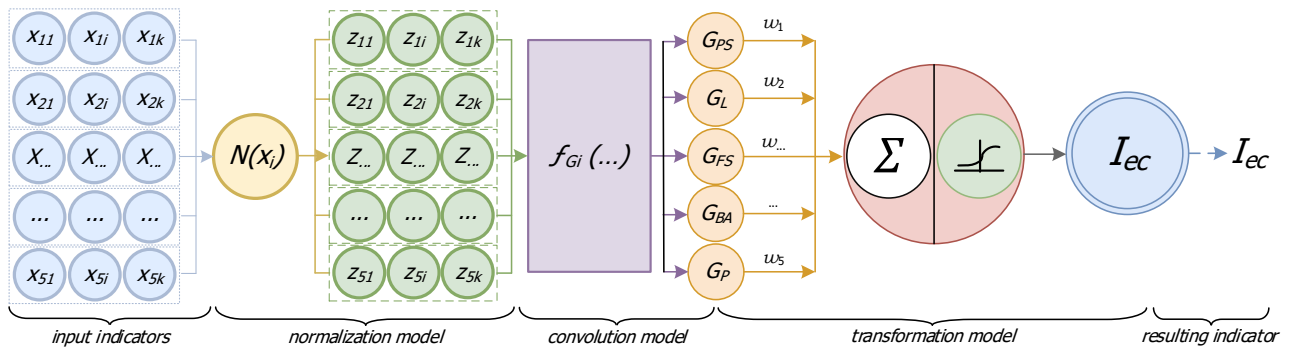


Figure 10. Determining SIEC model.

To reduce the load on the computing device, structurally, a neural network can be considered as a set of “partial” neural networks, each of which is assigned the “task” of calculating group integral indicators. The result of the work of “partial” neural networks is an array of G_i values and their weighting coefficients w_i – they are input data for a transformation model, the output of which is a certain quantitative value – a synthetic indicator of competitiveness.

The calculations of the synthetic indicators of competitiveness of the enterprise were made on the basis of the financial statements of LLC “Ahrokompleks “Zelena dolyna”, which specializes in the cultivation of cereals (except rice), legumes and oilseeds.

Here is the algorithm for calculating the group indicators of the asset condition of $G_{\{PC\}}$ LLC “Ahrokompleks “Zelena dolyna” in 2022. It will look like this (18):

$$G_{PC}^{2022} = \sqrt[n]{\prod_{i=1}^n z_i} - 1 = \sqrt[4]{1,326 * 1,996 * 0,976 * 0,916} - 1 = \sqrt[4]{2,366} - 1 = 1,240 - 1 = 0,240 \quad (18)$$

The remaining group indicators of competitiveness of the studied agricultural enterprises for 2015-2022 were calculated using a similar formula (Table 2).

Table 2. Group indicators of competitiveness of the agricultural enterprises of Vinnytsia region, 2015-2022.

GIES	Years								Deviation 2022 / 2015, +/-
	2015	2016	2017	2018	2019	2020	2021	2022	
LLC «Ahrokompleks «Zelena dolyna»»									
G_{PS}	0.090	0.527	0.292	0.373	-0.245	-0.328	0.126	0.240	0.150
G_L	0.135	0.934	0.538	0.562	0.499	0.361	0.424	0.410	0.275
G_{FS}	0.238	0.590	0.584	0.506	0.374	0.436	0.542	0.352	0.114
G_{BA}	0.472	0.688	0.556	0.442	0.396	0.228	0.223	0.229	-0.243
G_P	0.899	0.939	0.752	0.259	0.026	0.036	0.221	0.311	-0.588
PJSC «Dashkivtsi»									
G_{PS}	0.661	0.556	0.768	0.254	-0.124	0.554	0.560	0.411	0.222
G_L	0.409	0.333	0.321	0.334	0.420	0.402	0.423	0.395	0.036
G_{FS}	0.487	0.150	0.334	0.537	0.589	0.449	0.570	0.517	-0.078
G_{BA}	0.811	0.306	0.680	0.265	0.367	0.195	0.169	0.226	-0.307
G_P	0.781	0.057	0.479	0.333	0.266	0.260	0.576	0.601	-0.685
LLC «Selyshchanske»									
G_{PS}	0.412	0.326	0.318	0.682	0.332	0.383	0.203	0.325	0.028
G_L	0.430	0.508	0.350	0.439	0.286	0.293	0.141	0.215	0.126
G_{FS}	0.416	0.490	0.448	0.253	0.196	0.291	0.305	0.332	0.035
G_{BA}	0.932	0.471	0.017	0.512	0.333	0.290	0.469	0.591	-0.379
G_P	1.000	0.592	0.024	0.482	0.045	0.070	0.267	0.326	-0.313
PE «Dary sadiv»									
G_{PS}	0.404	0.450	0.327	0.068	0.018	0.393	0.282	0.325	-0.080
G_L	0.452	0.356	0.177	0.143	0.059	0.079	0.068	0.087	-0.365
G_{FS}	0.384	0.436	0.455	0.513	0.094	0.104	0.157	0.152	-0.232
G_{BA}	0.154	0.071	0.485	0.365	0.283	0.470	0.486	0.349	0.195
G_P	0.404	0.450	0.327	0.068	0.018	0.393	0.282	0.325	0.047
PE «Fortuna»									
G_{PS}	0.430	0.453	0.387	0.176	0.091	0.423	0.359	0.385	-0.045
G_L	0.454	0.403	0.284	0.255	0.164	0.190	0.176	0.199	-0.255
G_{FS}	0.419	0.446	0.456	0.484	0.208	0.218	0.268	0.263	-0.155
G_{BA}	0.258	0.180	0.471	0.408	0.359	0.463	0.471	0.399	0.141
G_P	0.311	0.445	0.239	0.311	0.310	0.370	0.406	0.344	0.033

Using the obtained group indicators, their weighting factors and synthetic indicators of the agricultural enterprise's competitiveness were determined. To illustrate the work of the algorithm for calculating synthetic indicators of the competitiveness of agricultural enterprises (17), we will provide the calculation of this indicator for the studied agricultural enterprises of the Vinnytsia region in 2022:

1. LLC «Ahrokompleks «Zelena dolyna»»:

$$I_{ec}^{2022} = \left[\frac{0.032_{G_{PS}}}{(0.240 * 0.133)} + \frac{0.137_{G_L}}{(0.410 * 0.333)} + \frac{0.094_{G_{FS}}}{(0.352 * 0.267)} + \frac{0.015_{G_{BA}}}{(0.229 * 0.067)} + \frac{0.062_{G_P}}{(0.311 * 0.200)} \right] = \mathbf{0.340}$$

2. PJSC «Dashkivtsi»:

$$I_{ec}^{2022} = \left[\frac{0.082_{G_{PS}}}{(0.411 * 0.200)} + \frac{0.053_{G_L}}{(0.395 * 0.133)} + \frac{0.138_{G_{FS}}}{(0.517 * 0.267)} + \frac{0.015_{G_{BA}}}{(0.226 * 0.067)} + \frac{0.200_{G_P}}{(0.601 * 0.333)} \right] = \mathbf{0.488}$$

3. LLC «Selyshchanske»:

$$I_{ec}^{2022} = \left[\frac{0.043_{G_{PS}}}{(0.325 * 0.133)} + \frac{0.014_{G_L}}{(0.215 * 0.067)} + \frac{0.089_{G_{FS}}}{(0.332 * 0.267)} + \frac{0.197_{G_{BA}}}{(0.591 * 0.333)} + \frac{0.065_{G_P}}{(0.326 * 0.200)} \right] = \mathbf{0.408}$$

4. PE «Dary sadiv»:

$$I_{ec}^{2022} = \left[\frac{0.087_{G_{PS}}}{(0.325 * 0.267)} + \frac{0.006_{G_L}}{(0.087 * 0.067)} + \frac{0.020_{G_{FS}}}{(0.152 * 0.133)} + \frac{0.116_{G_{BA}}}{(0.349 * 0.333)} + \frac{0.087_{G_P}}{(0.325 * 0.267)} \right] = \mathbf{0.316}$$

5. PE «Fortuna»:

$$I_{ec}^{2022} = \left[\frac{0.103_{G_{PS}}}{(0.385 * 0.267)} + \frac{0.013_{G_L}}{(0.199 * 0.067)} + \frac{0.035_{G_{FS}}}{(0.263 * 0.133)} + \frac{0.133_{G_{BA}}}{(0.399 * 0.333)} + \frac{0.069_{G_P}}{(0.344 * 0.200)} \right] = \mathbf{0.353}$$

The same formula (17) was used to calculate the competitiveness indicators of the studied agricultural enterprises for the remaining periods.

Thus, based on the financial reporting data of the agricultural enterprises in the Vinnytsia region, synthetic indicators of competitiveness of the agricultural enterprises were determined for 2015-2022 (Figure 11).

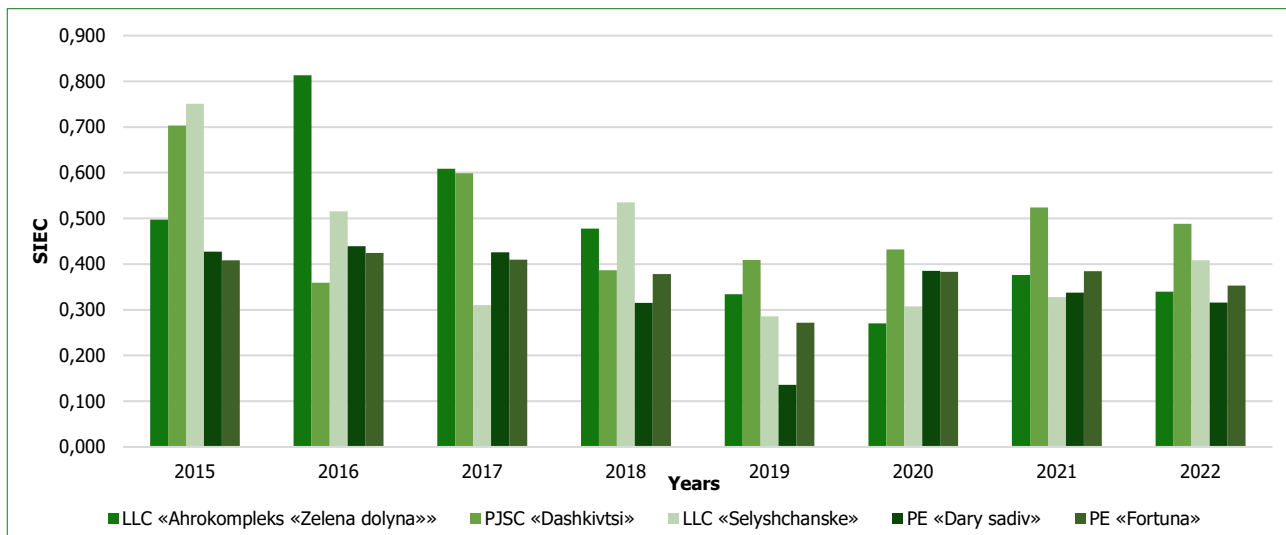


Figure 11. Dynamics of synthetic indicators of competitiveness of the agricultural enterprises of the Vinnytsia region, 2015-2022.

For the interpretation of the values obtained as a result of the model's work, it is proposed to use the Harrington psychophysical scale (Kalinkin, 2014). It provides an opportunity to establish the correspondence between quantitative and psychological parameters during the study of a particular system. It is worth noting that quantitative parameters refer to the characteristics of the studied object that are obtained in the process of research, in our case, this is a synthetic indicator of the competitiveness of enterprises, and psychological parameters refer to a certain linguistic assessment that corresponds to a certain level of a particular evaluated indicator. The idea of interpreting any indicator values into a certain linguistic assessment is to compare the values with intervals on a scale segment, and accordingly, a linguistic assessment is formed about the state of the research object. For linguistic interpretation, we propose to use a three-level scale of competitiveness (Table 3). Its advantage is the convenient clustering of research objects by characteristic features.

Table 3. The three-level scale of competitiveness. (Source: Koliadenko et al., 2021)

Intervals	Linguistic assessment
[0.63; 1]	High level
[0.37; 0.63]	Average level
[0; 0.37]	Low level

On the basis of the above three-level scale of competitiveness, the linguistic distribution of the SIEC values of the investigated agricultural enterprise was carried out (Figure 12, Table 4).

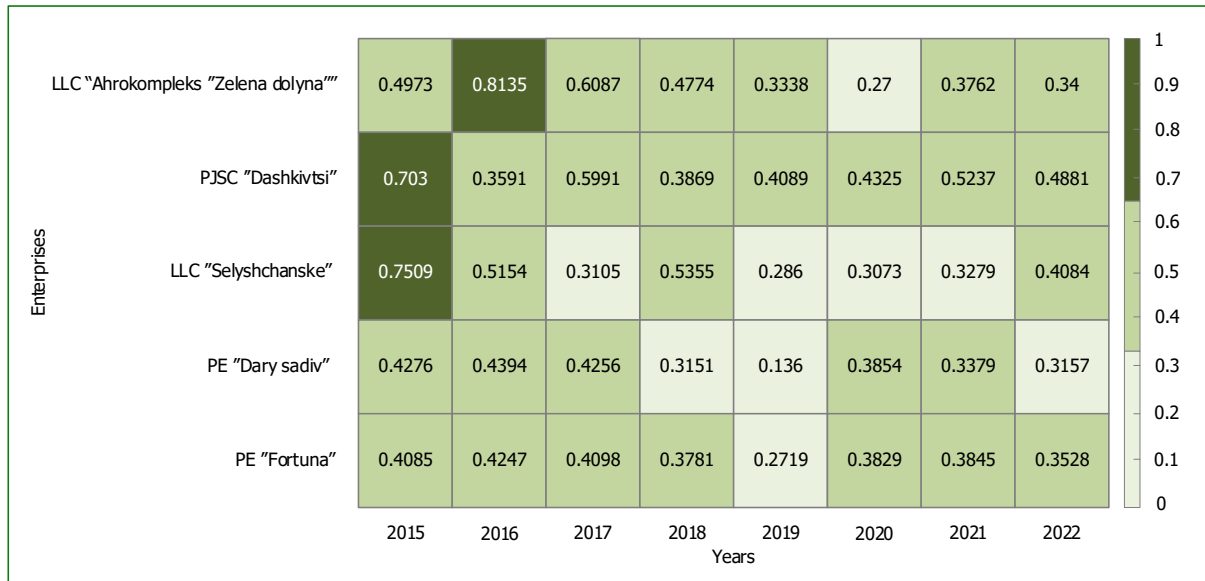


Figure 12. Linguistic map of the distribution of the level of competitiveness of agricultural enterprises.

Table 4. Linguistic distribution of values SIEC of the Vinnytsia region, 2015-2022.

Linguistic assessment	Years							
	2015	2016	2017	2018	2019	2020	2021	2022
LLC «Ahrokompleks «Zelena dolyna»»	Average level	High level	Average level	Average level	Low level	Low level	Average level	Low level
PJSC «Dashkivtsi»	High level	Low level	Average level	Average level	Average level	Average level	Average level	Average level
LLC «Selyshchanske»	High level	Average level	Low level	Average level	Low level	Low level	Low level	Average level
PE «Dary sadiv»	Average level	Average level	Average level	Low level	Low level	Average level	Low level	Low level
PE «Fortuna»	Average level	Average level	Average level	Average level	Low level	Average level	Average level	Low level

The performed calculations demonstrate the dynamics of the level of competitiveness of agricultural enterprises in the Vinnytsia region. The analysis shows that the vast majority of the studied enterprises have a negative dynamic of the competitiveness indicator. However, the situation of the enterprises LLC "Ahrokompleks "Zelena dolyna"" and LLC "Selyshchanske" has deteriorated the most, with their competitiveness falling by 31.6% and 45.6%, respectively. This is due to the fact that these enterprises were most likely oriented towards export, which was sharply limited after the start of the war. The situation of the enterprise PE "Fortuna" deteriorated the least, with its competitiveness falling by 13.6%. This is due to the fact that this enterprise was most likely oriented towards the domestic market, which, although it has suffered negative effects from the war, has still remained more stable. In 2022, the competitiveness of enterprises began to stabilize. This is due to the fact that Ukraine began to receive international assistance, which helped to mitigate the negative consequences of the war. Thanks to this international support, enterprises have been able to restore their productivity, expand their business and create new jobs. This, in turn, has contributed to the improvement of the country's overall

competitiveness in the global market. However, analyzing the dynamics of SIEC in terms of group indicators, it is necessary to note that the partial criteria of the enterprise's activity are above the normalized values, and the indicated negative dynamics are formed on the basis of their general decrease to the level of normalized boundaries of indicators.

DISCUSSION

In the modern world, where competition in the agricultural market is becoming increasingly fierce, the issue of competitiveness of agricultural enterprises is becoming increasingly relevant. In such an environment, where enterprises are forced to compete for resources, market positions and consumers, the analysis and evaluation of competitiveness become an obvious necessity.

The proposed research opens up new opportunities for in-depth analysis of the competitiveness of agricultural enterprises and the development of effective strategies for their development. The use of neural network tools allows for the consideration of a large number of factors that affect competitiveness, including those that can be difficult to assess initially. This makes the methodological approach particularly useful in modern conditions when rapid changes in the economic environment require a flexible and reliable analytical approach.

So, before implementing the methodological approach in practice, it is necessary to discuss the issue of selecting indicators for determining the competitiveness of agricultural enterprises. The main advantage of the proposed synthetic indicator of competitiveness is its ability to synthesize indicators that reflect various aspects of the activity of an economic entity.

However, the lack of a single vision of an "ideal" system of indicators for assessing the competitiveness of agricultural enterprises leads to a discussion of the outlined issue. For example, scientists (Arkhieriev, et al., 2019) generally propose to assess the competitiveness of enterprises based on their market share in combination with subjective consumer ratings, which, in our opinion, does not fully characterize the complexity of the concept of "competitiveness.". Instead, we believe that the most complete and reliable picture of the competitiveness of enterprises is provided by their financial statements and relevant financial performance indicators.

It is important to understand that neural networks are black boxes, and their results can be difficult to interpret. This can create problems when formulating strategies based on the data obtained. Therefore, the question of developing a unified scale for standardizing the obtained results for different stakeholders, including business leaders, agricultural business professionals, and researchers, remains open.

CONCLUSIONS

Based on the research carried out, a neural network model of a synthetic indicator of the competitiveness of agricultural enterprises was developed and presented. During the research, an analysis of scientific publications in the relevant field was carried out, which made it possible to develop an algorithm for the operation of a neural network model for determining the indicator of the competitiveness of agricultural enterprises. Based on the systematization of data from the field of diagnostics of the competitiveness of agricultural enterprises, a system of partial indicators of the competitiveness of agricultural enterprises was created and a structural model of assessing the competitiveness of agricultural enterprises was formed according to the "input-output" principle. This model provides the possibility of deep analysis and comparison of agricultural enterprises at different stages of their operation.

The presented neural network model for evaluating the competitiveness of agricultural enterprises was used to determine the level of competitiveness of the studied agricultural enterprises in the Vinnytsia region. Based on the data obtained, the level of their competitiveness for 2015-2022 was determined by linguistic interpretation of the obtained indicators on a three-level scale of competitiveness, namely: "low level", "medium level", and "high level" for each period of enterprise functioning.

Therefore, the presented neural network model for diagnostics of the competitiveness of agricultural enterprises is an effective tool for assessing the level of competitiveness of enterprises in the agricultural sector. The model allows for a comprehensive approach to assessing the competitiveness of agricultural enterprises, combining various factors and indicators of their activities. It allows us to obtain a well-founded quantitative indicator, which can be interpreted as a "competitiveness indicator". It can be used to compare enterprises, monitor their dynamics, and make informed decisions on improving competitiveness.

ADDITIONAL INFORMATION

AUTHOR CONTRIBUTIONS

Conceptualization: Illia Chikov, Denys Titov, Yuliia Okhota, Vyacheslav Prygotsky, Vitalii Nitsenko

Data curation: Illia Chikov, Olha Khaietska, Denys Titov, Yuliia Okhota, Vyacheslav Prygotsky, Vitalii Nitsenko

Formal Analysis: Illia Chikov, Olha Khaietska, Denys Titov, Vitalii Nitsenko

Writing – review & editing: Illia Chikov, Olha Khaietska, Denys Titov, Yuliia Okhota, Vyacheslav Prygotsky, Vitalii Nitsenko

Writing – original draft: Illia Chikov, Olha Khaietska, Denys Titov, Yuliia Okhota, Vyacheslav Prygotsky, Vitalii Nitsenko

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Чіков І., Хаєцька О., Охота Ю., Тітов Д., Пригоцький В., Ніценко В.

МОДЕЛЮВАННЯ СИНТЕТИЧНОГО ПОКАЗНИКА КОНКУРЕНТОСПРОМОЖНОСТІ АГРАРНИХ ПІДПРИЄМСТВ: МЕТОДИЧНИЙ ПІДХІД ВИКОРИСТАННЯ ІНСТРУМЕНТАРІЮ НЕЙРОННИХ МЕРЕЖ

Стаття присвячена розробленню методичного підходу до моделювання синтетичного показника конкурентоспроможності аграрних підприємств за допомогою інструментарію нейронних мереж.

У ході дослідження авторами було використано загальнонаукові й спеціальні методи дослідження, такі як: монографічний, логіко-теоретичний, статистичний та економіко-математичний, візуалізації, системного аналізу, таксономії та нейромережевого моделювання, узагальнення, логічної абстракції та генерації висновків. У дослідженні використані матеріали Державної служби статистики України, наукові розробки зарубіжних і вітчизняних учених із визначеної тематики, фінансова звітність аграрних підприємств Вінницької області ТОВ «Агрокомплекс «Зелена долина»», ПрАТ «Дашківці», ТОВ «Селищанське», ПП «Дари садів», ПСП «Фортуна», основний вид економічної діяльності яких за КВЕД 01.11 є вирощування зернових культур (крім рису), бобових культур і насіння олійних культур.

У статті розроблено та представлено неklasичний підхід до оцінки конкурентоспроможності аграрних підприємств, який ґрунтується на принципах нейромережевого моделювання. Він дозволяє отримати обґрунтований кількісний показник, який можна легко інтерпретувати в лінгвістичну оцінку за трирівневою шкалою конкурентоспроможності та використовувати для порівняння, моніторингу й ухвалення обґрунтованих рішень щодо підвищення конкурентоспроможності аграрних підприємств.

Наведений неklasичний підхід доповнює традиційні методи оцінки конкурентоспроможності, розширюючи їхні можливості та усуваючи певні обмеження. Використання нейромережевого моделювання при оцінці конкурентоспроможності дозволяє враховувати складні та нелінійні взаємозв'язки між різними факторами й показниками, що сприяє збільшенню об'єктивності й точності оцінки конкурентоспроможності, що в свою чергу дозволяє підприємствам ухвалювати ліпші рішення та вдосконалювати свої стратегії для досягнення успіху на ринку.

Результати дослідження можуть бути використані для підтримки стратегічного ухвалення рішень в аграрному секторі, визначення пріоритетних напрямів розвитку, удосконалення конкурентних стратегій підприємств і функціонування бізнес-процесів.

Ключові слова: аграрні підприємства, синтетичний показник, конкурентоспроможність, нейронні мережі, латентна ознака, моделювання, лінгвістична оцінка, шкала Харрінгтона

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