Methodology for Assessing the Quality of an Educational Program and Educational Activities of a Higher Education Institution Using a Neural Network

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Abstract: The article discusses a methodology for assessing the quality of educational programs and activities in higher education institutions using artificial intelligence tools such as the adaptive system of neuro-fuzzy inference (ANFIS) and an L-layer neural network. The purpose of the study was to address the problem of objectivity in self-assessment and identify potential problems and shortcomings in educational activities before the start of an accreditation examination. The study used student ratings on a four-level assessment scale as input data for the L-layer neural network, and the criteria for assessing the quality of the educational program as input variables for the ANFIS system. The hypothesis was that students with higher ratings of educational achievement would provide more objective assessments of the quality criteria of the educational program and activities. The results showed that the L-layer neural network made more accurate predictions than the ANFIS model. The article suggests that this approach can provide higher education managers with qualitative forecasts to determine the quality of educational services and identify potential problems before the start of an accreditation examination. However, the study acknowledges the need for further research on larger data volumes to improve the predictive capabilities of the models.

1 INTRODUCTION

In assessing the quality of education, as well as in conducting pedagogical research, we are faced with information that has non-numerical characteristics that are difficult to formalize. For example, the number of computers, the number of students, the area of educational premises in a higher education institution are measurable, but the evaluation of the educational program and educational activities according to the educational program is carried out according to non-numerical criteria. The institution in the process of self-assessment, and subsequently the experts in the process of accreditation examination, must assess according to the assessment scale, which covers four levels of compliance with the criteria: A, B, E, F.

As a result, there is a need to build methods for quantitative description of processes and subjects related to assessing the quality of the educational program and educational activities. Of particular importance is the quality of education, which means some total indicator that reflects the results of the educational institution, as well as compliance with the needs and expectations of society (different social groups) in the formation of individual competen-

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cies. The methods of quantitative evaluation of the educational program and educational activities under this program will allow the higher education institution to identify existing shortcomings and potential problems, as well as provide an opportunity to address them before the accreditation examination.

Assessing the quality of educational programs and educational activities is complicated by the fact that the value of this indicator depends on many factors, possibly with an unknown nature of influence. Also in this case there is a specificity of the "product" of education – a graduate of an educational institution, which should be considered as a complex system. There are various methods and algorithms for assessing the quality of educational activities. In this study, we propose a method of assessing the quality of educational programs and educational activities based on the neuro-fuzzy approach, due to the active development of analytical systems, based on the technology of artificial intelligence. The most popular and proven of these technologies are neural networks, which successfully solve a variety of "fuzzy" tasks – prediction, classification, recognition of handwritten text, language, images (Markova et al., 2018; Tarasenko et al., 2019; Kirichek et al., 2019; Porokhnya and Ostapenko, 2019; Horal et al., 2020; Valko and Osadchyi, 2020). In such problems, where traditional technologies are powerless, neural networks often act as the only effective solution. In this work, artificial neural networks are used to solve the problem of assessing the quality of educational programs and educational activities.

Mandatory conditions for accreditation are compliance with the educational program and educational activities of the higher education institution under this educational program with the criteria established by law. In particular, the forms and methods of teaching should contribute to the achievement of the stated goals of the educational program and program learning outcomes.

Since the educational program and educational activities must meet the requirements of a student-centered approach and the principles of academic freedom, the hypothesis of the study is that based on a sample of students and graduates of higher education, the quality of educational programs and educational activities, which will be able to adequately perform a comprehensive assessment of the quality of the educational program and educational activities.

Intelligent data processing using a neural network allows forming forecast probabilities of values of future results of accreditation examination in a higher education institution, which can contribute to the improvement of measures to improve the educational program. The results of forecasting can be used by the management of faculties and graduating departments as informative and recommendatory. In addition, guarantors of educational programs based on forecasts can plan activities and individual work with teachers to positively change the forecast. Thanks to the analysis of the received data it is possible to reveal weak points of the educational process that will give the chance to modernize it.

With this in mind, the article aims to substantiate, develop and implement a mathematical model of a comprehensive assessment of the quality of educational programs and educational activities based on the methods of the neuro-fuzzy approach.

1.1 Theoretical Background

Assessing the quality of educational activities according to clearly defined criteria and methodologies is an important task in the process of accreditation of educational programs, which are used to train applicants for higher education in Ukraine. In the process of preparing for accreditation and preparation of materials for self-assessment of the educational program, there are problems in determining the objectivity of self-assessment and finding potential problems and shortcomings of educational activities. Due to this problem, the urgent task is to find mathematical tools that could be used by managers of higher education institutions in their approaches to determining the quality of educational services offered.

The paradigm shift in educational philosophy and practice has led to focusing primarily on student learning outcomes. The educational process should be results-oriented – what exactly students know and can actually do. Accordingly, student-centered learning is an approach in which students influence the content, activities, materials, and pace of their learning. This model of learning puts the student at the center of the learning process (Black et al., 2015).

EU initiatives call for increased efficiency, international attractiveness, and competitiveness of higher education institutions. Wächter et al. (Wächter et al., 2015) considers different approaches to quality, quality assurance, and ratings, analyzes recent research, critically analyzes these approaches in a comparative perspective, provides recommendations and policy options for parliament.

The problem of determining a set of effective indicators that are easy to determine and can be applied to both large public universities and small regional private colleges, from university programs to alternative programs is also relevant for the United States (Hammerness and Klette, 2015).

Cherniak et al. (Cherniak et al., 2020) investigated the possibility of assessing the quality of qualimetry objects by graph analytical method, ie to apply the principle of determining the area and volume under curved surfaces both in the plane and in space, which are created by combining estimates of individual quality indicators on a dimensionless scale. It is shown that, as a rule, mathematical dependences are nonlinear and their research is reduced to the development of universal methods that could be applied to objects of qualimetry, regardless of their nature, complexity, importance, and more. Having unit quality indicators in a single (dimensionless) rating scale, it is proposed to determine a single comprehensive quality indicator of the object of qualimetry using the method of integration, which takes into account the evaluation of unit quality indicators.

Parvu and Ipate (Parvu and Ipate, 2007) propose a mathematical model based on a set of indicators that are adapted to the classification structure of intellectual capital, which is unanimously recognized worldwide, namely to the external and internal structure and competence of employees. The Rompedet method, an original product of the Romanian school of management (Isac et al., 2010), was used as a mathematical calculation tool.

When assessing the quality of education, we are faced with a huge number of different criteria, each of which may consist of many sub-criteria, therefore, the task of assessing the quality of education in its mathematical formulation is multi-criteria. Problem situations that are modeled and described by linear models and depend on many factors play an important role, so solving a multicriteria decision-making problem is often accompanied by solving multicriteria linear programming problems, or in other words, vector optimization problems.

Given these problems, mathematical models of integrated quality assessment using methods that are based on the convolution of criteria were also of interest for our study. Models and methods of multicriteria optimization are considered in (Kondruk and Maliar, 2019), in particular, the method of additive convolution of criteria and the method of multiplicative and minimax convolution of criteria. The method of multiplicative convolution of partial criteria to a single generalized indicator, which provides as a normalized divisor to use the maximum (minimum) values of partial criteria, obtaining which does not cause significant difficulties, ie is carried out on many available design solutions is considered in (Grytsyuk and Grytsiuk, 2014). Chervak (Chervak, 2010) uses one of the methods of solving the Paretian multicriteria optimization problem as a mathematical tool of the decision-making process. To organize the selection problems on the same admissible set of alternatives, the concept of the super criterion of any criterion is introduced; if the criterion is a super criterion of this criterion on this set, then the last criterion is a subcriteria of the first. It is shown that the solution of the problem of multicriteria selection by the Paretian convolution is reduced to the solution of the problems of scalar or lexicographic optimization.

The theory of artificial neural networks and models of deep learning is considered in the fundamental works (Goodfellow et al., 2016; Müller et al., 1995; Sivanandam et al., 2006), system design based on a neuro-fuzzy approach (Shtovba, 2007; Shtovba and Pankevych, 2018).

The use of neural networks to classify the status of a graduate of a higher education institution based on selected academic, demographic, and other indicators is considered by Lesinski et al. (Lesinski et al., 2016). A multilayer neural network with feedback is used as a model. The model was taught based on more than 5,000 records of entrance exams and university databases. Nine input variables consisted of categorical and numerical data that contained information about high school education, test results, assessment of high school teachers, parental assessment, and others. Based on these inputs, the multilayer neural network predicted the success of university entrants. With the help of the neural network, it was possible to predict the success of graduates and achieve the best performance with an accuracy of classification exceeding 95%. Black et al. (Black et al., 2015) examining the relationship between quality and success of high school students in college found no convincing evidence that exposure characteristics of high school diminish over time teaching students.

To address the issue of determining the quality of educational training, Mahapatra and Khan (Mahapatra and Khan, 2007) developed the EduQUAL methodology and proposed an integrative approach using neural networks to assess the quality of education. Four neural network models based on a feedback algorithm are used to predict the quality of education for different stakeholders. This study showed that the P-E Gap model is the best model for all stakeholders.

The need to introduce neural network technology in educational courses of educational institutions indicates by Semerikov et al. (Semerikov et al., 2022). Educational neural networks are often used for forecasting. For example, students must choose courses that interest them for the next semester. Due to limitations, including lack of sufficient resources and the overhead of several courses, some universities may not be able to teach all courses of the student's choice. Universities need to know each student's requirements for each course each semester for optimal course planning. Kardan et al. (Kardan et al., 2013) used a neural network to model student choice behavior and apply the resulting function to predict the final enrollment of students for each course. The results showed high prediction accuracy based on experimental data. Arsad et al. (Arsad et al., 2013), Osadchyi et al. (Osadchyi et al., 2018), Okubo et al. (Okubo et al., 2017b) prove that the use of neural networks in predicting educational processes will allow obtaining results with a much higher level of accuracy and less time. According to Abu Naser et al. (Abu Naser et al., 2015), an artificial neural network can correctly predict the success of more than 80% of future students.

Chaban and Kukhtiak (Chaban and Kukhtiak, 2020) analyze the problem of the social system, which consists of many students and teachers of higher education to create effective learning pairs "teacher-student". Elements of the theory of artificial intelligence based on artificial neural networks were used to form the mentioned learning pairs. Okubo et al. (Okubo et al., 2017a) propose to use a recurrent neural network (RNN) to predict students' final grades using journal data stored in educational systems.

Liu et al. (Liu et al., 2022) propose a method for assessing the quality of preparation for graduate school, which is based on the algorithm of neural network backpropagation and stress testing. This method creates a publicly available list of indicators consisting of 19 criteria in 4 groups of criteria, such as attitudes towards teaching, teaching content, approach to teaching, and the main characteristics of teachers. After the neural network algorithm is used to determine the optimal parameters of the evaluation model, a sensitivity test is used to identify indicators that have a significant impact on the quality of education. Also, scenario analysis is used to study the impact of the quality of education in pre-defined situations, providing theoretical and empirical support for assessing the quality of postgraduate teaching, improving the quality of education, and professional growth of teachers.

Educational institutions are constantly striving to improve the services they offer, their goal is to have the best teaching staff, improve the quality of teaching and academic success of students. Knowledge of the factors influencing student learning can help universities and learning centers adapt their curricula and teaching methods to students' needs. One of the first measures taken by educational institutions in the context of the COVID-19 pandemic was the creation of virtual learning environments (Pererva et al., 2020). To understand the factors influencing the university learning process in virtual learning environments, Rivas et al. (Rivas et al., 2021) applied several automatic learning methods to publicly available data sets, including tree-like models and various types of artificial neural networks.

The availability of educational data supported by learning platforms provides opportunities to study student behavior and solve problems in higher education, optimize the educational environment and ensure decision-making using an artificial neural network (Waheed et al., 2020).

Cader (Cader, 2020) uses a deep neural network to assess students' acquisition of knowledge and skills. It is noted that the obstacle to the application of the method in teaching is the relatively small amount of data in the form of available estimates required for neural network training. A new method of data augmentation is proposed – asynchronous data augmentation through pre-categorization, which solves this problem. Using the proposed method, it is possible to carry out neural network training even for small amounts of data.

Do and Chen (Do and Chen, 2013) present a neuro-fuzzy classifier that used the results of previous exams and other related factors as input variables and classified students based on their expected learning outcomes. The results showed that the proposed approach achieved high accuracy compared to the results obtained based on other known approaches to classification, in particular, Naive Bayes, neural networks, and others.

Fazlollahtabar and Mahdavi (Fazlollahtabar and Mahdavi, 2009) proposed a neuro-fuzzy approach based on evolutionary techniques to obtain the optimal learning pathway for both teacher and student. The neuro-fuzzy approach allows providing recommendations to the teacher for making pedagogical decisions based on the student's learning style. On the other hand, the neural network approach is used for the student to create a personalized curriculum profile based on the individual needs of the student in a fuzzy environment.

Taylan and Karagözoğlu (Taylan and Karagözoğlu, 2009) use a systematic approach to designing a fuzzy inference system based on a class of neural networks to assess student achievement. The developed method uses a fuzzy system, supplemented by neural networks, to enhance some of its characteristics, such as flexibility, speed, and adaptability, called the adaptive neuro-fuzzy inference system (ANFIS). The results of the ANFIS model are as reliable as statistical methods, but they encourage a more natural way of interpreting student learning outcomes.

In comparison with these works, this study fills a gap in the methods of a comprehensive assessment of the quality of educational programs and educational activities based on a neuro-fuzzy approach.

1.2 Methods

In this study, methods of mathematical modeling and computational experiment based on statistical processing of data assessments of the quality of educational programs and educational activities were used. The essence of the methodology of mathematical modeling is to replace the original object with its mathematical model and study it with the help of computer technology. Processing, analysis, and interpretation of calculation results were carried out by constant comparison with the results of statistical processing of expert estimates. In the course of the research, refinements were made and the mathematical model was revised and the cycle of the computational experiment was repeated.

The methodology for assessing the quality of the curriculum and educational activities is built using methods and tools of artificial intelligence, implemented in the package Fuzzy Logic Toolbox system MATLAB in the form of adaptive neuro-fuzzy output ANFIS.

A fuzzy inference system can be represented as a neuro-fuzzy network – a neural network of direct signal propagation of a special type, or ANFIS-model. The architecture of a neuro-fuzzy network is isomorphic to a fuzzy knowledge base. Neuro-fuzzy networks use differentiated implementations of triangular norms (multiplication and probabilistic OR), as well as smooth membership functions. This makes it possible to use fast algorithms for training neural networks based on the backpropagation method to tune neuro-fuzzy networks.

ANFIS implements the Sugeno fuzzy inference system through a five-layer feed-forward neural network. Purpose of network layers:

- first layer – terms of input variables;
- the second layer – antecedents (parcels) of fuzzy rules;
- the third layer is the normalization of the degree of implementation of the rules;
- the fourth layer is the conclusion of the rules;
- fifth layer – aggregation of the result obtained according to different rules.

The network inputs are not allocated to a separate layer. Figure 1 shows an ANFIS network with two input variables (x_1 and x_2) and four fuzzy rules. Three terms are used for the linguistic evaluation of the input variable, and two terms for the variable.

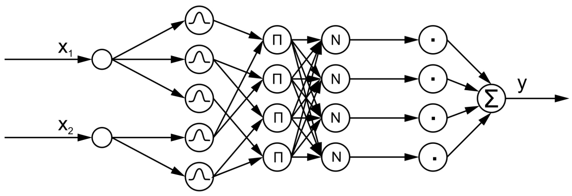

Figure 1: An example of an ANFIS network.

We will use the following notation:

- $x_1, x_2, ..., x_n$ – network inputs;
- y – network output;
- R_r : if $x_1 = a_{1,r}, ..., x_n = a_{n,r}$ it $y = b_{0,r} + b_{1,r}x_1 + ... + b_{n,r}x_n$ is a fuzzy rule with a serial number r;
- m – number of rules $\overline{r = 1,m}$,
- $a_{i,r}$ – fuzzy term with a membership function $\mu_r(x_i)$ used for linguistic evaluation of a variable x_i in the r-th rule $(r = \overline{1,m}, i = \overline{1,n})$;
- $b_{q,r}$ are the conclusion coefficients of the r-th rule $(r = \overline{1,m}, q = \overline{0,n})$.

ANFIS-network works as follows.

Layer 1. Each node of the first layer represents one term with a bell membership function. The inputs of the network are connected only to their terms. The number of nodes in the first layer is equal to the sum of the cardinalities of the term set of input variables. The degree of belonging of the value of the input variable to the corresponding fuzzy term is fed to the output of the node:

$$\mu_r(x_i) = \frac{1}{1 + \left|\frac{x_i - c}{a}\right|^{2b}}, \tag{1}$$

where a, b and c are membership function parameters that can be tuned.

Layer 2. The number of nodes in the second layer is m. Each node of this layer corresponds to one fuzzy rule. The node of the second layer is connected to the nodes of the first layer, which form the antecedents of the corresponding rule. Therefore, each node of the second layer can receive from 1 to n signals. The output of the node is the degree of execution of the rule, calculated as the product of the input signals. Let us denote the outputs of the nodes of this layer as $\tau_r, r = \overline{1,m}$.

Layer 3. The number of nodes in the third layer is also m. Each node of this layer calculates the relative level of execution of the fuzzy rule according to the formula:

$$\tau_r^* = \frac{\tau_r}{\sum_{j=1}^{m} \tau_j}. \tag{2}$$

Layer 4. The number of nodes in the fourth layer is also m. Each node is connected to one node of the third layer, as well as to all inputs of the network (figure 1 connections to the inputs are not shown). The node of the fourth layer calculates the contribution of one fuzzy rule to the network output by the formula:

$$y_r = \tau_r^*(b_{0,r} + b_{1,r}x_1 + \ldots + b_{n,r}x_n). \quad (3)$$

Layer 5. A single node of this layer sums up the contributions of all rules:

$$y = y_1 + \ldots + y_r + \ldots + y_m. \quad (4)$$

Typical neural network training procedures can be applied to tune an ANFIS network, as it uses only differentiated features. It is common to use a combination of gradient descent as a backpropagation algorithm and the least-squares method. The error backpropagation algorithm regulates the parameters of rule antecedents, that is, membership functions. The least-squares method evaluates the rule inference coefficients since they are linearly related to the network output.

Each iteration of the tuning procedure is performed in two steps.

In the first stage, a training sample is fed to the inputs, and, based on the discrepancy between the desired and actual behavior of the network, the optimal parameters of the nodes of the fourth layer are determined using the least-squares method.

In the second stage, the residual mismatch is transmitted from the network output to the inputs, and the parameters of the nodes of the first layer are modified by the backpropagation of the error. At the same time, the rule inference coefficients found at the previous stage do not change. The iterative tuning procedure continues as long as the mismatch exceeds a predetermined value. To tune the membership functions, in addition to the error backpropagation method, other optimization algorithms can be used, for example, the Levenberg-Marquardt method.

The ANFIS editor in Matlab allows you to automatically synthesize a neuro-fuzzy network from experimental data. In this case, the accessories of the synthesized systems are tuned (trained) in such a way as to minimize the deviations between the results of fuzzy modeling and experimental data. The ANFIS editor is loaded using the anfisedit command.

The ANFIS editor contains 3 top menus – File, Edit and View, visualization area, ANFIS properties area, data loading area, source fuzzy inference system generation area, training area, testing area, current information output area, as well as Help and Close buttons, which allows you to call the help window and close the ANFIS editor, respectively.

Participants in the experiment – full-time master's students (22 people) and graduates of higher education institutions of the previous term of study are the same specialties (32 people) – a total of 54 people. This number of respondents is due to the number of indicators of quality criteria because the data format of the artificial network in MATLAB supports square matrices, in this case, 54x54. Before the accreditation examination, students were offered questionnaires with a proposal to assess the quality of the educational program and educational activities of the specialty on an assessment scale covering four levels: F, E, B, A. Student assessments were used to form the vector of artificial neural network inputs. After the accreditation examination, the expert assessments were used to check the quality of the prediction of the artificial neural network.

The experience of European countries demonstrates the expediency of involving students in accreditation examination. For example, the Polish Accreditation Commission consists of 80 – 90 members appointed by the Minister of Science and Higher Education among the candidates nominated by the Senates of higher education institutions, the conferences of rectors of scientific schools and universities in Poland, the Parliament of Students of Poland (the President of the Student Parliament is a member of the Polish Accreditation Commission). In Slovakia, Academic Ranking and Rating Agency is a civic association founded in 2004 on the initiative of former student leaders and academics. The Slovenian Quality Assurance Agency for Higher Education SQAA-NAKVIS (Slovenian Quality Assurance Agency for Higher Education) appoints at least three members of each expert group, of which at least one foreign expert, an expert in the field of quality assessment of higher education and one representative from among students) and others (Tryhub, 2016).

To ensure the representativeness of the sample, the study of its design was carried out based on randomization. The decision on the statistical deviation of the null hypothesis regarding the differences between the averages, thus, was also associated with the procedure of random sampling.

The rating scale covers four levels of compliance by the requirements of the legislation (F, E, B, A) (Verkhovna Rada of Ukraine, 2019). Also, the legislation establishes 10 criteria for assessing the quality of the educational program (Verkhovna Rada of Ukraine, 2019):

1) design and objectives of the educational program (4);
2) structure and content of the educational program (9);

3) access to the educational program and recognition of learning outcomes (4);
4) teaching and learning according to the educational program (5);
5) control measures, evaluation of applicants for higher education and academic integrity (4);
6) human resources (6);
7) educational environment and material resources (6);
8) internal quality assurance of the educational program (7);
9) transparency and publicity (3);
10) learning through research (6).

In turn, each of these criteria has from 3 to 9 indicators (the number is indicated in parentheses). Together, all 10 criteria contain 54 indicators.

2 RESULTS

At the first stage of the study, the collection and statistical processing of data on the results of the assessment of students and graduates of higher education educational programs and educational activities on the educational program for each criterion.

In the second stage, a computational experiment was performed. The cycle of the computational experiment was carried out in several stages:

1) the choice of approximation and mathematical formulation of the problem (construction of a mathematical model of the phenomenon under study);
2) development of a computational algorithm for solving the problem;
3) implementation of the algorithm in the form of a program for the PC;
4) settlements on the PC;
5) processing, analysis and interpretation of calculation results, comparison with the results of statistical processing of expert estimates and, if necessary, refinement or revision of the mathematical model, i.e. return to the first stage and repeat the cycle of the computational experiment.

Assessing the quality of the curriculum and learning activities is complicated by the fact that each of the 10 criteria, in turn, consists of several indicators (3-9) and is due to many factors, possibly with an unknown nature of influence, which is also non-numerical. To assess the quality of the curriculum and training activities, it is proposed to use a two-tier system based on the ANFIS package and artificial neural networks to predict assessment scores.

The ANFIS hybrid system is a combination of the Sugeno neuro-fuzzy inference method with the ability to train a five-layer artificial neural network (ANN) of direct propagation with a single output and multiple inputs, which are fuzzy linguistic variables. As input variables of the ANFIS system, we use the criteria for evaluating the quality of the educational program of 10 groups of factors $V_i (i = 1, ..., 10)$.

The output variable of the ANFIS system is a numerical assessment of the quality of the curriculum and training activities and is defined as a function $y = f(V_1, V_2, V_3, V_4, V_5, V_6, V_7, V_8, V_9, V_10)$.

Layer 1 of the ANFIS system for the linguistic evaluation of input parameters uses the term set of all possible values of the linguistic variable. $A_{Vi} = \{\text{“}F\text{”}, \text{“}E\text{”}, \text{“}B\text{”}, \text{“}A\text{”}\}$. In symbolic form we write: $A_{Vi} = \{F < i >, E < i >, B < i >, A < i >\}$. The term set of the original linguistic variable y is the set of values of quality assessments of the curriculum and educational activities: $T_y = \{F, E, B, A\}$. The outputs of the nodes of layer 1 are the values of the membership functions at specific values of the input variables.

Layer 2 is non-adaptive and defines the preconditions of fuzzy production rules. Production rules – a form of representation of human knowledge in the form of a sentence type – if (condition), then (action). The rules provide a formal way to present recommendations, guidance, or strategies. They are ideal in cases where the knowledge of the subject area arises from the empirical associations accumulated during the work on solving problems in a particular field.

Each node of this layer is connected to those nodes of layer 1, which form the prerequisites of the corresponding rule. To solve this problem, four fuzzy production rules are formulated: $P = \{p_1, p_2, p_3, p_4\}$, because according to the features of the ANFIS network, the number of network rules must correspond to the dimension of the term set of the source variable y.

Nodes perform a fuzzy logical operation “I” (min). The outputs of the nodes of this layer are the degree of truth (fulfillment) of the preconditions of each of the four fuzzy production rules, which are calculated by the formulas:

$$\begin{cases} w_1 = \min(\mu_{F1}(V_1), \mu_{F2}(V_2), \mu_{F3}(V_3), \mu_{F4}(V_4)) \\ w_2 = \min(\mu_{E1}(V_1), \mu_{E2}(V_2), \mu_{E3}(V_3), \mu_{E4}(V_4)) \\ w_3 = \min(\mu_{B1}(V_1), \mu_{B2}(V_2), \mu_{B3}(V_3), \mu_{B4}(V_4)) \\ w_4 = \min(\mu_{A1}(V_1), \mu_{A2}(V_2), \mu_{A3}(V_3), \mu_{A4}(V_4)) \end{cases} . \quad (5)$$

Layer 3 normalizes the degree of implementation of each of the fuzzy production rules (calculation of the relative degree of implementation of the rules) as follows:

$$\overline{w}_h = \frac{w_h}{\sum_{i=1}^{h} w_i}, \tag{6}$$

where $h = 1, \ldots, 4$ is production rule number. Layer 4 calculates the contribution of each fuzzy production rule to the output of the network according to the formula.

$$y_h(v,V) = \overline{w}_h(v_h^{(0)} + v_h^{(1)}V_1 + v_h^{(2)}V_2 + v_h^{(3)}V_3 + \\ + v_h^{(4)}V_4 + v_h^{(5)}V_5), \tag{7}$$

where $v_h^{(0)}$ – coefficients of the initial function ($i = 0, \ldots, 5$).

Layer 5 summarizes the contributions of all the rules:

$$y = \sum_{i=1}^{4} y_i. \tag{8}$$

Training of the ANFIS network was carried out for 24 epochs by a hybrid method. During training, the type of membership functions, the type of initial function, and their coefficients are selected. As a result of training a fuzzy network for four rules, Gaussian functions were adopted as membership functions, and a linear function was adopted as the initial function. As a result of training, membership functions and their coefficients were also obtained.

To assess each of the 10 groups of factors that affect the quality of the curriculum and educational activities by the evaluation criteria, 10 modules are used, which are implemented using artificial neural networks. Thus, it is necessary to design neural networks, a mathematical model of a comprehensive assessment of the quality of the educational program and educational activities based on the methods of the neuro-fuzzy approach. For this purpose, the Neural Network Toolbox was used. To form neural networks, it is necessary to determine their topology, learning mechanism, and testing procedure. Also, the training of an artificial neural network requires input data – a sample of answers of students and graduates with reliable quality indicators, determined based on these criteria.

A standard L-layer feedforward neural network consists of a layer of input nodes (we will stick to the position that it is not contained in the network as an independent layer), $(L-1)$ hidden layers, and an output layer that is connected in series in the forward direction and does not contain a connection between elements within a layer and feedback between layers. The most popular class of multilayer feed-forward networks is formed by multilayer perceptrons, where each computational element uses a limit or sigmoidal activation function. A multilayer perceptron can form arbitrarily complex decision limits and implement arbitrary Boolean functions. The development of a backpropagation algorithm for determining weights in a multilayer perceptron has made these networks the most popular among researchers and users of neural networks. The vast majority of programs involve the use of such multilayer perceptrons. Networks consisting of successive layers of neurons are more commonly used. Although any network without feedback can be represented as successive layers, the presence of many neurons in each layer can significantly speed up calculations using matrix accelerators.

The popularity of perceptrons is due to a wide range of available tasks that can be solved with their help. In the general case, they solve the problem of approximating multidimensional functions, that is, constructing a multidimensional mapping $F : x \Rightarrow y$ that generalizes a given set of parameters $\{x^\alpha \Rightarrow y^\alpha\}$.

Depending on the type of output variables (the type of input variables is not critical), the approximation of functions can take the form of classification (discrete set of initial values), or regression (continuous initial values).

Many practical problems of pattern recognition, noise filtering, time series prediction, etc. come down to basic settings. The reason for the popularity of perceptrons is that, for their range of tasks, they are, firstly, universal, and secondly, they are efficient in terms of the computational complexity of devices.

As a result of the development of neurocomputing, a large number of efficient models of neural networks have been created, focused on solving various problems. Due to this, artificial neural networks are successfully used to solve a wide class of practical problems. Therefore, when solving a specific problem, it is necessary to solve the issue of choosing the most appropriate neural network model, its parameters, and the training method.

Typically, a network consists of many sensor elements (input nodes or source nodes) that form an input layer; one or more hidden layers of computational neurons, and one output layer of neurons. The input signal propagates through the network in a forward direction from layer to layer. Such networks are usually called multilayer perceptrons. They are a generalization of a single layer perceptron.

Multilayer perceptrons are successfully used to solve various problems. At the same time, supervised learning is performed using such a popular algorithm as the error back-propagation algorithm. This method consists of error correction (error-correction learning rule). It can be thought of as a generalization of the equally popular adaptive filtering algorithm, the mean squared error minimization (LMS) algorithm.

Multilayer perceptrons have three characteristic features.

1. Each neuron of the network has a non-linear activation function. It should be noted that this non-linear function is smooth (that is, differentiated everywhere), in contrast to the hard threshold function used in the Rosenblatt perceptron. The most popular form of a function that satisfies this requirement is the sigmoidal nonlinearity, defined by the logistic function

$$y_i = \frac{1}{1+exp(-v_j)}, \tag{9}$$

   where v_j is the induced local field (i.e., the weighted sum of all synaptic inputs plus the limit value) of neuron j; y_j is the output of the neuron. The presence of non-linearity plays a very important role, since otherwise the "input-output" mapping of the network can be reduced to a conventional single-layer perceptron. Moreover, the use of the logistic function is biologically motivated, since it takes into account the recovery phase of a real neuron.

2. The network contains one or more layers of hidden neurons that are not part of the input or output of the network. These neurons allow the network to learn how to solve complex problems by sequentially extracting the most important features of the input image (vector).

The network has a high degree of connectivity (connectivity), implemented using synaptic connections. Changing the level of network connectivity requires changing the plurality of synaptic connections or their weights.

The combination of all these properties, along with learning-by-doing, provides the computational power of a multilayer perceptron. However, these same qualities are the reason for the incompleteness of modern knowledge about the behavior of such networks. First, the distributed form of nonlinearity and the high connectivity of the network significantly complicate the theoretical analysis of a multilayer perceptron. Second, the presence of hidden neurons makes the learning process more difficult to visualize. It is in the learning process that it is necessary to determine which signs of the input signal should be given by hidden neurons. Then the learning process becomes even more difficult, since the search must be performed in a wide range of possible functions, and the choice must be made among alternative representations of the input images.

The emergence of the backpropagation algorithm was a landmark event in the development of neural networks, since it implements a computationally efficient method for training a multilayer perceptron. The backpropagation algorithm does not offer a truly optimal solution to all potential problems, but it is most effective in learning multilayer machines.

An artificial neural network for the analysis of indicators of the quality of the educational program and educational activities will have the number of input neurons (according to the number of indicators for all criteria) 54; output neurons – 54. Input signals were determined based on students' assessments of each indicator of this quality criterion, while the scale F, E, B, A were translated into numerical 1; 2; 3; 4 respectively. Part of the data is given in table 1.

Table 1: Input signals (T) based on students' assessments of quality criteria.

Indicators of quality criteria	Student grades								
	1	2	3	4	5	6	7	...	54
1	3	4	3	3	4	3	4	...	4
2	4	3	3	3	4	3	3	...	4
3	3	3	4	3	4	4	3	...	4
...	...	...	...	...	...	...	...	...	...
54	4	3	3	3	4	3	3	...	4

It is important that the neural network can predict expert assessments if student and graduate assessments are to be ranked in ascending order based on the determination of the grade point average. According to the hypothesis, we assume that students with higher academic performance are better acquainted with the goals, structure, and content of the educational program, the process and characteristics of teaching and learning according to the educational program, control measures, assessment system, and all other aspects of educational activities. assessments of the quality of the educational program and educational activities will be more objective.

The Neural Network Toolbox application package Matlab Mathematical Modeling Environment (version R2014a) was used in the work. After starting the Matlab system, enter the nntool command on the command line, which opens the window for entering data and creating a neural network (Neural Network / Data Manager) (figure 2).

After starting the MATLAB system, you need to enter the tool command on the command line, which will open the window for entering data and creating a neural network (Neural Network / Data Manager). Clicking the New button opens the Create Network or Data window. After selecting the Data tab in the Name field you must enter a new name of the input data "P", and in the Value field the values of the input data, in which the numbers 1-54 are indicators of

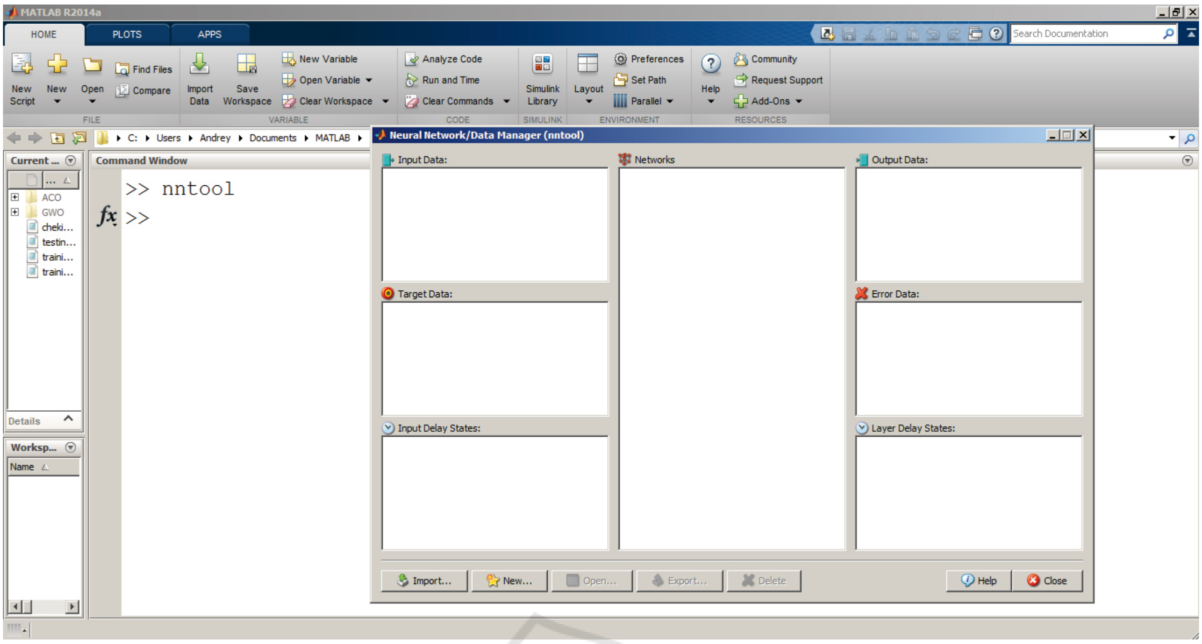

Figure 2: Data entry and neural network creation windows.

quality criteria, and 55-108 – students' and graduates' indicators quality criteria.

To create a new network, we chose New, to view the data you need to select Import. The data is contained in the P.mat file. This file is a matrix of two lines, in which the numbers 1-54 are indicators of quality criteria, and 55-108 – are the evaluation of students and graduates on the indicators of quality criteria. Its contents are stored in the P.txt file.

The next step is to import the data (figure 3).

The next step was to create data ("T") – goals, which are an array of size 54x54, which contains information about the grades given by the participants of the experiment – full-time master's students (22 people) and graduates of higher education institutions there are specialties (32 people) – a total of 54 people. This number of respondents is due to the number of indicators of quality criteria because the data format of the artificial network in Matlab supports square matrices, in this case, 54x54. The data is stored in a T.mat file. Its contents can be viewed using a text editor.

We import data in the same way as for the array P.

In the next step, a neural network was created (figure 4). An artificial neural network for the analysis of indicators of the quality of the educational program and educational activities will have the number of input neurons (according to the number of indicators for all criteria) 54; output neurons – 54. Input signals were determined based on students' assessments for each indicator of this quality criterion, while the scales F, E, B, A were converted to numerical 1; 2; 3; 4 respectively.

The configuration of the neural network of direct propagation is chosen based on a heuristic rule: the number of neurons of the hidden layer is equal to half of the total number of input and output neurons. The artificial neural network for the analysis of quality indicators of the educational program and educational activity will have the number of input neurons 2 (according to the dimensionality of the data – indicators of quality criteria and student evaluation); source neurons 54, therefore, the number of hidden neurons is 28. The View button allows you to view the network structure (figure 5).

In our case, 2 is the number of input neurons, which is known to be selected based on the dimension of the input data (1 – indicators of quality criteria; 2 – student assessments). Output neurons – 54. The configuration of the neural network of direct propagation (feed-forward backdrop) is chosen based on the heuristic rule: the number of neurons in the hidden layer is equal to half the total number of input and output neurons, so the hidden layer has 28 neurons.

The next stage is network training and coaching. Double-clicking with the left mouse button on the created neural network network1 in the window of the Neural Network / Data Manager opens a window with the network.

The View tab presents the neural network itself. Go to the Reinitialize Weights tab, where the Input Ranges column selects the P input from the Get from

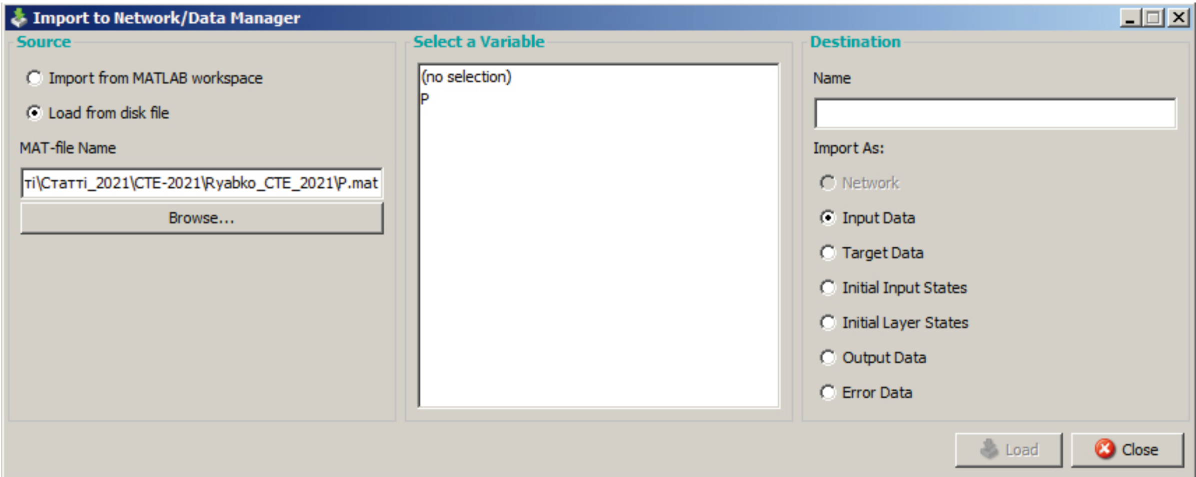

Figure 3: Importing data.

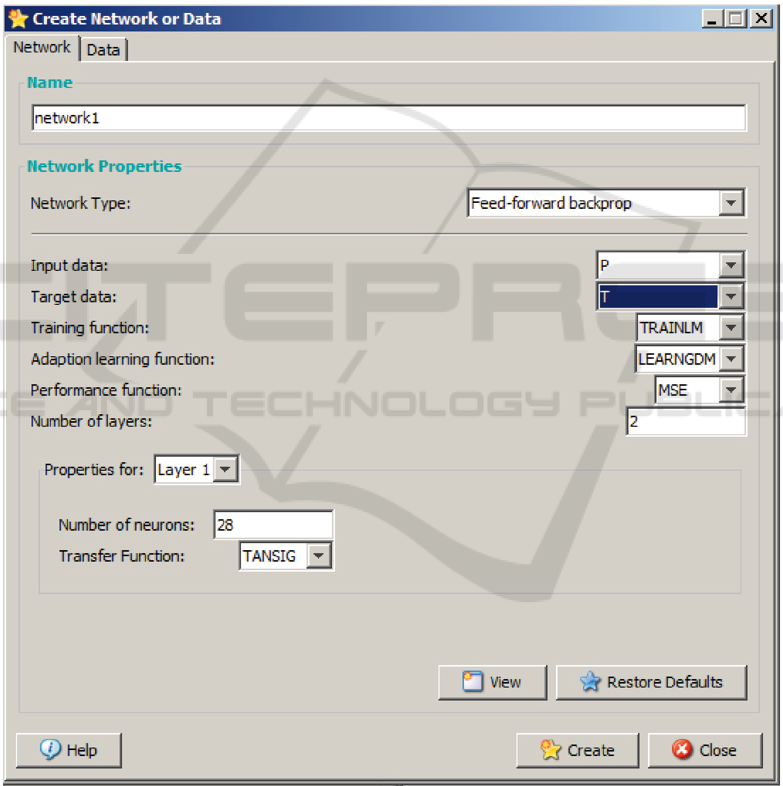

Figure 4: Creating a neural network.

the input list. Then press the Set Input Ranges and Initialize Weights buttons in succession allowing us to initialize the scales needed to initialize the entire network.

The next step is network learning.

Learning the backpropagation method involves two passes through all layers of the network: forward and backward. In a forward pass, the image (incoming vector) is fed to the sensor nodes of the network, after which it propagates through the network from layer to layer. As a result, a set of output signals is generated, which is the actual response of the network to a given input image. In forward traversal, all synaptic weights of the network are fixed. In a backward pass, all synaptic weights are adjusted according to the error correction rule, namely: the actual output of the network is subtracted from the desired (target) response, resulting in an error signal. This

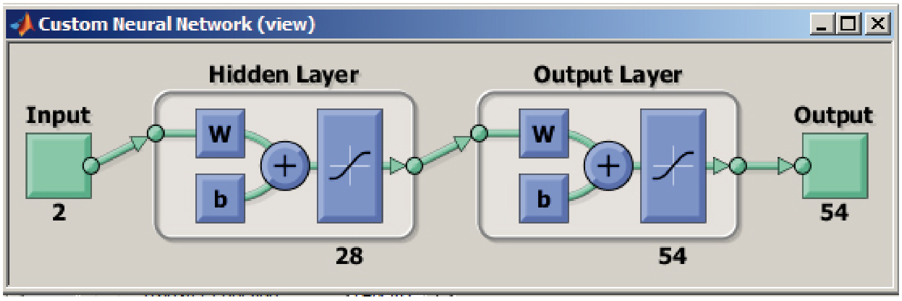

Figure 5: The structure of the neural network.

signal subsequently propagates through the network in the opposite direction of the synaptic connections. Hence the name – backpropagation algorithm. The synaptic weights are tuned to bring the network output as close as possible to the desired statistical meaning. The back-propagation algorithm is sometimes referred to as the simplified back-propagation algorithm. The learning process using this algorithm is called back-propagation learning.

Going to the Train tab opens a learning window in which P and T are selected instead of input data and targets, respectively (figure 6). On the right of the Training Results column, you need to change the name of the Outputs and Errors to O and E, respectively. Then pressing the Train Network button will start network training, the process of which can be observed in the Neural Network Training window. You can close the window after graduation.

After the training was completed, two types of data appeared in the Neural Network / Data Manager window: Output Data (O) and Error Data (E). Double-clicking on data O opens a window with data output. By clicking the Export button in the manager window, and then clicking Export again in the window that opens, you can transfer the data to the Matlab workspace, where it will be presented in the most presentable form. You can view the results in the O.mat and E.mat files.

You can calculate that the average network error is 0.0321, which indicates the efficiency of the system.

After learning the network, you can proceed to data forecasting. Returning to the Neural Network / Data Manager window, you need to create additional input by clicking the New button. Going to the Data tab, the name of the data changes, for example, to P1, and the values are set as follows: values 1-54 still indicate the numbers of indicators of quality criteria of educational programs and educational activities, and 56-109 assessments of students and graduates quality, and the last column – projected expert assessments.

Next, you need to return to the Network window. In the Simulate tab of the input values house, the P1

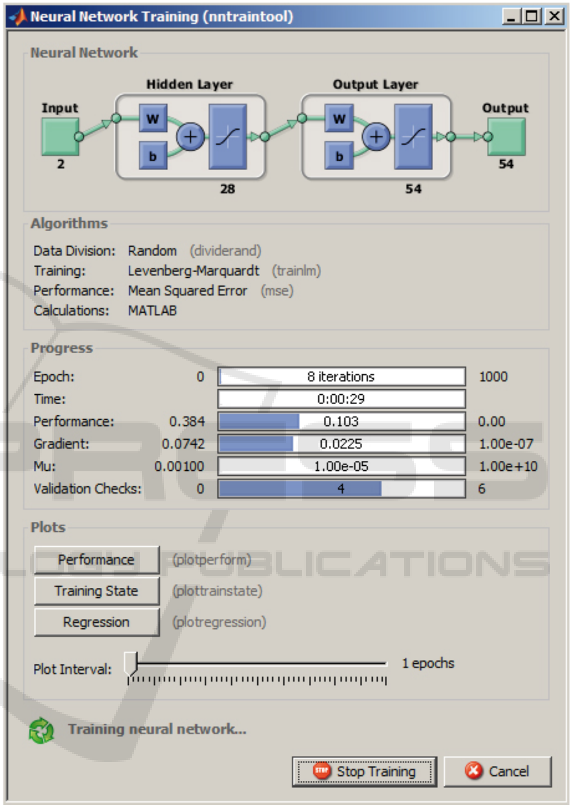

Figure 6: Neural network learning.

array is selected, and the Outputs output value is renamed to forecast (figure 7).

After clicking the Simulate Network button, you can return to the Neural Network / Data Manager window and, by clicking the Export button, copy the source forecast array to the Matlab workspace. After receiving the table in the workspace, pay attention to the last column, which is responsible for forecasting (figure 8).

The data obtained in the study can be viewed in the forecast.mat file.

Comparing the data issued by the system and the real data, we can see that the neural network does make predictions that are quite close to reality. Com-

Table 2: Output signals (O).

Indicators of quality criteria	Student grades								
	1	2	3	4	5	6	7	...	54
1	3.1985	3.252	3.3058	3.3541	3.3933	3.4235	3.4475	...	3.9704
2	3.4521	3.3478	3.2644	3.2035	3.1633	3.1404	3.1319	...	3.9997
3	3.1516	3.1812	3.219	3.2627	3.3062	3.3417	3.3638	...	3.9992
...	...	...	...	...	...	...	...	...	...
54	4	3.4192	3.3522	3.3128	3.291	3.2798	3.2756	...	3.9716

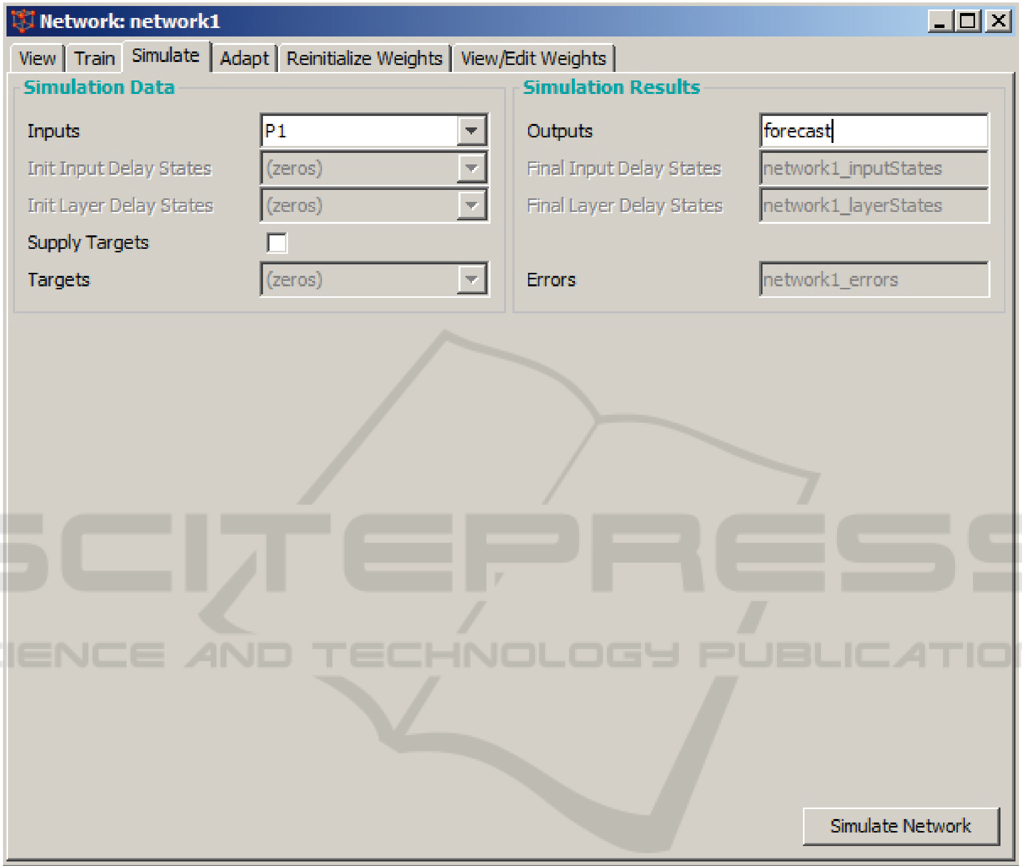

Figure 7: Simulate.

pared with expert estimates, the average absolute error is 0.0321, the relative error is 7.08%.

In the second part of the experiment, forecasting was carried out using a different type of neural network – a neuro-fuzzy network, or ANFIS-model.

Expert estimates are used as validation data. Create data files: training.dat, testing.dat, checking.dat. It should be noted that attempts to consider large data volumes lead to a reduction in the number of observations in the training sample and its simultaneous unjustified growth, which can negatively affect the network's ability to learn. So, first you need to turn the available information into a form that is understandable and meaningful for the neuro-fuzzy network. Consider the average value of the assessment of each of the 10 criteria for assessing the quality of the educational program. For training, we use the average scores of all students for each of the 10 criteria. For testing, the marks of students numbered from 12 to 30 are used, for verification – the marks that were put by 31 students.

We preliminarily transpose the data, so the numbers of students will be in the rows, and the grades according to the quality criteria will be in the columns. The data in the files contains 10 columns – 9 grades (incoming) and 1 grade (source). The first file contains 54 lines and 10 columns. The second has 18 rows and 10 columns. The third has one row and 10

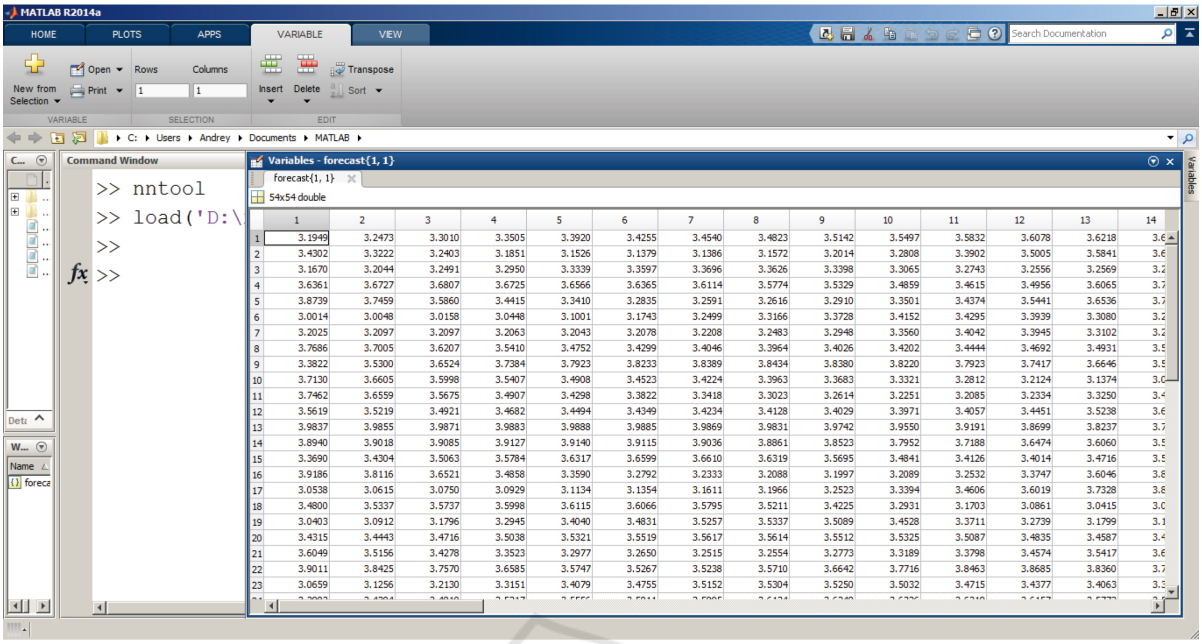

Figure 8: Getting a table with forecasting in the work area.

Table 3: Errors (E).

Indicators of quality criteria	Student grades								
	1	2	3	4	5	6	7	...	54
1	-0.199	0.748	-0.306	-0.354	0.607	-0.424	0.552	...	0.0000237
2	0.548	-0.348	-0.264	-0.203	0.837	-0.140	-0.132	...	0.029607
3	-0.152	-0.181	0.781	-0.263	0.694	0.658	-0.364	...	0.00027
...	...	...	...	...	...	...	...	...	...
54	0.58076	-0.3522	-0.3128	-0.2909	0.7202	-0.2755	-0.2769	...	0.028442

Table 4: Neural network forecast and expert evaluation.

Indicators of quality criteria	Forecast	Estimates
1	3.999977	4
2	3.974844	4
3	3.999750	4
4	3.999379	3
5	3.956661	4
6	3.991731	4
7	3.985698	4
...	...	...
54	3.970182	4

columns.

Anfis Editor is used to building MATLAB fuzzy neural networks. Run the editor with the anfisedit command. In the Load data menu, select Training, and From disk, click the load data button. In the window that opens, select the previously created training.dat file. In the Load data menu, select Testing and From disk, click the load data button. In the window that opens, select the previously created testing.dat. In the Load data menu, select Checking and From disk, and click the load data button. In the window that opens, select the previously created checking.dat. The visualization area contains two types of information: when training the system, the learning curve in the form of a graph of the dependence of the learning error on the iteration ordinal number; when loading data and testing the system – experimental data and simulation results.

Experimental data and simulation results are displayed as a set of points in two-dimensional space. In this case, the serial number of the data line in the sample (training, test, or control) is plotted along the abscissa axis, and the value of the initial variable of this sample line is plotted along the ordinate axis. The following markers are used: blue dot (.) – test set; blue circle (o) – training sample; blue plus (+) – control sample; a red asterisk (*) – simulation results.

Then, having set the Generate FIS menu switch to the Grid partition position, you should press the Generate FIS button. In this case, the model has 10 input variables, each of which corresponds to 9 terms

Training.dat file (first three lines):
3.5000 3.3333 3.5000 3.4000 3.5000 3.3333 3.3333 3.5714 3.3333 3.1667
4.0000 3.4444 3.2500 3.8000 3.7500 3.5000 3.6667 3.4286 3.6667 4.0000
3.2500 3.6667 3.2500 3.4000 3.5000 3.6667 3.0000 3.5714 4.0000 3.8333

Testing.dat file (first four lines):
3.2500 3.4444 3.7500 3.6000 3.2500 3.8333 3.5000 3.4286 3.6667 3.5000
3.7500 3.6667 4.0000 3.2000 3.5000 3.3333 3.1667 3.8571 3.6667 3.6667
4.0000 3.5556 3.5000 3.6000 3.5000 3.8333 3.5000 3.2857 3.3333 3.8333
3.5000 3.5556 3.2500 3.4000 3.5000 3.6667 3.6667 3.5714 4.0000 3.5000

Checking.dat file:
3.5000 3.3333 3.2500 3.4000 4.0000 3.3333 3.8333 3.2857 3.0000 3.8333

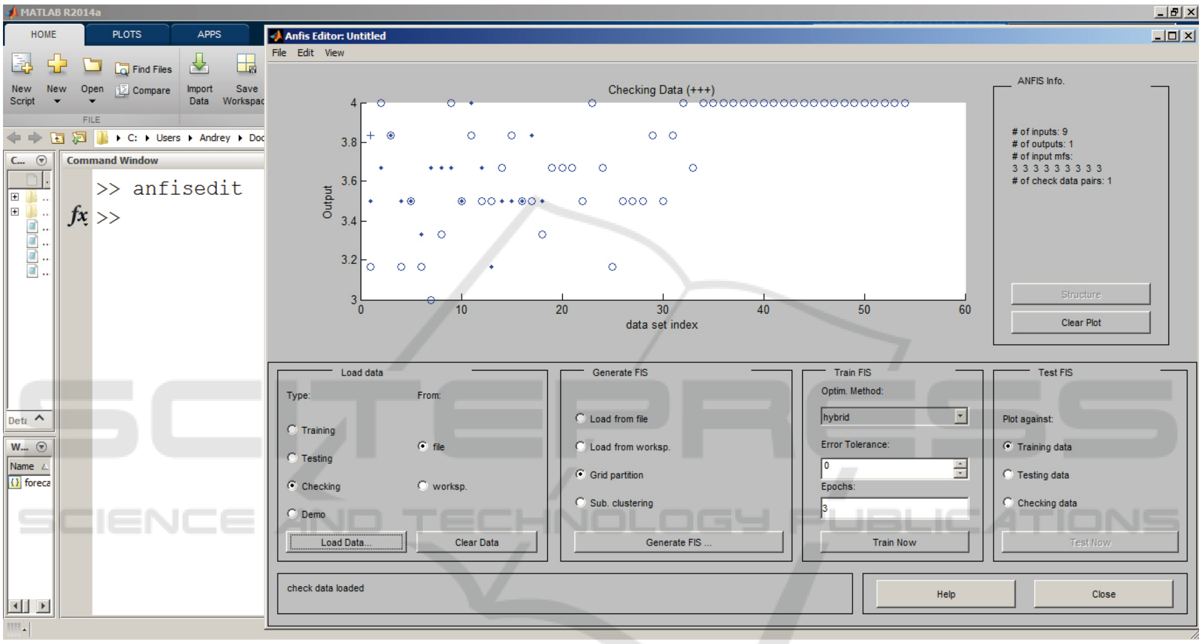

Figure 9: Data for network training and validation.

of the gaussmf type. The original variable is determined by a linear function. Let's generate a Sugeno-type fuzzy inference system by pressing the Generate FIS button. In the window that opens, set 3 membership functions of the gaussmf type for each input variable. The choice of the property function here is because we assume a normal distribution for a random variable, defined by a Gaussian function according to probability theory. For the output variable, we set the membership function const.

To train the hybrid network, we will choose the backdrop method (error backpropagation) with an error level of 0 and a number of cycles of 10. Let's start training the hybrid network (figure 10).

As can be seen from figure 10, according to the training results, the average error is approximately 0.007.

We test the fuzzy inference system first on the training set.

Now let's test the resulting fuzzy inference system on the known values of expert estimates. Now we download this sample in testing mode in the Anfis editor. The results are shown in Figure 12. The mean score of the experts is 3.99; network prediction of the neural fuzzy network is 3.51. The relative forecast error is 12.57%.

Comparing the prediction errors of the neuro-fuzzy network (12.57%) and the L-layer feed-forward neural network (7.08%), we can see that the latter makes a more accurate prediction. It should be noted that the ANFIS model requires significantly more computing resources from the computer, which forced us to reduce the number of input variables to 10, which corresponded to the number of program

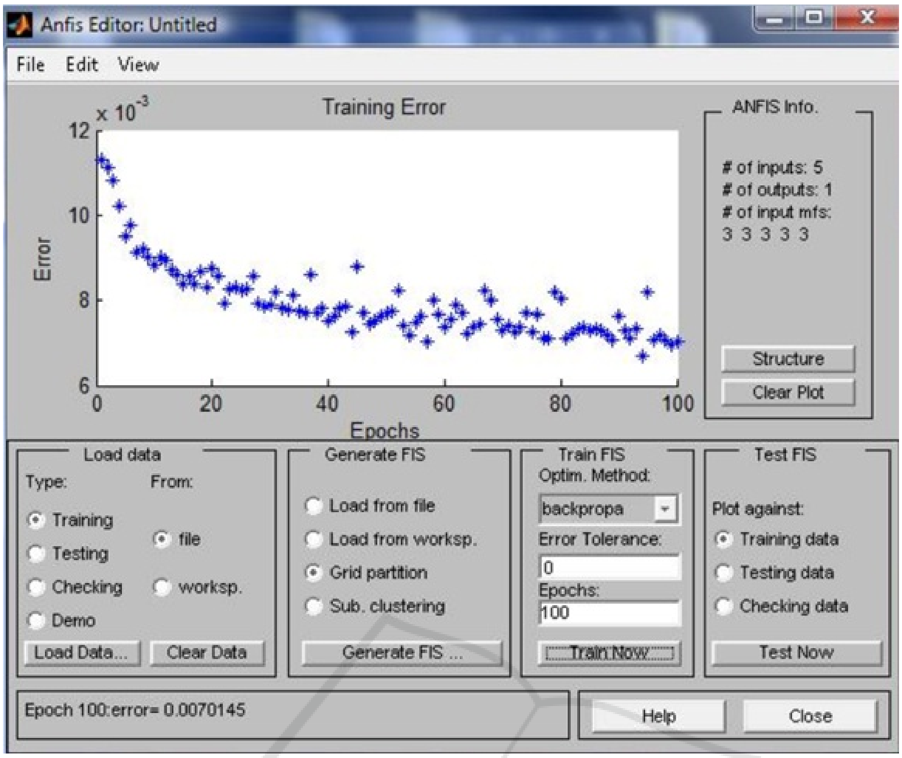

Figure 10: Network training error.

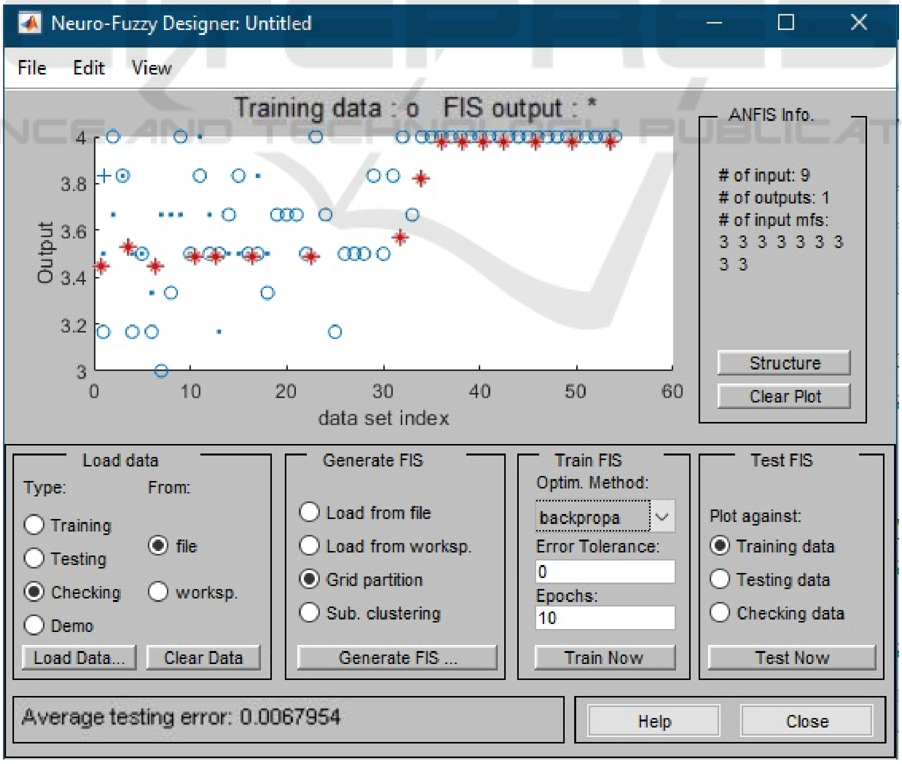

Figure 11: Network training results.

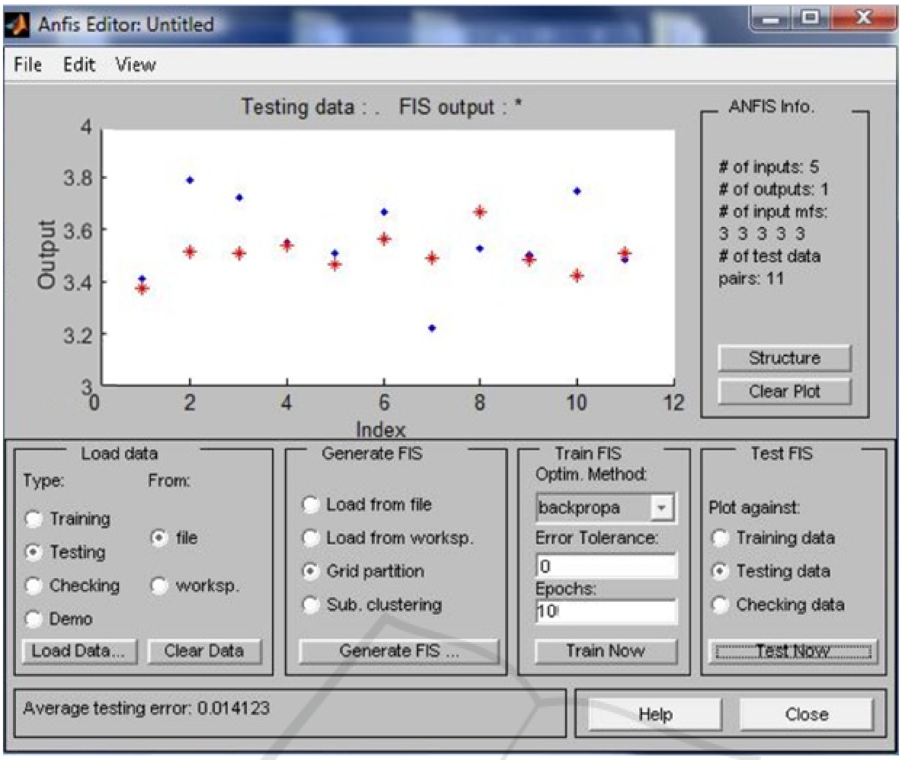

Figure 12: The results of network testing on known values of expert estimates.

evaluation criteria, and use the average values of quality indicators for each of the criteria. Of course, the problem requires further study of large data volumes of other accreditation examinations, but in general, this approach has demonstrated very good predictive capabilities.

Table 4 also shows that the quality of the program and educational activities is at a fairly high level, which reflects the average score of the peer review.

3 DISCUSSION

The study aimed to demonstrate the possibility of predicting the assessment of the quality of educational programs and educational activities can be adequately addressed through an artificial neural network and obtain a comprehensive assessment of the quality of educational programs and educational activities based on a possible neuro-fuzzy approach. The mathematical model involves the use of neural networks and is based on the technology of analytical processing of statistical data. Standard methods of mathematical statistics are used to analyze the estimates received from respondents.

Debatable are proposals for using students as experts in the educational program and educational activities; it is more appropriate to use teachers from other educational institutions, but in the process of preparing for introspection, this approach can be considered quite appropriate.

The results of the neural network should be considered not as final, but as a test. As noted, for more detailed conclusions, it is necessary to train the network on a larger amount of experimental data.

The network structure has room for further improvement and customization in future studies.

The assumption that based on a sample of students and graduates of higher education the quality of the educational program and educational activities can prepare a sample for setting up and teaching artificial neural networks is confirmed by ordering the quality of the curriculum of students and graduates. teaching. In practice, this allows you to predict the results and identify existing shortcomings and eliminate them before the accreditation examination. However, the difficulty of this method is to choose the architecture of the neural network and prepare a training sample to configure the neural network. In particular, in the future, it is planned to increase the volume of the input vector of the artificial neural network, and the form is based on estimates of teachers, stakeholders, and experts.

4 CONCLUSIONS

As a result of a mathematical model of a comprehensive evaluation of the quality of educational programs and educational activities based on the methods of neuro-fuzzy approach, first managed to work out a mechanism for obtaining a quantitative evaluation of educational programs and educational activities in this program that will allow the institution of higher education detect shortcomings and potential problems and solve them before the accreditation examination. Secondly, based on a sample of students and graduates of higher education to evaluate the quality of educational programs and educational activities, you can prepare a training sample for setting up and learning an artificial neural network that can adequately perform a comprehensive assessment of educational programs and educational activities. This can be done by arranging the assessments of the quality of the curriculum and the educational activities of students and graduates in ascending order based on the determination of the average grade point average. It is emphasized that these methods are effective provided they meet the requirements of a student-centered approach and the principles of academic freedom.

Based on a sample of students and graduates of higher education, the quality of the educational program and educational activities was prepared to prepare a training sample for setting up and teaching artificial neural network, which was able to adequately perform a comprehensive assessment of the quality of educational programs and educational activities. A comparison of the results of the operation of an artificial neural network of direct propagation with one output and several inputs with real data shows that the neural network does make predictions close to reality. Compared with expert estimates, the average absolute error was 0.0321; the relative error was 7.08%.

The results of the study can be used in the practice of higher education institutions to predict the results and identify existing shortcomings and eliminate them before the accreditation examination.

We see prospects for further research in the application of software products based on the theory of neural networks to automate the processes of the organization, control, and analysis of the educational process; introduction of neural network software for direct training of students in certain disciplines.

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