Ministry of Education and Science of Ukraine
Black Sea Universities Network

ODESA NATIONAL UNIVERSITY OF TECHNOLOGY

International Competition of Student Scientific Works

BLACK SEA SCIENCE 2022

PROCEEDINGS

ODESA, ONUT 2022

Ministry of Education and Science of Ukraine

Black Sea Universities Network

Odesa National University of Technology

International Competition of Student Scientific Works

BLACK SEA SCIENCE 2022

Proceedings

Odesa, ONUT 2022

UDC 001.8(063)

Black Sea Science 2022: Proceedings of the International Competition of Student Scientific Works / Odesa National University of Technology; B. Iegorov, M. Mardar (editors-in-chief) [*et al.*]. – Odesa: ONUT, 2022. – 749 p.

Proceedings of International Competition of Student Scientific Works «Black Sea Science 2022» contain the works of winners of the competition.

The author of the work is responsible for the accuracy of the information.

Odesa National University of Technology, 2022.

Organizing committee:

Prof. Bogdan Iegorov, D.Sc., Rector of Odesa National University of Technology, Head of the Committee

Prof. Maryna Mardar, D.Sc., Vice-Rector for Scientific and Pedagogical Work and International Relations of Odesa National University of Technology, Deputy Head of the Committee

Prof. Baurzhan Nurakhmetov, D.Sc., First Vice-Rector of Almaty Technological University (Kazakhstan)

Prof. Michael Zinigrad, D.Sc., Rector of Ariel University (Israel)

Prof. Plamen Kangalov, Ph.D., Vice-Rector for Academic Affairs of "Angel Kanchev" University of Ruse (Bulgaria)

Prof. Heinz Leuenberger, Ph.D., Professor of the Institute of Ecopreneurship of University of Applied Sciences and Arts (Switzerland)

Prof. Edward Pospiech, Dr. habil., Professor of the Institute of Meat Technology of Poznan University of Life Sciences (Poland)

Prof. Lali Elanidze, Ph.D., Professor of the Faculty of Agrarian Sciences of Iakob Gogebashvili Telavi State University (Georgia)

Dr. Dan-Marius Voicilas, Ph.D., Associate Professor of the Institute of Agrarian Economics of Romanian Academy (Romania)

Prof. Stefan Dragoev, D.Sc., Vice-Rector for Scientific Work and Business Partnerships of University of Food Technologies (Bulgaria)

Prof. Jacek Wrobel, Dr. habil., Rector of West Pomeranian University of Technology (Poland)

Dr. Mei Lehe, Ph.D., Vice-President of Ningbo Institute of Technology, Zhejiang University (China)

Dr. V. Kozhevnikova, Ph.D., Associate Professor of the Department of Hotel and Catering Business of Odesa National University of Technology, Secretary of the Committee

INTRODUCTION

International Competition of Student Scientific Works “Black Sea Science” has been held annually since 2018 at the initiative of Odesa National University of Technology (formerly Odesa National Academy of Food Technologies) with the support of the Ministry of Education and Science of Ukraine. It has been supported by Black Sea Universities Network (the Association of 110 higher education institutions from 12 countries of the Black Sea Region) since 2019, and by Iseki-FOOD Association (European Integrating Food Science and Engineering Knowledge into the Food Chain Association) since 2020.

The goal of the competition is to expand international relations and attract students to research activities. It is held in the following fields:

- Food science and technologies
- Economics and administration
- Information technologies, automation and robotics
- Power engineering and energy efficiency
- Ecology and environmental protection

The jury includes both Ukrainian and foreign scientists. In the 4 years that the competition has been held, the jury included scientists from universities of 24 countries: Angola, Azerbaijan, Benin, Bulgaria, China, Czech Republic, France, Georgia, Germany, Greece, Israel, Italy, Kazakhstan, Latvia, Lithuania, Moldova, Pakistan, Poland, Romania, Serbia, Slovakia, Switzerland, Turkey, USA.

At the same time, every year the geography has expanded and the number of foreign jury members has increased: from 46 jury members representing 25 universities from 12 countries in 2018, to 73 jury members of the 46 universities from 19 countries in 2022.

More than a thousand student research papers have been submitted to the competition from both Ukrainian and foreign institutions from 25 countries: China, Poland, Mexico, USA, France, Greece, Germany, Canada, Costa Rica, Brazil, India, Pakistan, Israel, Macedonia, Lithuania, Latvia, Slovakia, Romania, Kyrgyzstan, Kazakhstan, Bulgaria, Moldova, Georgia, Turkey, Serbia.

The interest of foreign students in the competition grew every year. In 2018, the students representing 15 institutions from 7 countries have submitted 33 works. In 2021 the number of submitted works increased to 73, authored by the students of 40 institutions from 18 countries.

The competition is held in two stages. In the first stage, student research papers are reviewed by members of the jury who are experts in the relevant fields. In the second stage of the competition, the winners of the first stage have the opportunity to present their work to a wide audience in person or online.

All participants of the competition and their scientific supervisors are awarded appropriate certificates, and the scientific works of the winners are included in the electronic proceedings of the competition. Every year the competition receives a large number of positive responses from Ukrainian and foreign colleagues with the desire to participate in the coming years.

3. INFORMATION TECHNOLOGIES, AUTOMATION AND ROBOTICS

SYNTHESIS OF THE CONTROL SYSTEM WITH NEUROCONTROLLER

Author: Sholopko Dmitry
Advisor: Gurskiy Alexander
Odessa National Technological University (Ukraine)

Abstract. *The synthesis of the control system with a neurocontroller is considered in this article. The neurocontroller was developed based on the characteristics of a typical regulator using the MATLAB/Simulink software environment. A comparative analysis of the quality of regulation of various control systems, such as a control system with a typical PID controller, a control system with a fuzzy controller and a neurocontroller, is presented. The results of modeling various control systems under conditions of deterministic and random disturbances are considered.*

Keywords: *Neuroregulator, Fuzzy controller, Control system, Neural network, Neurocontrol, PID controller.*

I. INTRODUCTION

Potential applications of artificial neural networks are those where human intelligence is inefficient and traditional calculations are time consuming or physically inadequate. The relevance of the use of neural networks increases many times when there is a need to solve poorly formalized problems. The main areas of application of neural networks: automation of the classification process, automation of forecasting, automation of the recognition process, automation of the decision-making process; management, encoding and decoding of information; approximation of dependencies, etc.

Pieces of neural networks at the same time are widely known in the various subject areas themselves. One of the most important directions in the selection of piecewise neural networks is neurocontrol in systems of automatic circulation of different types. Neurofeedback is the first step in intellectual healing, when the quality of the instrument for unraveling the task of healing is blocked by piecewise neural networks.

The artificial neural network as a neuroregulator performs nonlinear conversion of the input signal and the formation of the control effect. The controller can have a large number of optimized parameters (coefficients of interneuronal connections), which makes it possible to optimize it for almost any object with a nonlinear static characteristic. In this paper, a neural network is a mathematical model with optimized parameters that will perform the functions of a previously developed fuzzy logic controller.

II. LITERATURE ANALYSIS

The development of neural network of control algorithms is due to modern progress in information technology. Neurocontrol is a special case of intelligent control that uses artificial neural networks to solve problems of controlling dynamic objects [1–3]. Neural networks have a number of unique properties that make them a powerful tool for creating control systems: the ability to learn from examples and generalize data, the ability to adapt to changes in the properties of the control object and the environment, suitability for the synthesis of linear controllers.

Known examples of practical applications of neural networks for solving problems of controlling the initial[4, 5], robot body, engine speed [6], hybrid car engine], electric furnace, turbogenerator [7], welding, pneumatic cylinder.

To implement control system, based on ANN, the production of neurochips and neurocontrollers (NC) is currently growing.

The noted positive features of neurocontrollers make it possible to take into account a significant factor in increasing fuzzy control in neurocontrol.

This approach is quite effective for controlling non-linear objects.

III. OBJECT, SUBJECT, AND METHODS OF RESEARCH

The neurocontroller in our case is an artificial neural network characterized by nonlinear characteristics. Due to this, the use of a neurocontroller based on the neural network will achieve higher results in management. A neural network is a sequence of neurons (neuroelements) connected by synapses. The structure of the neural network came into the world of programming directly from biology. The most common structure - multilayer, used as controllers of neural network control algorithms

The mathematical model used as a neuroelement in the neural network control algorithm is similar to the known most common models, which are similar to the formal McCulloch-Pitts neuron model. In this model (Figure 1), the signals received at the inputs of the neuroelement are multiplied by their weight. The signal of the first input x_1 is multiplied by the corresponding weight w_1. As a result, we obtain x_1w_1. And so to the nth entrance. As a result on the last input we receive x_nw_n. Then all multiplications are transferred to the adder. Based on his name, you can understand what he is doing. It simply summarizes all the input signals multiplied by the corresponding weights:

$$x_1w_1 + x_2w_2 + \cdots + x_nw_n = \sum_{i=1}^{n} x_iw_i$$

Just to give a balanced amount to the exit is quite meaningless. The neuroelement must somehow process it and generate an adequate output signal. It is for these purposes and use the activation function. It converts the weighted sum into a number, which is the output of the neuron.

Due to the fact that the fuzzy regulator determines the increase in control action, both positive and negative values, the synthesis of neurocontrollers must choose the activation functions of neurons that take values from -1 to 1. In our case, we will use the hyperbolic tangential function (tansig). This function allows you to get the output values of various characters (for example, from -1 to 1), which may be necessary in the control system. Graphical representation of the function is shown in Figure 2.

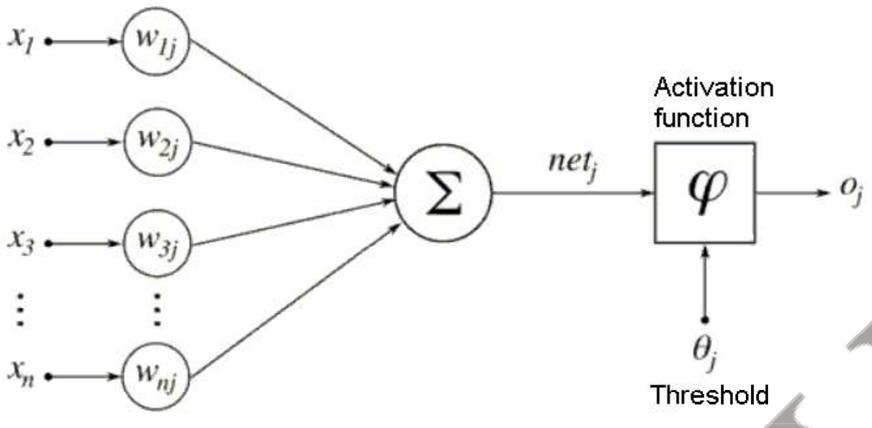


Fig. 1. Block diagram of the model of the neuroelement of the neural regulator

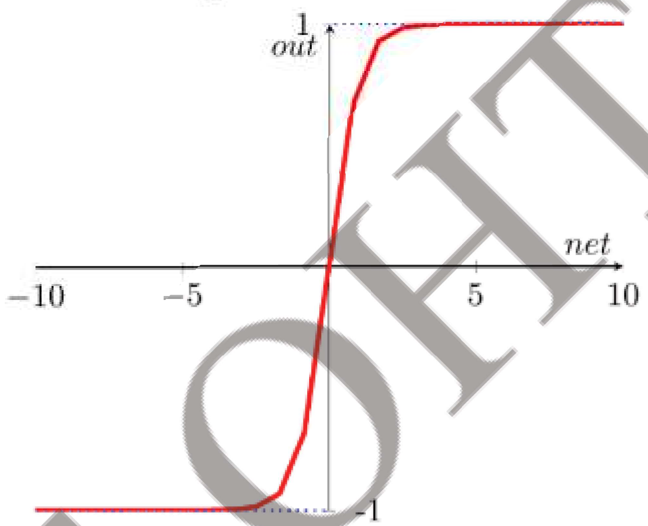


Fig. 2. Graphical representation of the activation functions of an artificial neuron, which is detected in the neuroregulator

Analytically, the function is written as follows:

$$f(net)=\frac{2}{1+\exp(-\alpha\cdot net)}-1$$

, where net is the input argument.

It is known that a single-layer neural network has limited capabilities. Multilayer four-layer is already redundant to solve various problems. In this case, the neurocontroller will be represented by a neural network with two layers, as shown in Figure 3. Figure 3 also shows the errors of each neuron for backpropagation correction. If such a structure is insufficient, it is necessary to increase the number of neurons in the input layer of the network and increase the number of layers to three.

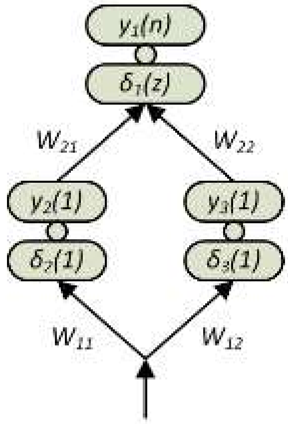


Fig. 3. Block diagram of the neuroregulator of the integral or proportional component

The MATLAB software environment was used to determine the weights between neural connections by the inverse propagation method, which allows to create a given neural network based on input and output signal values. Thus, to train the neural network, it is necessary to specify the input and output values of the signals of the neurocontroller, and more precisely, the values of control errors and the increase in control influence.

The artificial neural network, which acts as a regulator, is synthesized on the basis of the characteristics of a fuzzy logic controller. These characteristics are presented in tabular form in the form of input and output values of the fuzzy controller (table 1). The data presented in Table 1 are based on a fuzzy controller model.

Table 1. Input and output values of the controller signals

№	**ΔT**	**u**	**Δu**
1	1,5	13,48	0,05056
2	1,2	10,79	0,04045
3	0,9	8,09	0,03034
4	0,6	5,393	0,02022
5	0,3	2,697	0,01011
6	0	0	0
7	-0,3	-2,697	-0,01011
8	-0,6	-5,393	-0,02022
9	-0,9	-8,09	-0,03034
10	-1,2	-10,79	-0,04045
11	-1,5	-13,48	-0,05056

Next, create an M-file in the Mathlab environment and in this file prescribe commands to create and train our neurocontroller. Input and output values of neurocontrollers were obtained on the basis of the characteristics of the fuzzy logic controller, obtained on the basis of simulation schemes presented in Figure 4.

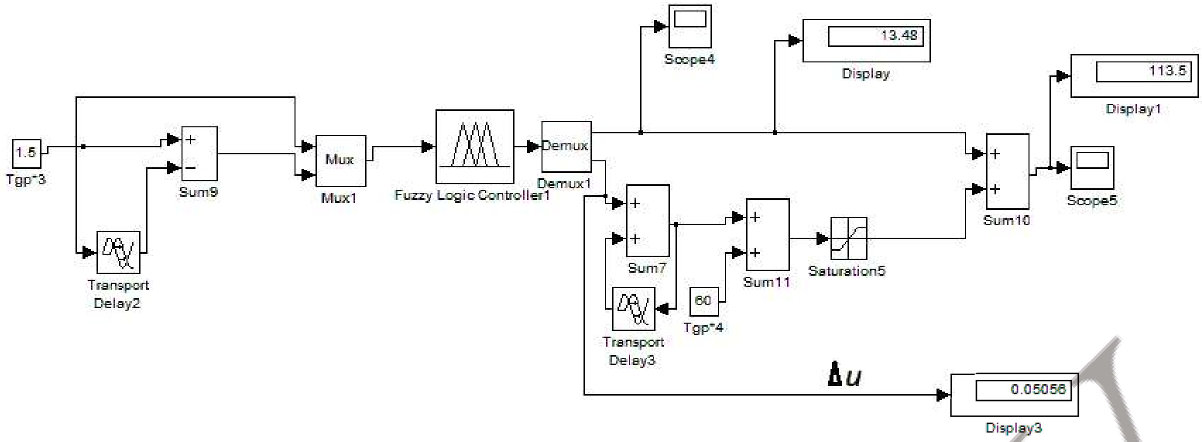


Fig. 4. Scheme of data acquisition for neural network training

The executable code was written in the M-file, which is presented in Figures 5 and 6 according to the proportional and integral component of the controller. The presented executable code can also be written in the command line Mathlab - command window, resulting in the generation of the corresponding neural network.

```
» p=[-1.5 -1.2 -0.9 -0.6 -0.3 0 0.3 0.6 0.9 1.2 1.5];
» t=[-0.1348 -0.1079 -0.0809 -0.05393 -0.02697 0 0.02697 0.05393 0.0809 0.1079 0.1348];
» net=newff([-1.5 1.5], [2 1], {'tansig' 'tansig'});
» net.trainParam.epochs=100;
» net=train(net, p, t);
TRAINLM, Epoch 0/100, MSE 0.826665/0, Gradient 2.59336/1e-010
TRAINLM, Epoch 25/100, MSE 1.04072e-008/0, Gradient 3.72063e-005/1e-010
TRAINLM, Epoch 50/100, MSE 4.87942e-009/0, Gradient 7.66684e-006/1e-010
TRAINLM, Epoch 75/100, MSE 3.47343e-009/0, Gradient 3.73493e-006/1e-010
TRAINLM, Epoch 100/100, MSE 2.79983e-009/0, Gradient 2.30556e-006/1e-010
TRAINLM, Maximum epoch reached, performance goal was not met.

» a=sim(net,p)

a =

  Columns 1 through 7

   -0.1347   -0.1079   -0.0810   -0.0540   -0.0269    0.0001    0.0270

  Columns 8 through 11

    0.0539    0.0809    0.1078    0.1349

» gensim(net)
```

Fig. 5. Executive code for generating a neural network that reproduces the proportional component of the neurocontroller

In this executable code, p is the input value of the neural network (control error), t is the corresponding value of the output of the neural network. On the third bar we set the range, the number of layers of the neural network and the activation function. We also set the number of training steps, neural network training and generation command.

```
» p=[-1.5 -1.2 -0.9 -0.6 -0.3 0 0.3 0.6 0.9 1.2 1.5];
» t=[-0.05056 -0.04045 -0.03034 -0.02022 -0.01011 0 0.01011 0.02022 0.03034 0.04045 0.05056];
» net=newff([-1.5 1.5], [2 1], {'tansig' 'tansig'});
» net.trainParam.epochs=100;
» net=train(net, p, t);
TRAINLM, Epoch 0/100, MSE 0.179928/0, Gradient 2.20533/1e-010
TRAINLM, Epoch 25/100, MSE 1.38645e-008/0, Gradient 3.01186e-005/1e-010
TRAINLM, Epoch 50/100, MSE 5.85436e-009/0, Gradient 6.30847e-006/1e-010
TRAINLM, Epoch 75/100, MSE 1.35436e-009/0, Gradient 5.01382e-005/1e-010
TRAINLM, Epoch 100/100, MSE 4.43248e-010/0, Gradient 7.63926e-006/1e-010
TRAINLM, Maximum epoch reached, performance goal was not met.

» a=sim(net,p)

a =

  Columns 1 through 7

   -0.0506   -0.0404   -0.0303   -0.0202   -0.0101    0.0000    0.0101

  Columns 8 through 11

    0.0202    0.0303    0.0404    0.0506

» gensim(net)
```

Fig. 6. Execution code for generating a neural network that reproduces the integral component of the neurocontroller

The accuracy characteristics of the training are shown in Figure 7, from which it can be seen that somewhere in step 70 of the training, the weight adjustment between neural connections was completed.

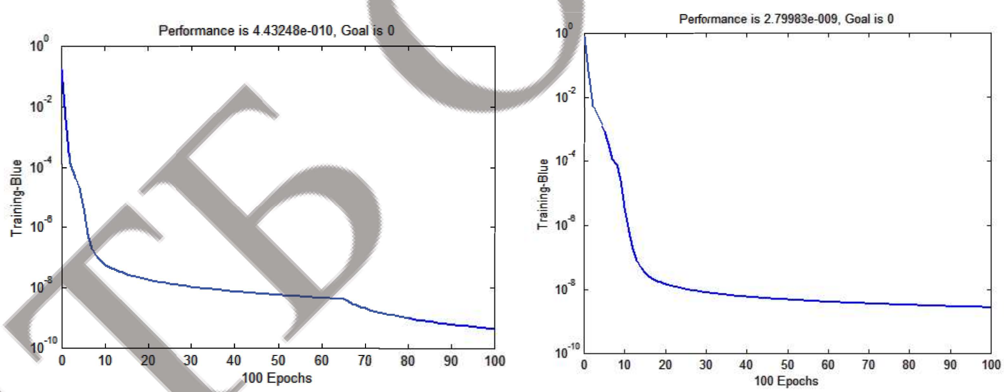


Fig. 7. Characteristics of the accuracy of learning the proportional (right) and integral (left) component of the neurocontroller

The generated neural networks were defined in the simulation scheme instead of a fuzzy controller, as shown in Figure 8. In this method with a neuro-synthesized model of the SAR-regulator environment MATLAB \ Simulink, the block diagram is shown in Figure 8.

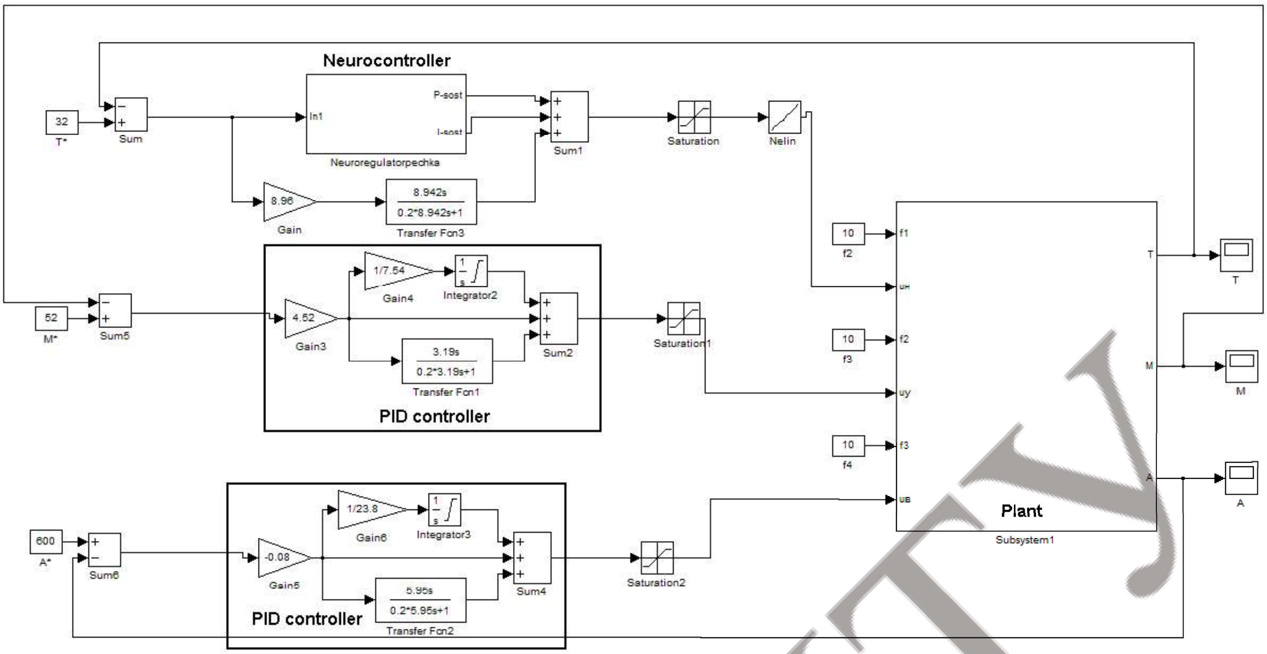


Fig. 8. Block diagram of the ACS model with neurocontroller, which is represented by MATLAB \ Simulink.

Based on these parameters of the formed neural network, the scheme of the neurocontroller in the environment MATLAB \ Simulink was determined. The scheme of the neurocontroller, which is presented in Figure 9, is an expanded scheme, which is presented in the previous figure 8.

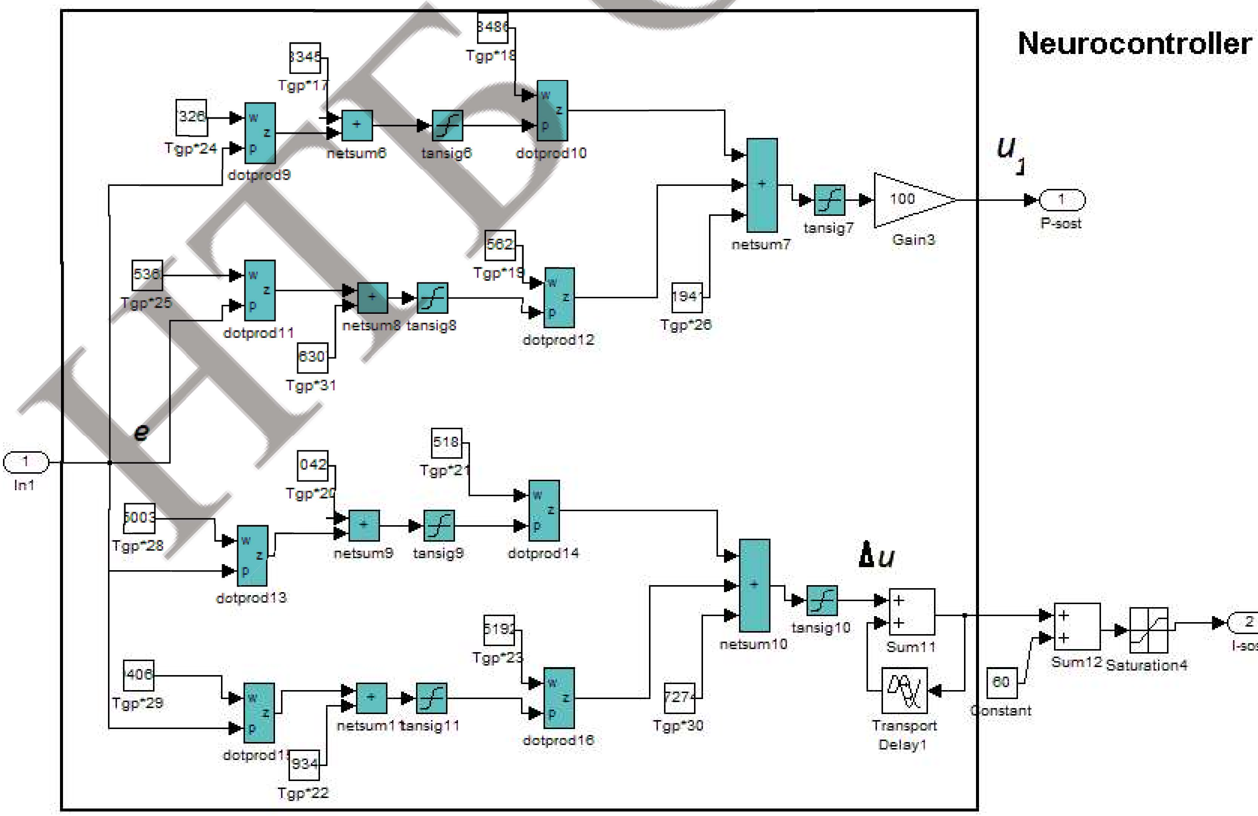


Fig. 9. Scheme of neuralcontroller modeling

IV. RESULTS

. As a result of modeling SAR with a neurocontroller, graphs of transients were obtained in the same conditions as in the modeling of SAR with a fuzzy regulator and a traditional PID regulator. These graphs are presented in Figures 10. From the graphs of transients, it is possible to see that the quality of regulation of SAR with a neurocontroller works at night no worse than automatic control system with a fuzzy regulator and PID-regulator. But with the help of optimization it was possible to achieve the best possible figure.

As can be seen from Fig. 9. A regulator synthesized on the basis of artificial neural networks has 8 interneuron connections, as well as 6 offsets. It was found by trial and error that it is optimal to optimize only 4 weights in the input layer, as changing the values of other coefficients causes errors in statistics in the system.

It can be concluded that based on the quality of regulation of different automatic control system, you need a neurocontroller of optimization in the same conditions as the previous traditional PID-controller to determine the final conclusion on the feasibility of using different automatic control system.

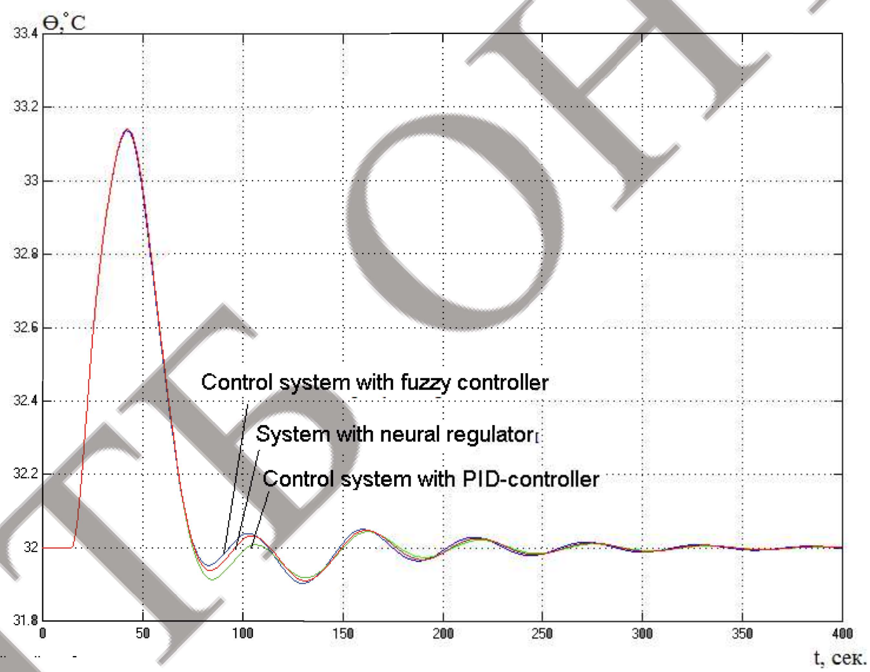


Fig. 10. Graphs of transients on the control channel «Uн – θ», obtained in the simulation of different automatic control system

To improve the quality control, parametric optimization of automatic control system with a neural controller was performed. Four tuning parameters of neurocontrollers were optimized - the weights of the neural combined first-input layer of the artificial neural network. Optimization of the neural regulator was performed under the same conditions as when optimizing the automatic control system with a traditional PID-controller. Thus, the integrated indicator of the quality of functioning in the optimization was chosen in the same way as in the optimization of SAR with a traditional PID controller. In the MATLAB \ Simulink 5.2 software environment, a automatic control system model with a neurocontroller and a parametric optimizer was identified, the block diagram of which is shown in Figure 11.

As a result of parametric optimization, graphs of transients before and after optimization were obtained, as well as optimal determined weights of interneuron connections of the first layer of the neural network. The graphs of the corresponding transients and the values of the weights are presented in accordance with the results optimization window presented in Figure 12. Figure 12 shows the optimal result obtained in 8 previous processes, optimized by a certain integrated criterion of the quality of the system.

After optimization it is possible to check up system on roughness From results of the analysis of system of check of system on quality (fig. 13) it is possible to see that the system is rough, and means, working.

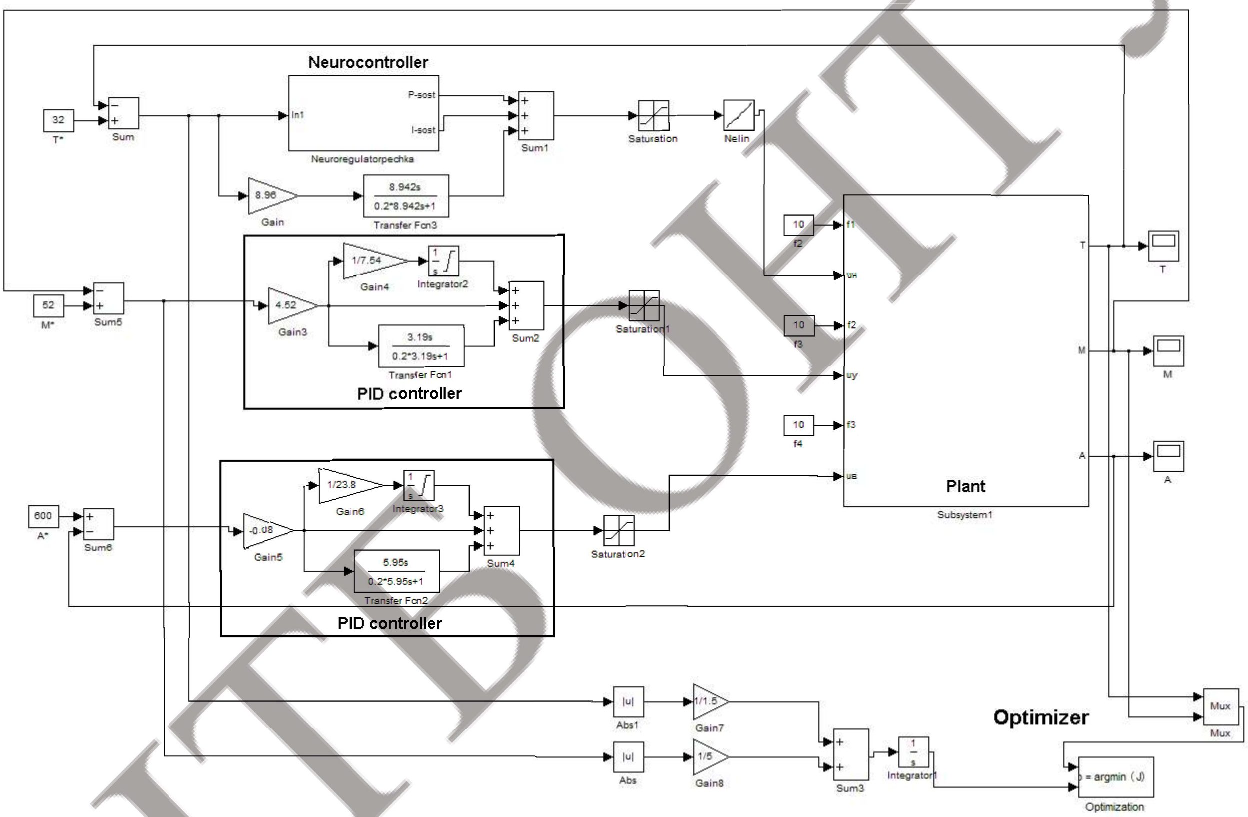
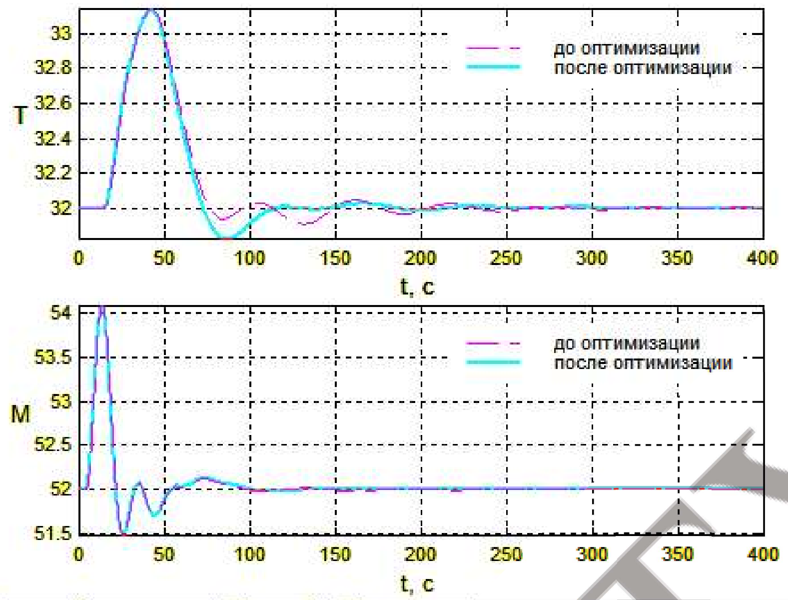


Fig. 11. Block diagram of the automatic control system model with neural controller and parametric optimizer, implemented using MATLAB \ Simulink to determine the optimal parameters of the control system for nonlinear conditions of static characteristics of the control channel «Uн – θ»

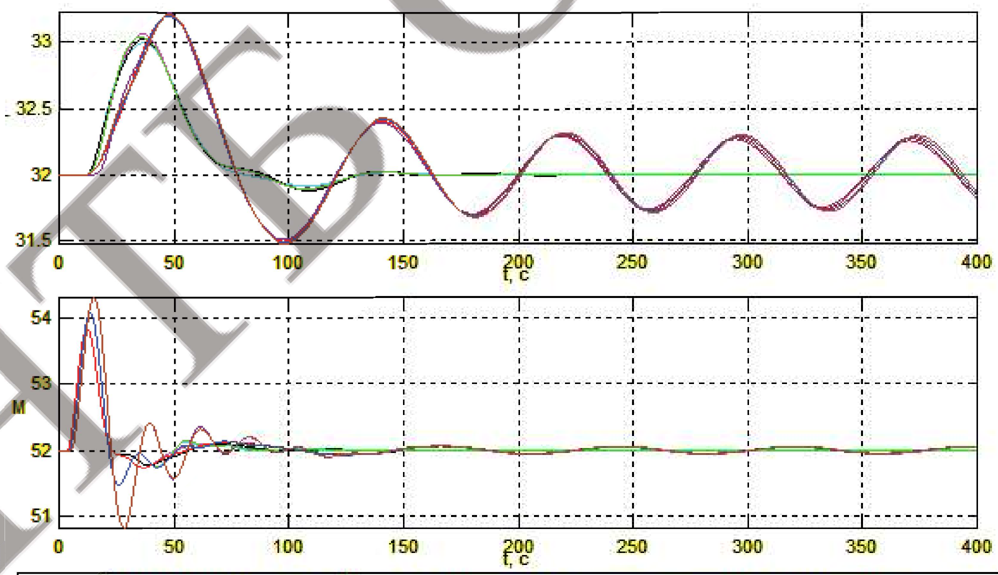


Имя переменной	Оптимальное значение	Нижний предел	Начальное приближение	Верхний предел
k1	0.17251	-10	0.2106	10
k2	-0.17272	-10	-0.1629	10
k3	-0.28291	-10	-0.0576	10
k4	-0.27016	-10	0.0776	10

Значение критерия оптимальности:
до - 35.6433
после - 34.4203
оптимизации.

Количество шагов процедуры оптимизации:
максимальное - 1000
фактическое - 156

Fig. 12. Window of results of optimization of parameters of the controller represented by an artificial neural network



Значения параметров объекта управления и значения критерия оптимальности.

1. k5=0.8 k6=0.8 J=29.2372 k7=0.8 k8=0.8
2. k5=0.8 k6=0.8 J=29.8928 k7=1 k8=0.8
3. k5=0.8 k6=0.8 J=29.9162 k7=0.8 k8=1
4. k5=0.8 k6=1 J=29.9288 k7=0.8 k8=0.8
5. k5=0.8 k6=0.8 J=30.5654 k7=1 k8=1
6. k5=1.2 k6=0.8 J=80.3907 k7=0.8 k8=0.8
7. k5=1.2 k6=0.8 J=82.0699 k7=1 k8=1.2
8. k5=1.2 k6=0.8 J=82.7932 k7=0.8 k8=1
9. k5=1.2 k6=0.8 J=86.7004 k7=0.8 k8=1.2

Fig. 13. Window of results of check of automatic control system with a neurocontroller on roughness

At the final stage of automatic control system development, a comparative analysis of the functioning of different automatic control system on the quality of regulation was performed. As a result of modeling different automatic control system, graphs of transients under deterministic and random perturbing effects were obtained.

Thus, Figure 14 presents graphs of transients under deterministic perturbation.

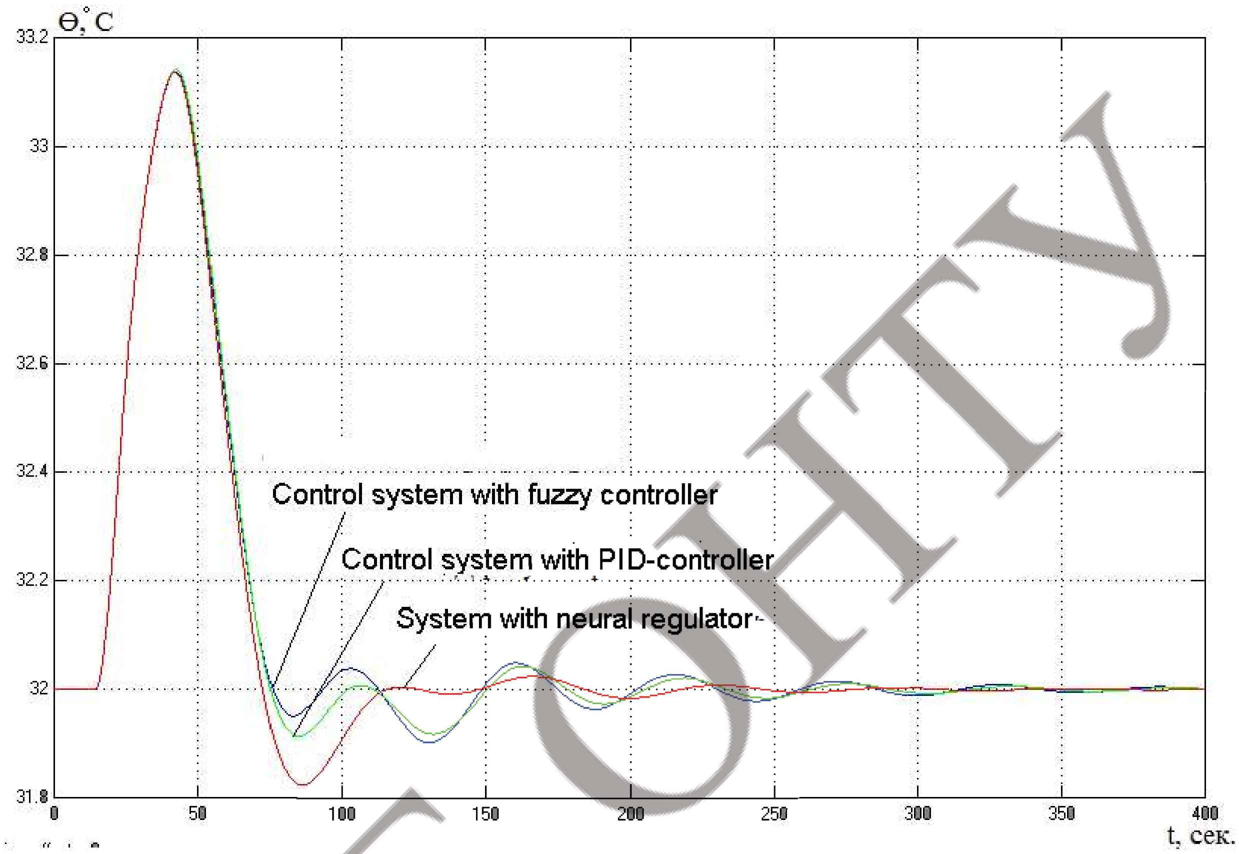


Fig. 14. Graphs of transients under deterministic deterministic influence, according to the control channel «Uн – θ», obtained in the simulation of different automatic control system

Also on the basis of the analyzer of probabilistic characteristics which was built in the MATLAB \ Simulink environment, quality of regulation of various automatic control system at casual disturbing influences was defined. This level compares the standard squares of the deviations of the values of the error of regulation of different automatic control systems under random influences. The results presented in Figure 15, in the image of the analysis of the results window, which shows the standard deviations and mathematical expectations of the value of the control error in different automatic control system.

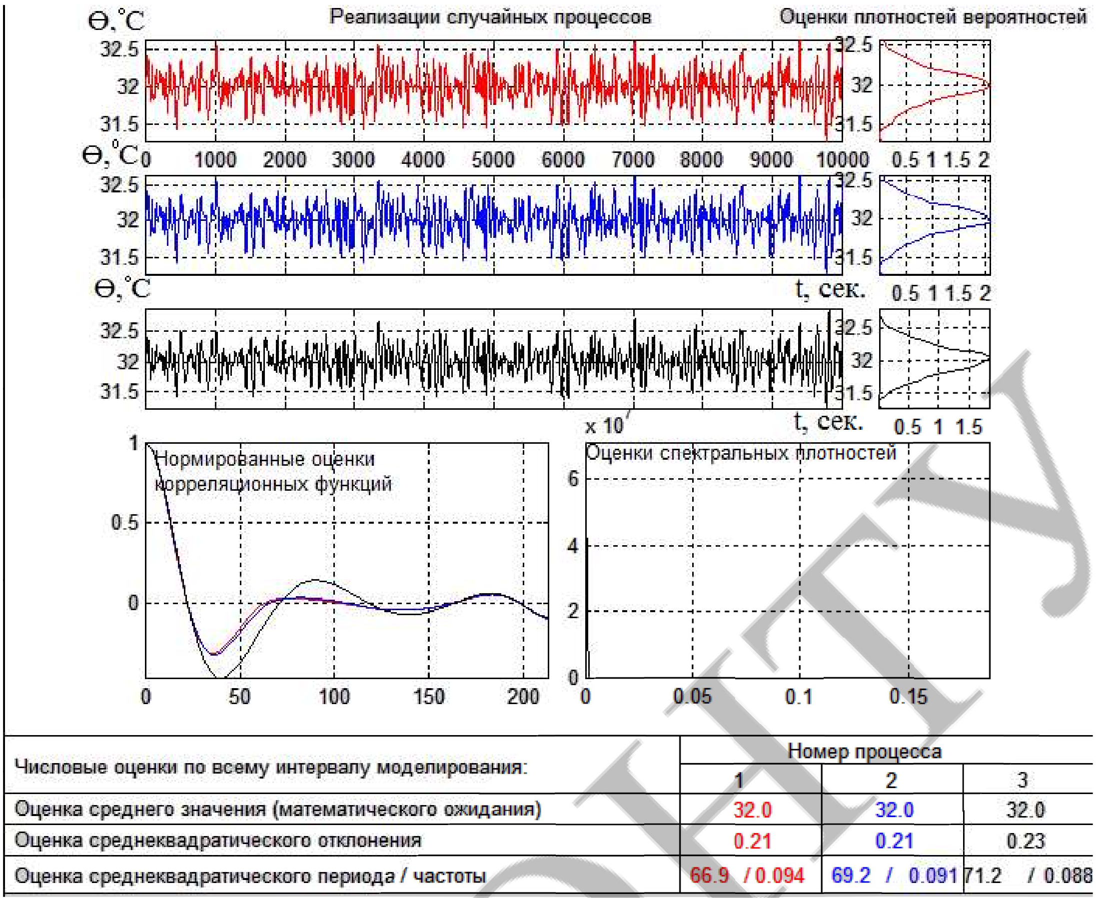


Fig. 15. Window of the results of the analysis of the analyzer of probabilistic characteristics

From the figures above it can be seen that the automatic control system with a neural controller works almost equally with the automatic control system with a PID controller and with a fuzzy controller.

V. CONCLUSIONS

In the process of work, a model of automatic control system with a fuzzy regulator was developed. The fuzzy controller is developed in the corresponding MATLAB \ Simulink environment editor. The functions of belonging to fuzzy sets were determined, the base of rules of functioning of the regulator in tabular form and in the window of the corresponding editor was formed, the algorithm of fuzzy output - Sugeno 0-order was defined. Mamdani's algorithm was also considered.

It was found that the quality of regulation of such automatic control system operates almost identically to the automatic control system with a traditional PID controller for a control object with a nonlinear static characteristic on the control channel «Uн – θ».

For further implementation of parametric optimization of automatic control system, according to the characteristics of the fuzzy regulator, a certain artificial neural network was trained, which can act as a neurocontroller. The training of the artificial network was also performed using the MATLAB \ Simulink environment. An automatic control system model with a regulator representing an artificial neural network was developed. Parametric optimization of automatic control system with neurocontroller was performed under the same conditions as automatic control system with traditional PID-controller.

As a result of modeling different automatic control systems, it was found that the quality of regulation of automatic control system with neurocontroller works worse than automatic control system, for integrated quality indicators according to other 1212, automatic control system with fuzzy regulator - 1080, and 1087 for automatic control system with traditional PID-controller. The standard deviation of the regulated changes from the set value, random perturbations, is almost the same for different automatic control system: with traditional PID-controller - 0.21, with fuzzy controller - 0.21, with neurocontroller - 0.23.

Thus, based on the synthesis and analysis of different automatic control system, it can be concluded that the neurocontroller is of fundamental suitability for practical use on the basis of an industrial controller for control objects with nonlinear characteristics for control channels.

VI. REFERENCES

1. Uskov A.A. Intellektual'nye tekhnologii upravleniya [Tekst] / A.A. Uskov, A.V. Kuz'min. – M.: Goryachaya liniya. Telekom, 2004. – 144 s.
2. Kruglov V.V. Nechetkaya logika i iskusstvennye nejronnye seti [Tekst] / Kruglov V.V., Dli M.I., Golunov R.YU. – M. : Fizmatlit, 2001. – 302 c.
3. Terekhov, V. A., and A. N. Nikonov. "Sintez nejroregulyatora nelinejnyh dinamicheskih ob"ektov na osnove odnoj modeli bifurkacii." Mekhatronika, avtomatizaciya, upravlenie 1 (2010): 31-42.
4. Gundy-Burlet K., Krishnakumar K., Limes G., Bryant D. Augmentation of an Intelligent Flight Control System for a Simulated C-17 Aircraft // J. of Aerospace Computing, Information, and Communication. — 2004. — Vol. 1, N 12. — P. 526—542
5. Kondrat'ev A. I., Tyumencev YU. V. Nejrosetevoe adaptivnoe otkazoustojchivoe upravlenie dvizheniem manevrennogo samoleta // XII Vserossijskaya nauchno-tekhnicheskaya konferenciya «Nejroinformatika — 2010»: CHast' 2. — M.: NIYAU MIFI, 2010. — S. 262—273.
6. Terekhov V. A., Efimov D. V., Tyukin I. YU. Nejrosetevye sistemy upravleniya: Ucheb. posobie dlya vuzov. — M.: Vyssh. shkola 2002. — 183 s.
7. Venayagamoorthy G.K., Harley R.G., Wunsch D.C. Implementation of Adaptive Critic-based Neurocontrollers for Turbogenerators in a Multimachine Power System, IEEE Transactions on Neural Networks. — 2003. — Vol. 14, Issue 5. — P. 1047—1064.