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Research article

MODELLING THE LEVEL OF THE ENTERPRISE' RESOURCE SECURITY USING ARTIFICIAL NEURAL NETWORKS

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Abstract. Significant attention is paid to increasing the efficiency of using resources by business entities due to the growing dependence between economic growth and the number of consumed resources, problems with access to various types of resources on the market, as well as their exhaustion in the face of growing needs. At the same time, various digitization tools are widely used to solve these problems. This paper considers artificial neural networks as a tool for modelling and forecasting the level of resource security in the economic activity of an enterprise, which is divided into separate functional blocks (production, personnel, finance). To this end, a multi-layer perceptron model (MLP) was used by constructing and training a network on several possible architectures in order to select the one with the highest classification quality. In the process of training, testing and verification of MLP networks, 32 indicators were used as input data, characterizing the state and efficiency of using various types of enterprise resources, for 85 enterprises over the five years of their operation. The initial data were the values of the safety zone, which were set separately for each indicator, subsystem and enterprise using economic-mathematical modelling on the basis of determining the acceptable limits of indicator fluctuations. As a result, four MLP networks were selected (one network for each of the three functional subsystems, as well as one for the enterprise as a whole), which were characterized by the highest value of quality at each stage of calculations (training, testing, verification). The performed calculations proved that artificial neural networks can be a useful and convenient tool for determining the security level of an enterprise in various directions of its economic activity (types of consumed or involved resources), and therefore can be more widely used by business entities to increase the validity of management decisions.

Keywords*:* artificial neural networks, enterprise resource security, modelling, multilayer perceptron, prediction.

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1. Introduction

In accordance with the goals of sustainable development, approved by the resolution of the UN General Assembly "Transforming our world: the 2030 Agenda for Sustainable Development" [1], countries should reorient to rational models of consumption and production (Goal 12), which will ensure increased efficiency in the use of resources [2–5]. The implementation of this goal is primarily aimed at overcoming the dependence between economic growth and the deterioration of the environment [6–11], because production and consumption, on the one hand, are the driving force of the economy, and on the other hand, they lead to the rapid depletion and scarcity of resources [12–17], causing a destructive impact on the environment [18–23]. This statement can be confirmed empirically on the basis of statistical information regarding the number of consumed resources and the level of the country’s economic development.

One of the indicators that serves as an indicator of achieving the stated goal of sustainable development is the Material Footprint (MF). Total MF represents the sum of the material footprint for biomass, fossil fuels, metallic ores, and non-metallic ores, and is, accordingly, calculated as the raw material equivalent of imports plus domestic production minus the raw material equivalent of exports. In turn, MF per capita describes the average material use for final demand [1].

The country's economic development can be characterized on the basis of the Global Innovation Index 2022 (hereinafter GII-2022), as well as the division of the World Bank into groups (by income level) [24–26]:

- high-income countries (gross national income (GNI) per capita exceeds $13,205);
- countries with a higher-than-average income level (GNI per capita is in the range of $4,256–$13,205);
- countries with a lower-than-average income level (GNI per capita ranges from $1,086 to $4,255);
- low-income countries (GNI per capita is less than $1,085).

A graphical presentation of the relationship between the material footprint and the level of development and innovation for a sample of 121 countries is shown in Fig.1. Based on the visual analysis of the correlation field, it becomes possible to make an assumption about the existence of a direct, close connection between the innovativeness level of the country's economy and the number of natural resources consumed, which can be described by a linear function. According to Fig. 1, it can be concluded that moving from the origin of the coordinates along the trend line, there is a gradual transition from the least developed countries to the developed ones; moreover, a high level of resource utilization and GII are characteristic of developed countries. Thus, statistical data confirm the statement that the most developed innovative countries consume the largest number of resources. Accordingly, the development of countries with a high level of innovation should be aimed at intensifying production and increasing the efficiency of resource consumption (when the return on the production factors use increases, and the number of resources consumed either remains unchanged or decreases).

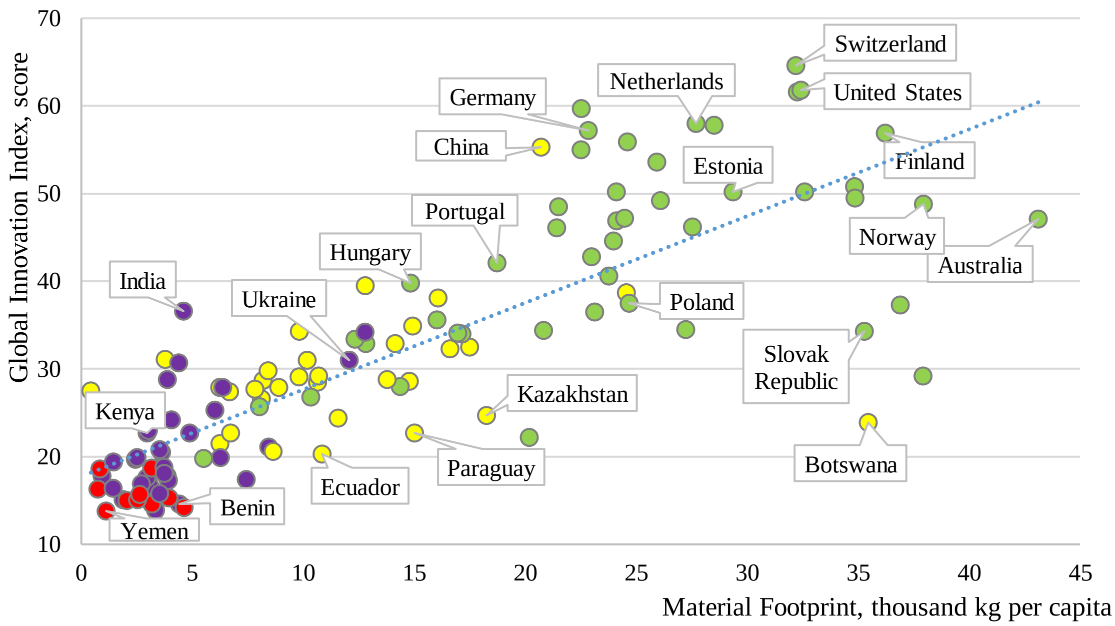

Figure 1. Correlation field of the material footprint dependence on the level of the country's innovative development.

Note. The green colour denotes countries with a high level of income, yellow marks those above average; purple denotes those below average; red colour marks countries with a low level of income.

Source: compiled by the author based on the data [27–29].

Recognition of the growing dependence of countries on the availability and accessibility of resources, as well as the emergence of shortages of certain raw materials, results in increased attention to ensuring resource security, both at the level of the state and at the level of a specific business entity.

Therefore, modern global challenges and the spread of uncertainty in the conditions of enterprises' economic activity make it necessary to ensure their security in the context of achieving sustainable development. The levelling of internal and external risks, which are not only tactical, but also systemic in nature, presupposes a balanced development of an enterprise and, above all, its resource potential. Resource security of an enterprise acts as an important subsystem of the economic security system, which is a structural component of the mechanism of the enterprise's adaptation to internal and external conditions of operation. At the same time, the object to be protected by resource security is the components of the economic, ecological and social balance of an enterprise as an open system, which determines a decisive role of the regulating level of the enterprise's resource security in ensuring its sustainable development. In this context, the issue of modelling the level of resource security of a modern company is gaining relevance.

The article has the following structure: (a) Section 2 analyses the theoretical landscape of the meaningful content of the enterprise's resource security, its main indicators and approaches to determining and substantiating the research purposes; (b) Section 3 describes the input and output data used in resource security level modelling, their sources, and research methods and tools; (c) Section 4 outlines the empirical conclusions regarding the proposed methodology for building and using artificial neural networks for modelling the level of the enterprise's resource security; (d) Chapter 5 summarizes the results of the performed research, its limitations and outlines the prospects for further research.

2. Literature Review

To forecast the level of the enterprise's resource security, it is necessary to use adequate models formed on the basis of an accurate and objective evaluation of the current security state of economic entities. The analysis of literary sources [6-9] proved that the most common approach to substantiating the level of security in economic activity is a functional approach, in which the state of the system is examined in terms of functional subsystems, thereby identifying problem areas, in particular, in the enterprise's activities. However, Kharazishvili et al. [34] point out that when using the functional approach in practice, in most cases there are certain shortcomings and limitations. For example, when performing an integral assessment, it is unreasonable to determine the threshold values of economic security indicators, which are subjectively set by experts in the range from 0 to 1 (with a span of 0.2), which is unlikely in practice. In addition, in the case of a significant pairwise correlation, it is proposed to reduce the weight of the "most important" indicators, which contains subjectivism and, undoubtedly, reduces the scientific and practical value of the obtained results. In turn, the main disadvantages of the functional approach at the micro level, according to Kozachenko & Pogorelov [30], are as follows: the normalization of the values of single indicators and the following two integral convolutions (single and complex indicators) lead to a significant gap between the obtained estimates of economic security and its real state; retrospective values of the indicators are used in the evaluation, as a result of which the obtained economic security estimates are of interest for analytical activities, but are practically unsuitable for making current and strategic management decisions; there are no substantiated recommendations regarding the indicators that will most accurately characterize each of the components of the enterprise's economic security; difficulties arise with individual indicators that do not have a generally accepted meaning, since not only the selected indicators, but also their marginal values, play an important role in determining the level of economic security; a significant drawback is the practical impossibility to determine the impact of qualitative characteristics on the level of economic security, for example, the reputation of the enterprise, the level of trust in it by counterparties, the dedication of personnel, etc. Therefore, the shortcomings of the functional approach indicated by scientists are mostly due to the use of imperfect methodological tools.

The second most widely used is the indicator approach to justifying the safety level. It is based on a comparison of the actual values of the enterprise's performance indicators with their limit values – indicators. For example, Vasyltsiv & Mykytiuk [31] claim that a methodological approach to assessing the level of economic security of an enterprise should involve determining the state of enterprise security, and, accordingly, assigning a business entity to one or another level, based on exceeding the actual values of individual indicators of the enterprise's critical limitations indicators, but which are not the same for all levels, but are selected exclusively taking into account the level of security that they characterize. Thus, the authors mentioned propose to compare a significant number of indicators with their average industry values, the so-called indicators. For the case described in [31], it is difficult to objectively justify the threshold values of the indicators that are characteristic of each individual security level. Kozachenko & Pogorelov [30] singled out features regarding the use of the indicator approach that make it difficult to solve the task of establishing normative threshold values of indicators that are not always taken into account by researchers in the field of economic security, namely:

- due to the presence of cause-and-effect relationships and interdependencies between various indicators, the list of indicators of the economic security of the system cannot be established unambiguously;
- threshold values should be established taking into account the interrelationship of economic security indicators due to the possible dependence of the threshold values of security indicators on the values of other indicators;
- in fact, there is no clearly known, predetermined threshold, the crossing of which will indicate that the system will instantly enter an irreversible crisis state. For economic systems, the presence of a threshold band, a critical zone, within which the probability of a crisis situation becomes noticeably high, is more characteristic. The system is able to stay in this dangerous zone without a complete loss of stability for a certain period, which depends on the availability of reserves and the degree of survivability of the system;
- at the same time, it is expedient to reduce the studied set of safety indicators by selecting individual types (parts) from it, and by determining the appropriate groups of indicators for the selected types.

Thus, the above-mentioned specificity of the indicator approach makes it impossible to take into account the individualized features of the enterprises' development and leads to an artificial overestimation or underestimation of the existing level of security.

Some issues in determining the level of resource security of organizations are outlined by Gushchenskaya & Anfalova [35], who propose to use a system of indicators of the availability, security and efficiency of resource use. To bring such a system to a single basis, each indicator undergoes a normalization procedure and is adjusted to the level of significance. As the authors rightly note, such procedures allow ranking the indicators by the strength of influence and multiplying their influence when calculating the integral indicator of resource security. However, the normalization method chosen in the mentioned publication (according to the reference value) does not allow repeating accurately the dynamics of the input indicators in the case of their multi-directionality (when a company seeks to maximize some indicators and minimize others), and the determination of the significance of indicators based on expert evaluation introduces a high level of subjectivism in forming an integral indicator of resource security, which leads to obtaining estimates that are insufficiently accurate and reliable.

Taking into account the advantages, disadvantages and the revealed specificity of the researched approaches to evaluating security in economics, it appears to be expedient to synthesize functional and indicator approaches with their further improvement through the use of modern economic-mathematical methods and digitalization tools when justifying the level of resource security. It is worth noting that digitization tools are special automated technologies for collecting, processing, and analysing large volumes of structured or unstructured data that allow decision-making, forecasting, recognition of patterns of cluster formations, etc., based on the identification of meaningful factors [36–42].

One of the most common and effective digitalization tools is artificial neural networks, which are dynamic systems capable of generating output signals in response to input neurons. Churchland & Sejnowski [43] claim that the neural network is a special case of the method of pattern recognition, clustering and discriminant analysis, and from the point of view of the multi-parameter problem of nonlinear optimization, the process of training a neural network is carried out for its future use.

Simon Haykin in his work [44] refers to specific properties of neural networks, such as nonlinearity; transformation of input information into output based on a number of algorithms; adaptability; obviousness of the response; contextual specificity of information; fault tolerance; scalability; uniformity of analysis and design. These properties are implemented in the topology of the network, which is a logical structure with many neurons (nodes, cells) connected by synapses. The architecture of a neural network is represented by a number of neurons' layers: input (a set of computing elements that receive signals from the external environment), hidden (a set of computing elements that receive signals from other elements), output (a number of neurons that correspond to the final result of neural network calculations). Thus, neural networks are able to accumulate experimental knowledge and provide it for further processing [14].

Existing structures (architectures) of neural networks are divided [43,44] into 3 fundamental classes:

- single-layer direct propagation networks – there is an input layer of source nodes, information from which is transmitted to the output layer of neurons (computing nodes), but not vice versa. At the same time, a single layer means a layer of computing elements (neurons);
- multilayer networks of direct propagation are characterized by the presence of one or more hidden layers, the nodes of which are called hidden neurons, or hidden elements. The function of the latter is to mediate between the external input signal and the output of the neural network. Such a network makes it possible to highlight the global properties of data using local connections due to the presence of additional synaptic connections and an increase in the level of interaction among neurons;
- recurrent networks differ from direct propagation networks by the presence of at least one feedback, in addition, this class of networks can use its internal memory to process arbitrary sequences of inputs.

In economic activity, multi-layer networks of direct propagation, which are also called multi-layer perceptron, have become the most widely used in practice. The spread of this class of neural network architecture is due to its high quality in solving forecasting, clustering and recognition tasks. In a perceptron, neurons are organized into layers, and the elements of each layer are connected only to the neurons of the previous layer, and information is propagated from previous layers to subsequent layers. The choice of the number of layers of the network and the number of neurons in each layer affects the ability of the network to solve the respective tasks.

After determining the number of layers and elements in each of them, there are values for the weights and thresholds of the network that would minimize the prediction error produced by the network. Simon Haykin [44] notes that knowledge enters the neural network from the surrounding environment and is used during the learning process. Connections between neurons, called synaptic weights, are used to accumulate knowledge. The procedure used for the process of training a neural network is called a learning algorithm, the main paradigms of which are reduced to the following:

- assignment of confidence coefficients – methods are used that assign confidence or distrust coefficients to all results obtained by some learning machine;
- supervised learning (with a teacher) – under this learning paradigm, the weights of the neural network are changed using sets of training samples that include input values and known output values [45–48];
- unsupervised learning (without a teacher) - methods are used in which the weights of the neural network are changed using sets of inputs (output values are not required). That is, when using this approach, there are no labelled examples, according to which the neural network is trained.

The constructed and trained neural network model must be tested. For this purpose, a test sample is formed, which was not used during the training of a neural network. If, according to the test results, the appropriate values of the initial parameters of the test sample are obtained, then the built network is adequate and can be used in the future for object recognition and forecasting.

Summing up, it is worth noting that digitalization tools, in general, and neural network modelling, in particular, have not yet become widely used in forecasting the level of resource security of an economic entity due to their complexity, the need for special software, appropriate training and preparation, etc. However, the advantages of these tools (which include: the speed of information processing and the ease of its updating; the possibility of filtering out "noises" that lead to making incorrect decisions; reducing the costs of various types of resources, and others) make it possible to obtain more accurate modelling results, due to which business processes' optimization is carried out and competitive advantages of the business entity over other market players are formed.

Taking into account the above, the purpose of the article is to develop a modelling methodology for determining the level of resource security of an economic entity based on the use of artificial intelligence methods, including neural networks.

3. Materials and Methods

3.1. Input Data for Neural Network Modelling

This study uses a combination of functional and indicator approaches as a theoretical foundation for substantiating the level of resource security of business entities. In particular, on the basis of the functional approach, an analysis of the enterprise's resource security is carried out according to the main functional subsystems (financial, personnel, production), which allows characterizing the results of the enterprise's activities in relation to its handling the main types of resources to the fullest extent. In turn, the indicator approach was used to establish the threshold values of the indicators with the further development of methods that allow setting the boundaries of the zone of the system's safe existence (vectors of the threshold values of the indicators) taking into account the specifics of the enterprise's activity; as well as the formation of an integral convolution both for indicators and for their limit values, on the basis of which quantitative determination of the general level of the enterprise's resource security is performed.

In order to form a representative set of initial indicators characterizing the specified functional subsystems of an enterprise, the works [50–53] were analysed and those indicators that have the highest frequency of occurrence and there is the possibility of their calculation for a large number of business entities based on the database of Stock market infrastructure development agency of Ukraine (SMIDA). The advantages of the specified source of information comprise availability and variety of information for a long-term period of time; wide geography, belonging to different sectors of the economy and different sizes of research objects; as well as an annual update of information. Among the shortcomings, there should be noted the presence of a time lag in the posting of reports and, as a result, the ageing of information over a period of 1 to 3 years.

This study selected 32 indicators that characterize the state and efficiency of using various types of enterprise resources, in particular:

- the personnel subsystem is described by 7 quantitative indicators (labour productivity, average monthly salary, labour resources, the share of wages in the cost of production, profitability of labour costs, the share of arrears from wages in the amount of loan sources of enterprise financing, salary return);
- the financial subsystem is determined by 18 quantitative indicators (coefficient of autonomy, financing ratio, financial leverage ratio, coverage ratio, quick liquidity ratio, absolute liquidity ratio, asset turnover ratio, inventory turnover ratio, accounts receivable turnover ratio, accounts payable turnover ratio, the ratio of payables and of receivables, the ratio of securing current assets with own funds, the ratio of working capital manoeuvrability, the ratio of equity capital manoeuvrability, profitability of operations, profitability of products, profitability of equity capital, profitability of assets);
- the production subsystem is characterized by 7 quantitative indicators (the coefficient of fixed assets' wear and tear, return on capital, material intensity of products, the share of fixed assets in assets, the share of circulating production assets in working capital, the index of permanent assets).

It should be noted that changes and clarifications may be made to the specified list of functional subsystems and indicators depending on the specifics of the industry, the available information and the goals of the resource security research of the economic entity. Each of the indicators from the created list is assigned to stimulators (have a direct relationship with the final results of activity – the growth of the indicator increases the results of entrepreneurial activity) or de-stimulators (have a feedback relationship – the decrease of the indicator characterizes the improvement of the enterprise's work). To bring the indicators to the same orientation and dimension (range from 0 to 1), they are normalized according to a single normalizing function using the combined method [34]:

- for stimulator indicators:

$$z_i = \frac{x_i}{k_{norm}} \tag{1}$$

- for de-stimulatory indicators:

$$z_i = \frac{k_{norm} - x_i}{k_{norm}} \tag{2}$$

where x_i is the value of the indicator in the i-th period; k_{norm} is the normalization coefficient (taken to be 5-10% greater than the maximum value of x).

To form the initial sample of input data used for training, testing and verification of artificial neural networks, the activities of 85 Ukrainian enterprises were analysed according to SMIDA data. The selected companies belong to different sectors of the economy, are characterized by different sizes and efficiency of functioning, and are also geographically located in different regions. Taking these factors into account during the random selection of enterprises made it possible to generate sample data that reflect the structural properties of the general population, and therefore can be used to reproduce and model its characteristics. For each of the studied objects, the above-mentioned 32 indicators were calculated for a five-year period (from 2015 to 2019 inclusive), which was between the crisis years for the Ukrainian economy, and their normalization was performed.

3.2. Output Data for Artificial Neural Networks

In order to obtain reliable results regarding the level of resource security of the enterprise, which are used as initial data for training neural networks, research must be conducted in homogeneous groups. For this purpose, 85 selected enterprises were clustered by Ward's method into four types according to the nature of their behaviour with resources [19]. The developed typology of enterprises makes it possible to individualize the limits of safe fluctuation of indicators for a separate economic entity, taking into account its potential capabilities.

To substantiate resource security zones for basic types of enterprises, procedures are carried out in the following sequence:

Step 1 – determining the type of distribution of each indicator (normal, lognormal, exponential) by constructing distribution histograms and quantile graphs.

Step 2 – calculating the vector of limit values of the indicators, based on the method of the Student’s t-criterion, taking into account the type of the indicators' distribution, their statistical characteristics and the enterprise’s belonging to a certain type – that is, the limits of safe fluctuation of each of the indicators are established for each of the types of enterprises (Table 1).

Table 1. Formulas for calculating vectors of indicators' limit values

Distribution type	Lower threshold value	Lower optimal value	Upper optimal value	Upper threshold value
Normal	$\mu - t * \sigma$	$\mu - \sigma$	$\mu + \sigma$	$\mu + t * \sigma$
Exponential	$\mu - \sigma / k_{as}$	μ	$\mu + \sigma$	$\mu + t * \sigma$
Lognormal	$\mu - t * \sigma / k_{as}$	$\mu - \sigma / k_{as}$	$\mu + \sigma$	$\mu + t * \sigma$

Note: μ is the average value of a certain indicator; σ is its mean square deviation; k_{as} is the asymmetry coefficient; t is the confidence coefficient selected from statistical tables of the Student’s t-distribution.
Source: [34].

For indicators that have established normative values (for example, the coefficient of absolute liquidity, the coefficient of autonomy, and others), the definition of the vector of threshold values is performed on the basis of their well-known norms.

Step 3 – convolution of indicators' normalized values and their thresholds for each subsystem (first-level convolution), as well as the final convolution of integral indices and thresholds (second-level convolution) according to a multiplicative form that takes into account the nonlinearity of economic processes (formula 3):

$$\begin{cases} I_{RS,t} = I_{prod}^{a_{1,t}} * I_{HR}^{a_{2,t}} * I_{fin}^{a_{3,t}};\ P_{\text{i}} = \prod_{j=1}^{n} p_{ij}^{a_{ij}};\ \bar{p}_{ij} = \left[p_{ij}^{LT};\ p_{ij}^{LOV};\ p_{ij}^{UOV};p_{ij}^{UT}\right]; \\ I_{prod,t} = \prod_{i=1}^{7} z_{prod,t}^{a_i}; \\ I_{HR,t} = \prod_{i=1}^{7} z_{HR,t}^{a_i}; \\ I_{fin,t} = \prod_{i=1}^{18} z_{fin,t}^{a_i}. \end{cases} \tag{3}$$

where $I_{RS,t}$ is the integral index of the enterprise's handling of resources; $I_{prod,t}$ is the integral index of the production subsystem; $I_{HR,t}$ is the integral index of the personnel (HR) subsystem; $I_{fin,t}$ is the integral index of the financial subsystem; $a_{1,t}, a_{2,t}, a_{3,t}, a_{ij}$ are weighting factors; $z_{prod,t}, z_{HR,t}, z_{fin,t}$ are normalized values of indicators characterizing, respectively, the production, personnel and financial subsystems of the enterprise; p_{ij}^{LT}, $p_{ij}^{LOV}, p_{ij}^{UOV}, p_{ij}^{UT}$ are the threshold values of the indicators of the corresponding subsystem (LT – Lower Threshold; LOV – Lower Optimal Value; UOV – Upper Optimal Value; UT – Upper Threshold).

In turn, the weight coefficients (a_{ij}) used in the model are calculated based on the weight of the dispersion (entropy method), which allows taking into account the uncertain nature of socio-economic systems and the load of each component in the integral index. Therefore, the weighting factors are determined by the following formula:

$$a_{ij} = \frac{D_{ij}}{\sum_{i=1}^{n} D_{ij_i}} \tag{4}$$

where D_{ij} is the dispersion of the *i*-th indicator of the *j*-th subsystem; *n* is the number of indicators characterizing the *j*-th subsystem of the enterprise.

Therefore, in accordance with the specified procedure, a safety zone is determined for each year of operation of each enterprise: zone 1 – upper critical, zone 2 – upper threshold, zone 3 – optimal, zone 4 – lower threshold, zone 5 – lower critical. In this way, the initial data, on the basis of which the training of neural networks is carried out, is formed.

3.3. Research Method

Neural network modelling of the resource security level of the enterprise was performed sequentially according to the following stages:

- forming input data as a sample of 85 enterprises and 32 indicators, each of which was calculated for five years (that is, the initial matrix of input data had a size of 425*32);
- forming initial data on the basis of which the neural network is trained (zone 1 – upper critical, zone 2 – upper threshold, zone 3 – optimal, zone 4 – lower threshold, zone 5 – lower critical);

- selecting architecture and defining a network structure (multilayer perceptron with a hidden layer);
- neural network training (70% of the data was used for training);
- neural network testing and validation (data breakdown: 15% for testing and 15% for validation).

In the general case, the input conditions of neural networks are data on *n* objects, each of which is represented as a set of *j* observations, that is, it is characterized as a point *x* in the *j*-dimensional space of observations. The classification task is reduced to the division of objects into a number of similar groups, which is carried out on the basis of information extracted from training data. Since in this study, the values of the output layer are given, the problem is solved using a multilayer perceptron (MLP).

Graphically, the nonlinear neuron model is shown in Fig. 2.

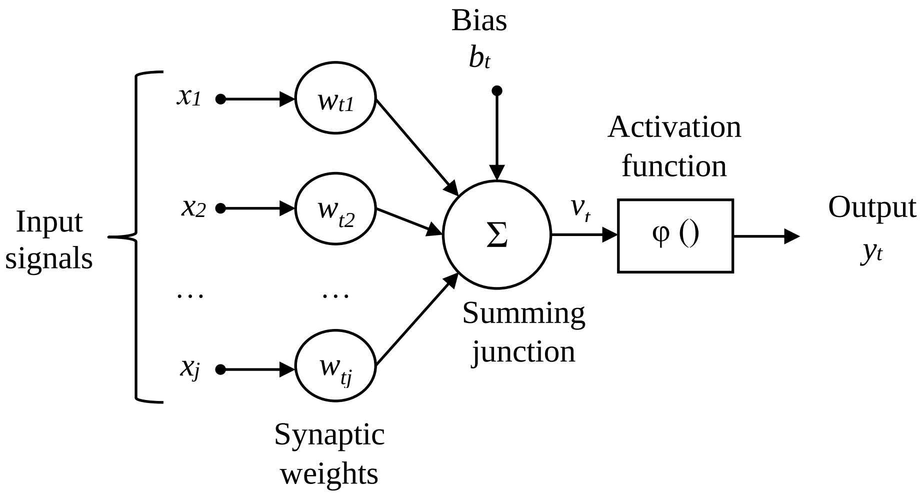

Figure 2. Nonlinear model of a neuron, labeled *t*.
Source: [44].

The bias (b_t) has the effect of increasing or lowering the net input of the activation function, depending on whether it is positive or negative, respectively [44].

Mathematically, the functioning of neuron *t* is described by the following formulas [44]:

$$u_t = \sum_{i=1}^{j} x_j * w_{tj} \quad (5)$$

$$y_t = \varphi(u_t + b_t), \quad (6)$$

where *j* is the number of input neurons; x_j is the value of the *j*-th neuron input; w_j is the weight of the *j*-th synapse (including the threshold element); b_t is the bias; u_t is the linear combiner output due to the input signals; $\varphi()$ is the activation function; y_t is the output signal of the neuron.

When building MLP networks, different activation functions are used both for the neurons of the hidden layer (logistic, hyperbolic tangent, linear, exponential) and for neurons in the output layer (sinusoidal, hyperbolic tangent, exponential Softmax function). The most widely used activation function is the sigmoidal function, exemplified by the logistic function given by the expression [44]:

$$\varphi(v) = \frac{1}{1 + exp(-av)} \tag{7}$$

where a is is the slope parameter of the sigmoidal function.

Also, the sigmoidal function can have the form of a hyperbolic tangent, in which case it is defined by the formula:

$$\varphi(v) = tanh(v) \tag{8}$$

For the task of neuro-modelling, it is advisable to use the structure of a neural network containing an input layer (for individual subsystems, the number of input neurons corresponds to the number of indicators that characterize this subsystem, while for determining the general level of enterprise resource security, the number of input neurons is 32), and an output layer, which contains 5 neurons (the answer about the assessment of the level of resource security of an enterprise or subsystem). The general architecture of neural networks used in modelling the level of enterprise resource security is shown in Fig. 3.

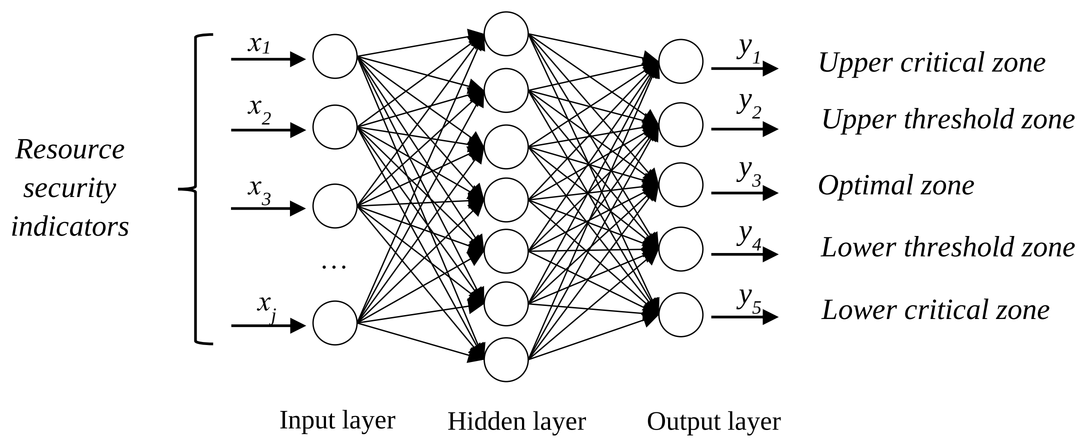

Figure 3. The structure of neural network models for determining the level of resource security of an enterprise and individual subsystems
Source: developed and designed by the authors.

Neural network training is performed using the STATISTICA Automated Neural Networks (SANN) software product for enterprises whose resource security level is known (pre-calculated), while the program constructs a neural network using the sorting method, determines the optimal neural network topology, and trains it. The multilayer perceptron is trained on the basis of the BFGS algorithm (Broyden–Fletcher–Goldfarb–Shanno), which is based on the error minimization rule. The neural network, in response to received input data, generates output data, which it then compares with the target (set) parameters and calculates the error value. Afterwards, the weights and biases are adjusted to minimize the error; the training process continues until the network reaches a predefined minimum allowable error [55]. One of the two functions is chosen as the criterion for stopping the calculations [55,56]:

- cross-entropy function *(E_{CE}):*

$$E_{CE} = -\sum_{i=1}^{N} t_i \ln\left(\frac{y_i}{t_i}\right) \tag{9}$$

where N is number of records in the used data file; y_i is calculated values of outputs in the network model; t_i is actual values of outputs recorded in the data file.

- mean square error *(MSE):*

$$MSE = \frac{1}{n}\sum_{i=1}^{N}(target_i - output_i)^2 \tag{10}$$

where *target* and *output* denote experimental and predicted values, respectively, *n* is the number of data points.

4. Calculation Results

The results of constructing, training and testing neural networks (with multilayer perceptron architecture) for the production subsystem of the enterprise are shown in Table 2 and Fig. 4. The presented results were obtained on the basis of 7 input indicators, which characterize the level of economic security by production activity for 85 companies over 5 years. In this way, five MLP networks were formed.

Table 2. MLP networks are built for modelling the level of security according to the production subsystem of an enterprise

No.	Network structure	Teach – quality, %	Test-quality, %	Valid-quality, %	Average-quality, %	BFGS	Error function	Activation function for hidden layer	Activation function for output layer
1	MLP 7-5-5	91.25	85.94	79.69	85.62	86	MSE	Hyperbolic	Softmax
2	MLP 7-12-5	98.32	93.75	89.06	93.71	139	MSE	Logictic	Hyperbolic
3	MLP 7-4-5	83.84	70.31	59.38	71.18	48	MSE	Logictic	Sine
4	MLP 7-8-5	56.52	50.79	34.92	47.41	105	Cross-entropy	Hyperbolic	Softmax
5	MLP 7-4-5	84.51	67.19	59.38	70.36	48	MSE	Logictic	Exponenta

Source: developed and designed by the authors.

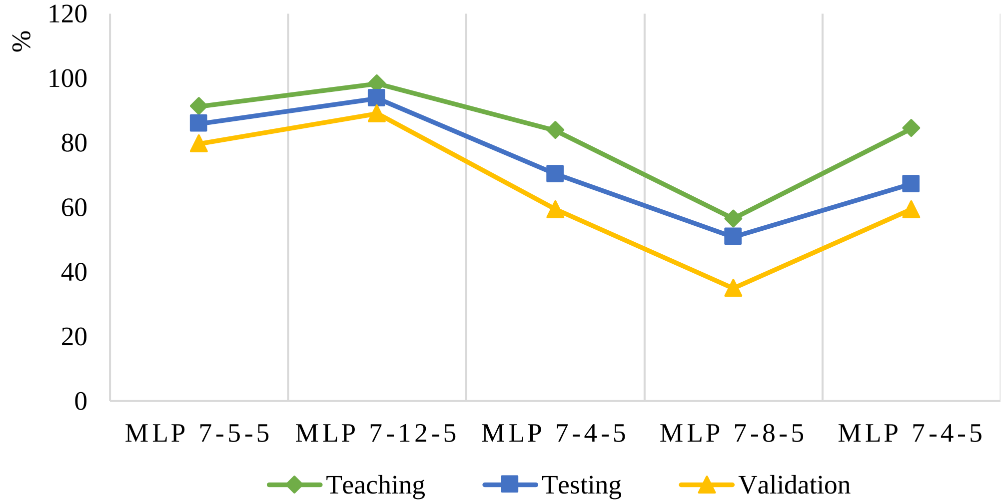

Figure 4. Results of the quality of MLP networks' modelling the level of security by the production subsystem of an enterprise (in graphic form)
Source: developed and designed by the authors.

The calculation results presented in Table 2 and Fig. 4 show that the MLP 7-12-5 network (7 source nodes, 12 hidden neurons, and 5 output neurons) turned out to be the best among the generated networks, as the average value of its quality was 93.71%. In addition, the MLP 7-12-5 network also turned out to be the best among the constructed ones in terms of the quality of training, testing and verification. Thus, the empirical results confirmed that the quality of the network, or rather the accuracy of object classification by the network, depends on the selected activation functions between the layers, the number of neurons in the hidden layer, the learning algorithm and its stopping rule. In general, the accuracy of MLP networks increases as the number of neurons in the hidden layer increases. But exceeding a certain limit on the number of hidden neurons can worsen the simulation results. In turn, the best combination of activation functions chosen for the hidden layer and the output layer was the combination of the logistic function and hyperbolic tangent, and high-quality results were obtained for the combination of hyperbolic tangent and Softmax. Other combinations of activation functions in this case were characterized by lower efficiency. In the calculations of the best classifier, the criterion for stopping the calculations (error function) was the mean squared error.

The next step of the research was the training, testing and verification of MLP networks' modelling the level of security for the financial and HR subsystems, as well as the enterprise as a whole. This procedure was performed similarly to the one by which the construction and selection of the MLP network for the production subsystem were carried out. The obtained results of the selection of the best neural networks for each individual subsystem and an enterprise as a whole are presented in Table 3.

Therefore, the constructed networks are characterized by rather high quality, since the correctness of determining the values of the training sample ranges from 91.58% to 98.32%; values of the test sample are from 84.38% to 93.75%; values of the verification sample are from 81.25% to 89.06%. The best combinations of activation functions in these cases turned out to be: a combination of hyperbolic tangent and Softmax (for the personnel subsystem and the enterprise as a whole), a combination of logistic and exponential functions (for the financial subsystem). In the calculations of the best classifiers, the criterion for stopping the calculations (error function) was equal parts mean squared error and cross-entropy.

Table 3. A summary of the highest quality MLP networks constructed for each enterprise subsystem

Enterprise subsystem	Network structure	Teach – quality, %	Test-quality, %	Valid-quality, %	BFGS	Error function	Activation function for hidden layer	Activation function for output layer
Production subsystem	MLP 7-12-5	98.32	93.75	89.06	139	MSE	Logictic	Hyperbolic
HR subsystem	MLP 7-4-5	96.30	84.38	81.25	76	Cross-entropy	Hyperbolic	Softmax
Financial subsystem	MLP 18-9-5	91.58	92.19	82.81	90	MSE	Logictic	Exponenta
Total	MLP 32-13-5	92.59	89.06	85.94	90	Cross-entropy	Hyperbolic	Softmax

Source: developed and designed by the authors.

The results of classifying enterprises and their functional subsystems by security zones, obtained by the highest quality of the constructed MLP networks for the training sample, are shown in Table 4.

Table 4. Results of object classification in the training sample

Network name	Results	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	All zones
Production subsystem							
MLP 7-12-5	Total	63.00	46.00	65.00	41.00	82.00	297.00
	Correct	62.00	46.00	63.00	40.00	81.00	292.00
	Incorrect	1.00	0.00	2.00	1.00	1.00	5.00
	Correct (%)	98.41	100.00	96.92	97.56	98.78	98.32
	Incorrect (%)	1.59	0.00	3.08	2.44	1.22	1.68
Human resources subsystem							
MLP 7-4-5	Total	56.00	47.00	67.00	42.00	85.00	297.00
	Correct	54.00	46.00	63.00	41.00	82.00	286.00
	Incorrect	2.00	1.00	4.00	1.00	3.00	11.00
	Correct (%)	96.43	97.87	94.03	97.62	96.47	96.30
	Incorrect (%)	3.57	2.13	5.97	2.38	3.53	3.70
Financial subsystem							
MLP 18-9-5	Total	54.00	48.00	69.00	41.00	85.00	297.00
	Correct	50.00	44.00	62.00	37.00	79.00	272.00
	Incorrect	4.00	4.00	7.00	4.00	6.00	25.00
	Correct (%)	92.59	91.67	89.86	90.24	92.94	91.58
	Incorrect (%)	7.41	8.33	10.14	9.76	7.06	8.42
In total for enterprise							
MLP 32-13-5	Total	57.00	47.00	68.00	41.00	84.00	297.00
	Correct	52.00	43.00	63.00	38.00	79.00	275.00
	Incorrect	5.00	4.00	5.00	3.00	5.00	22.00
	Correct (%)	91.23	91.49	92.65	92.68	94.05	92.59
	Incorrect (%)	8.77	8.51	7.35	7.32	5.95	7.41

Source: developed and designed by the authors.

The MLP-network algorithm accurately checks the conformity of the simulation result with the given initial parameter values. Even a slight deviation of the simulated result from the original value means an incorrect decision, which is not taken into account in estimating the percentage of the classifier quality. The average percentage of incorrect classifications was: zone 1 – 5.33%; zone 2 – 4.74%; zone 3 – 6.64%; zone 4 – 5.47%; zone 5 – 4.44%.

5. Discussion and Conclusions

The performed calculations proved that artificial neural networks can be a useful and convenient tool for determining the security level of an enterprise in various areas of its economic activity (types of resources consumed or involved). The speed of processing input data by neural networks and the formulation of modelling results allows timely detection of threats in the enterprise's activities and taking appropriate measures to eliminate them.

Despite the actual conclusions regarding the quality of constructed neural networks, this study has certain limitations and debatable points. First, the list of indicators and functional subsystems, by which the level of enterprise's security is assessed, depends on the specific goals of the research and available information, and therefore it can be specified in further research. Secondly, taking into account the rapid and significant improvement and spread of using neural networks in practical activities, additional scientific, methodological and practical interest is the justification of the possibility of using other architectures of neural networks, followed by a comparison of the quality of such models with those obtained in this work.

In addition, the existing experience of using neural networks in other spheres of activity and a series of experiments conducted by various scientists [56–59] allows stating that a possible way to improve the quality of constructed MLP networks is to increase the number of objects on which their training is carried out, as well as changing the number of neurons in the output layer, which will allow the neural network to more accurately recognize the differences of one classification group from another.

So, modelling the level of resource security of an enterprise is a complex process aimed at solving various tasks that differ in the set of studied parameters, time periods, the composition of objects for comparison, etc. The use of neural network modelling within the scope of this study to justify the level of resource security of the enterprise, which is carried out by building neural networks for each subsystem and the enterprise as a whole, contributes to the solution of such problems as, for example:

- determining the security zone for a certain subsystem or enterprise, which was not included in the sample of studied business entities;
- substantiating the effect of a change in input indicators on a change in the safety zone for a single subsystem or object as a whole of one or another type;
- forming predictive scenarios for future periods regarding options for achieving the desired level of resource security by adjusting the values of input indicators.

In general, the proposed approach to modelling the level of resource security of an economic entity contributes to increasing the degree of validity of relevant management decisions and expanding opportunities for forecasting the consequences of their implementation.

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