Intellectual Improvement of the Control System for Harmful Emissions of a Ship's Utilizing Boiler

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Abstract

Modern experience in the development and operation of automatic control systems for power units of sea and river vessels shows that the introduction of intellectual technologies is an indispensable condition for increasing their efficiency. The range of tasks of artificial intelligence includes constant monitoring of all technical systems of the ship and timely prevention of malfunctions. The neural network will be able to calculate the probability of an emergency situation on the ship and develop options for its prevention. The analysis of practical problems in the field of operation of modern marine vessels showed that the issues of saving fuel resources of ship installations, reducing the content of harmful emissions into the atmosphere remain relevant in the conditions of tightening of the normative indicators of nitrogen oxides and sulfur and the increase in the cost of energy resources. The article offers an improvement of developing a neural network system for controlling the content of harmful emissions into the atmosphere of a ship's steam boiler. The improvement assumes the adaptation of the settings of a typical regulator depending on the indicators of the quality of the control process. Simulation modeling of the proposed control system showed its effectiveness in comparison with a typical control system.

Keywords

neuro-fuzzy network, automatic control system, ship's steam boiler, nitrogen oxides

1. Introduction

Currently, there are a number of approaches to reducing the concentration of nitrogen oxides (NOx) in the flue gases of marine power equipment, for example: primary methods, which consist in suppressing the formation of NOx in boiler furnaces or combustion chambers of diesel engines, and secondary methods of reducing NOx emissions, which consist in the treatment of flue gases after boiler or diesel. Despite the large volume of performed studies, most of the works are aimed at reducing emissions of nitrogen oxides by methods of selective catalytic and non-catalytic reduction of nitrogen oxides [1-3]. Although these methods provide a high degree of flue gas purification, they are associated with significant financial costs and are based on the use of dangerous chemical reagents. Also, according to [4], scrubbers are installed on more than 5% of the total number of vessels, and industry analysts predict that their number will hardly exceed 10-20% in the near future. Therefore, the problem of development and implementation on ships the new, relatively economically inexpensive and environmentally effective methods of cleaning the exhaust gases of ship diesels and boilers from nitrogen and sulfur oxides is urgent.

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Currently, analytical models are used in the most common methods of developing automatic control systems (ACS) of units of ship power plants v(SPP), which are adjusted in the process of setting up and further operation of power facilities [5-10]. Taking into account the perspective of the development of the methods of the theory of artificial intelligence and the beginning of their implementation in autonomous self-propelled guns, the joint application of neural networks with mathematical models, obtained at the stage of designing SPP units, seems to be the most appropriate [11]. At the same time, analytical models are used at the initial stage of operation of SPP units, which are subsequently adjusted by neural networks. Theoretical models are based on the physical properties of the processes occurring in SPP units and roughly describe the existing relationships of all regulated parameters, and the neural network studies and implements the necessary corrections in the model, specific for certain modes of operation and conditions of their operation. This approach is proposed to be used to increase the indicators of the operation processes of SPP units, for example, a ship's steam utilization boiler (SUB).

It is known that the dynamic parameters of the SUB characteristics determined for the initial stage of start-up are very different from the same parameters determined for the final stage of start-up or normal operation. For example, the delay in the temperature of the steam along the path of the steam boiler along the channel of the regulating influence is much larger, and the amplification gains K are smaller in the initial stage of start-up compared to the end of start-up and exit to the specified operating mode, etc. [12-14]. Taking into consideration all mentioned above, the need to use adaptive intelligent control systems for complex, multi-mode steam-generating processes (SUB control loops) with the function of approximating the values of the controlled parameters, as well as having the property of self-learning, may be appropriate.

The improvement of development and adjustment of intelligent ACS with SUB parameters, on the example of ACS of the content of nitrogen oxides in outgoing gases of SUB when the ship is in the control zones of harmful emissions is proposed.

2. Stages of the methodology of the development of the intellectual ACS

Different development methods are used in neural network regulators (neural network controllers of NC), for example, error E and its derivative E' were used as input parameters in NC, a number of authors added one more to the existing inputs - the second derivative of error E" [13], which significantly complicates the process of creating a vague rule base and leads to a significant increase in its size. Thus, despite all the variety of methods for developing intelligent control systems, there is no method for setting up fuzzy and neuro-fuzzy regulators proposed in the SUB.

Based on this, an adaptive neuro-fuzzy proportional-integral (PI controller) technique is proposed for effective control of processes in the SUB.

Stages of the technique:

- development of the structural scheme of the adaptive ACS (determination of input and output parameters);
- collection of information about the object's behavior under the influence of uncontrolled parametric and external disturbances (accumulation of data on changes in the input and output parameters of the ACS for the purpose of obtaining a training sample for the neural network);
- development of a production fuzzy rule base that takes into account the experience of an expert adjuster when manually adjusting the parameters of the PI - regulator;
- fuzzification of input and output parameters;
- development of the structure of the neuro-fuzzy network (NFN), definition of the learning method;
- training of NFN;
- approbation of the results of NFN training with the help of simulation.

The proposed method of training NFN consists in connecting the database to the control circuit in order to collect information about the actions of the operator when setting up the regulation system (adjustable parameters of the regulator), as well as when remotely controlling the SUB equipment.

Accumulated data during the adjustment of the ACS and the operation of the SUB can be used as a training sample for a neuro-fuzzy network, which, after training, can repeat the actions of an experienced operator (Figure 1).

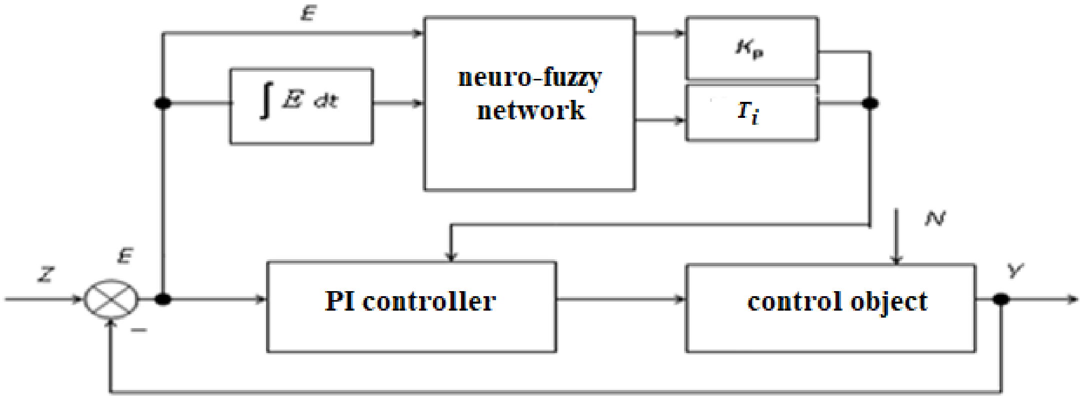


Figure 1: The structure of the adaptive neuro-fuzzy ACS by the parameters of the SUB with PI - regulator: E - error; dt – integral of error (input parameters of NFN); Z – tasks; Y is the initial value; N – external disturbance; Kp, Ti – settings of the PI controller (output parameters of the NFN)

Also, after training, the NFN will be able to independently adjust the typical PI and PID - regulator without the participation of the adjuster and operator of the SUB. The proposed structural diagram of an adaptive ACS SUB with a neuro-fuzzy network performs the function of adaptation by determining the optimal parameters of a typical PI controller in the ACS using the SUB parameters shown in Figure 1.

3. Approbation at the control object

Approbation of the proposed system was carried out during the simulation of ACS of steam generators of fishing vessels. This class of ships is equipped with technological equipment that consumes a large amount of steam and electricity. Such vessels have powerful auxiliary boilers and power plants at their disposal. The main operational time of these vessels is fishing when the main engines are running at share loads or not working at all. For the efficient use of fuel on production and processing vessels in terms of cost efficiency, heat utilization of the exhaust gases of main engines (ME) and diesel generators (DG) is used in the utilization SUB [5]. In Figure 2. the scheme of the disposal horizontal marine water-tube boiler of the La Mont brand with a steam capacity of 30 ton per hour is shown with the proposed system of neural network adaptive control of the process of steam pressure stabilization and regulation of the NOx indicator in the exhaust gases at the outlet of the disposal boiler.

When the vessel is moving, the heat of the exhaust gases of the ME is utilized, and during fishing and in the parking lot - the heat of the exhaust gases of the DG. Changing the operating modes of the ship's utilization steam boiler is carried out by a neural network adaptive PI controller (PLC), which receives data from the steam pressure device (PE) and the NOx content gas analyzer (QE) (see Figure 2). The output control influences of the controller are:

- changing the position of rotary valves that change the flow of exhaust gases and thereby stabilize the steam pressure;
- changing the rotation speed of the exhaust gas extractor in order to reduce the content of harmful emissions into the atmosphere when the vessel is in the corresponding control zone using a PLC controller with a 1-1 communication signal.

The transfer function of the object (SUB) on the control channel (the speed of operation of the DH exhaust fume hood - the content of NOx in the atmosphere) is an oscillating link, which was obtained on the basis of experimental data.

There are certain difficulties in setting up a typical PI - or PID - regulator with an oscillating link, so the formula method operates with a delay that is absent in this case. Thus, as adjustment methods, it is necessary to use the method of damped oscillations or the methods of adaptive expert control [7,14,15].

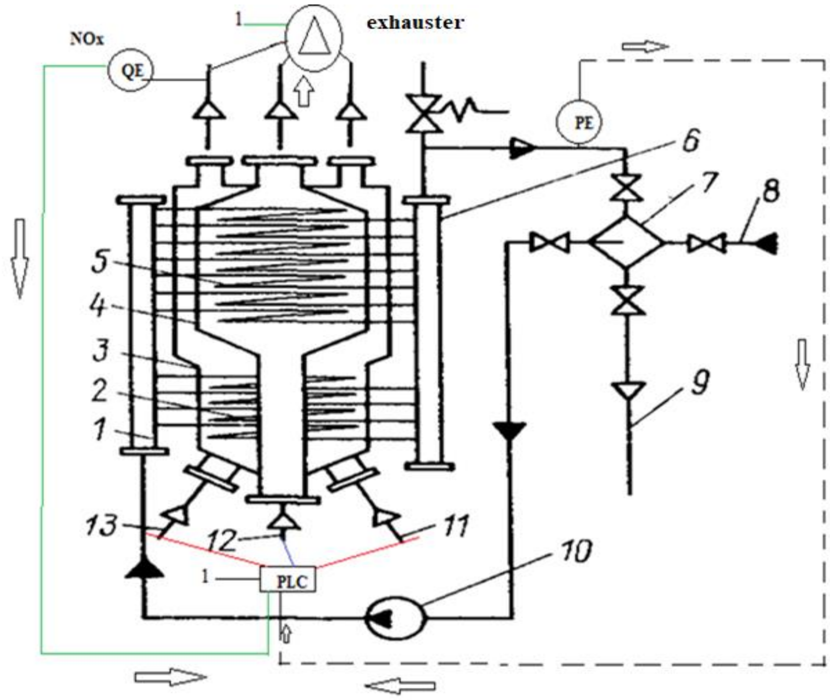


Figure 2: SUB scheme with the possibility of parallel operation on the exhaust gases of ME and DG and the improvement system of neural network adaptive control of vapor pressure and NOx content in exhaust gases: 1 - water collector; 2 - the heating surface is washed with DHW exhaust gases; 3 - external case; 4 - internal body; 5 - the heating surface is washed by the exhaust gases of the DH; 6 - steam-water collector; 7 - separator; 8 - feed water pipeline; 9 - pipeline of saturated steam; 10 - circulation pump; 11,13 - gases from DH; 12 - gases from DH; PE - pressure sensor; PLC - adaptive PI - controller with IBM True North neural network processor; QE is a gas analyzer

Also, an external disturbance N is applied to the control object (SUB), the transmission function of the object through the channel of external disturbance: (change in the operating modes of the DG - NOx content) is presented in the form of an inertial link (Figure 3).

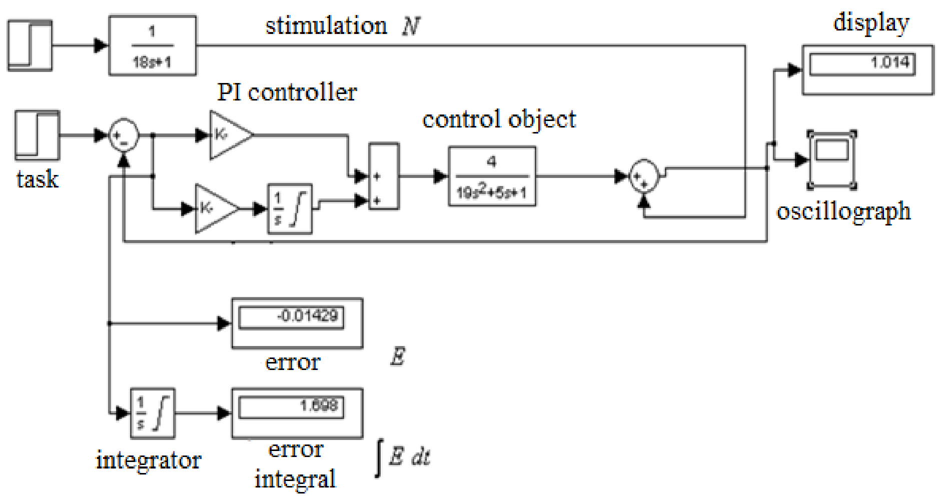
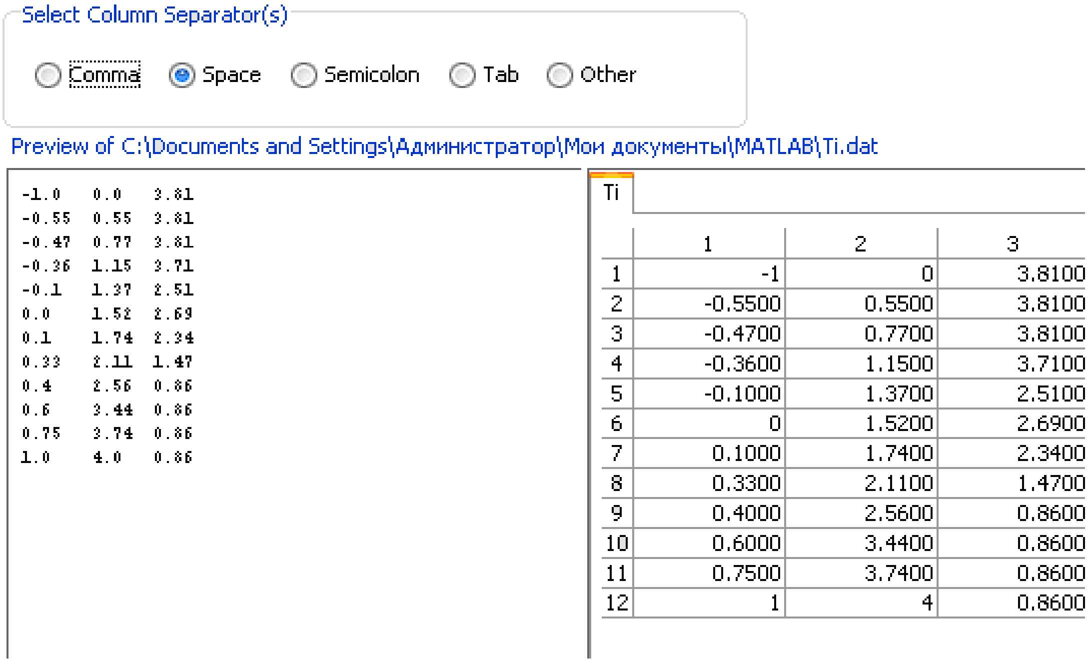


Figure 3: Structural diagram of the ACS model of the content of harmful emissions of SUB into the atmosphere

When modeling the influence of parametric Z (change in exhaust gas flow rate) and external N disturbances, that is, changes in the values of the transfer functions of the object through the control channels and external disturbance, readings were taken: errors and the integral at optimal settings of the PI - regulator Kr and Ty, which were study sample for NFN. In order to fully collect information about the object's behavior and cause-and-effect relationships between the values of the error E, the error integral and the settings Kp,Ti, an experiment was conducted in the MatLab (Simulink) program [17] (see Figure 3).

4. Simulation modeling

The results of the virtual simulation were automatically stored in the program database (Figure 4). To use (EC) of the form: IF - THEN, it is assumed to use the theory of fuzzy logic [9,19] and the Fuzzy Logic Toolbox (FLT) program (Figure 5).



	1	2	3
1	-1	0	3.8100
2	-0.5500	0.5500	3.8100
3	-0.4700	0.7700	3.8100
4	-0.3600	1.1500	3.7100
5	-0.1000	1.3700	2.5100
6	0	1.5200	2.6900
7	0.1000	1.7400	2.3400
8	0.3300	2.1100	1.4700
9	0.4000	2.5600	0.8600
10	0.6000	3.4400	0.8600
11	0.7500	3.7400	0.8600
12	1	4	0.8600

Figure 4: Database for training NFN

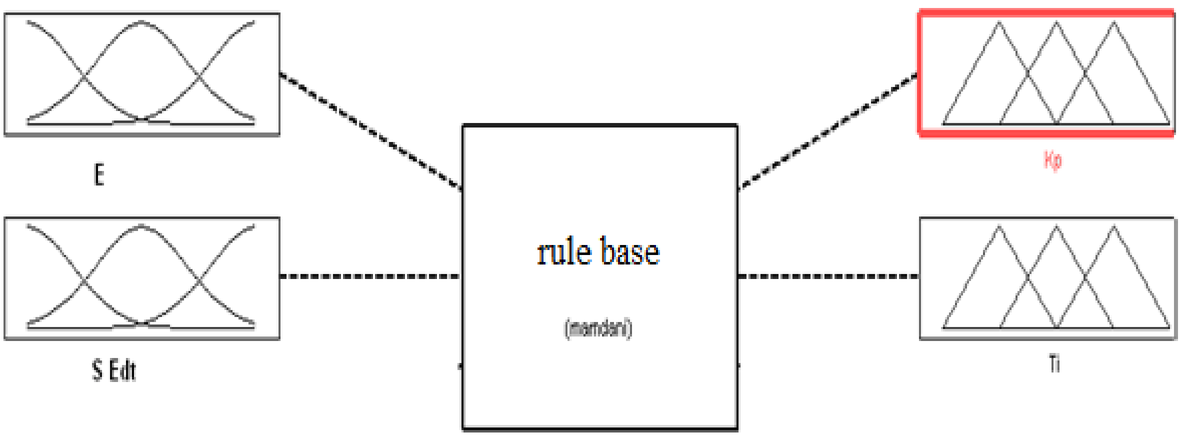


Figure 5: Graphical interface of the FLT editor

In Figure 5. the following designations are presented for the development of a fuzzy expert system for calculating the adaptive parameters of the PI - regulator in the fuel combustion control system of the marine utilization boiler: E - regulation error; SEdt – error integral (input parameters of the Mamdani algorithm expert system); Kp – proportionality coefficient; T_i are constant integrations (output parameters of the expert system). Three triangular membership functions are used to describe input and output variables. The type and range of accessory functions is selected based on the experience of an expert adjuster of automatic ship boiler control systems.

When performing the fuzzification of the input and output linguistic variables "error", "error integral", "proportionality coefficient", "constant integration" Numerical universal, the type, name and number of belonging functions are determined based on the experiment;

$$E_1 = otr \stackrel{\Delta}{=} (e_1(t), \mu_1(e_1(t)));\ E_2 = nul \stackrel{\Delta}{=} (e_2(t), \mu_2(e_2(t)));\ E_3 = pol \stackrel{\Delta}{=} (e_3(t), \mu_3(e_3(t))),\quad (1)$$

$$E_i \in E; i = \overline{1,3}; e(t) \in E,$$

where E is the universal set of errors; e(t) is the current value of the error at a certain time; $\mu_i(e_i(t))$ is a function of belonging to the fuzzy set $e_i(t)$, otg is negative, nul is zero, pol is additional. The following terms are also used: mal – small value, sred – medium, bol – large value.

Fuzzy sets (membership functions) for the integral of the error and settings of the PI controller are determined in a similar way.

The graph of membership functions "error" LP is presented in Figure 6. The membership function of the Z-type is represented by the term "negative error" otg "" can be represented in the form: f_z (x, -0.6, -0.1) = [1, x< - 0.6; -0.1 – x/0.5; 0, -0.1 <x].

For a vague knowledge base, production rules have been compiled in the form of statements by an expert on setting up ACS SUB:

IF E = otr , AND $\int$Edt = mal , THEN Kp = sred, AND Ti = sred OTHER WISE, etc.

where otr is negative; mal – small; sred - average.

The values of the input and output parameters of the knowledge base are test data of the adaptive neuro-fuzzy network (Adaptive Network Based Fuzzy Inference System) ANFIS [17], the purpose of which is to make a forecast about the nature of transient processes and the selection of new values of the parameters of the PI controller, if the object will tend to an unstable state. This network operates according to the Sugeno algorithm [19], which is widely used in fuzzy controllers of SUB ACS.

Depending on the variants of the membership functions μ(E) of the input variable "error E". When fuzzifying other input and output parameters of the NFN, the Z (1), triangular (2) and S membership functions are used as in Figure 6.

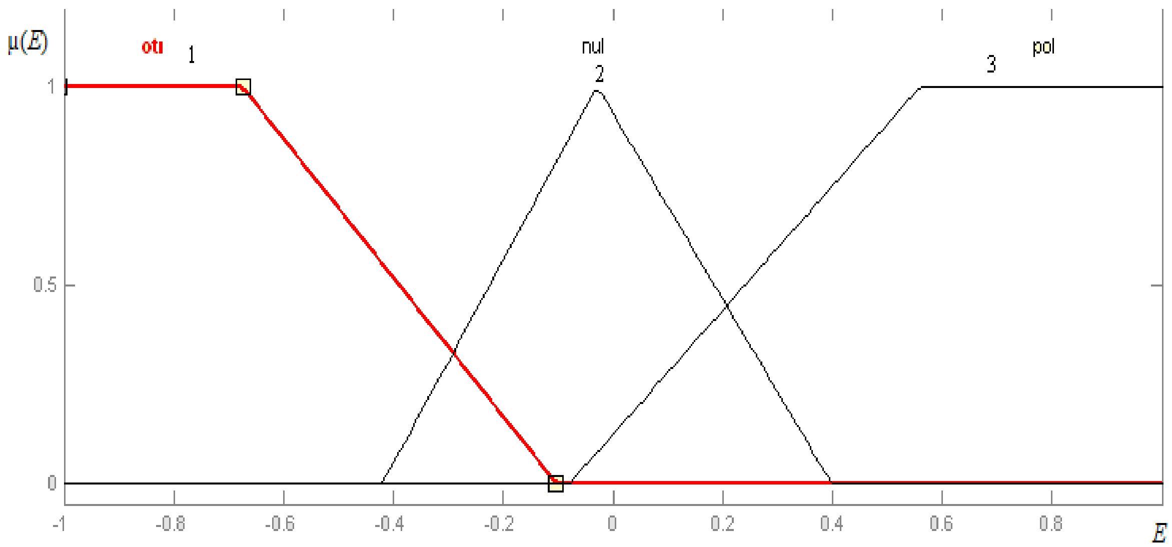


Figure 6: Membership functions μ(E) of the variable "error E":otr – negative; nul – zero; pol is positive

Neuro-fuzzy network of the ANFIS type is a multilayer neural network without feedback, the inputs and outputs of which are represented in the form of linguistic variables. The creation of the network

(Figure 7) is carried out in the Matlab package, which allows you to create and load a model of an adaptive neural system, perform training, visualize the structure, change and adjust parameters, as well as use the training network to obtain the results of fuzzy output.

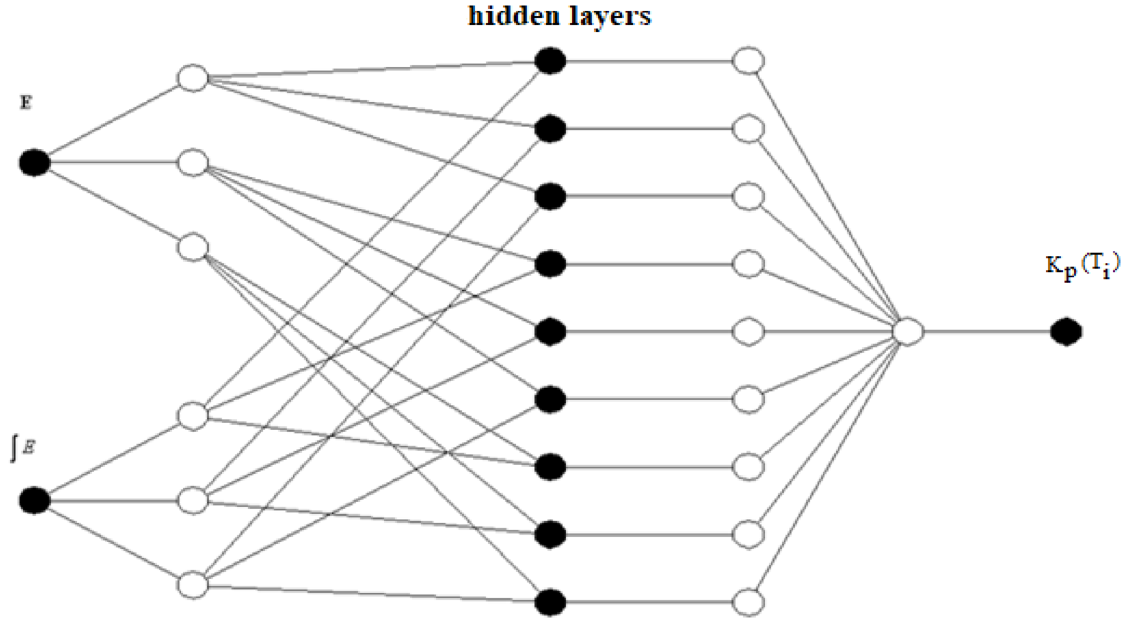


Figure 7: The structure of the proposed NFN for adaptation of ACS SUB

An adaptive system of neuro-fuzzy inference has been developed for approximating the dependence representing the cause-and-effect relationship between Kr, Ty and E, $\int Edt$. The backpropagation method of the error [13] is chosen for training the NFN.

In the process of training the NFN, 40 cycles were used for each of the settings of the Kp and Ti regulators.

To analyze the adequacy of the created NFN for issuing the expected parameters of the PI - controller, the editor of the rule base (Rule Viewer) of the MatLab program (Fuzzy Logic Toolbox) was used. The values of input and output parameters obtained in the program E = - 0.675; $\int Edt$ = 3.19; Kp=0.5; Ti = 10, determine the adequacy of NFN, because they coincide with the test ones.

An experiment was conducted in the MatLab (Simulink) program to test the NFN and check its effectiveness in finding the optimal settings of the adaptive PI controller controlling the object under conditions of uncertainty or multimode (influence of parametric perturbation).

At the same time, the new transmission function of the SUB control object on the control channel after the influence of a parametric disturbance (changes in the operation mode of the ME and DG), determining the value of E and $\int Edt$ and substituting them into the program, the NFN calculated the adaptive settings for the PI controller in the self-propelled vehicle of fuel combustion in the SUB: Kp = 0.42 and Ti = 50.

When entering them into the virtual PI controller in the Simulink program and approving the experiment in work [19], a fading adaptive transient process (Figure 8) with overregulation was observed at the output of the adaptive ACS:

$$G = ((Y_{max} - Y_{inst}) / Y_{inst}) \cdot 100\,\% = ((1{,}25 - 1)/1) \cdot 100\,\% = 25\,\%$$

The analysis of the quality indicators of the adaptive transition process (see process 2 in Figure 8) demonstrates their expected values - regulation time Tc = 47 seconds, overregulation G = 25 %, in contrast to the non-adaptive ACS of the NOx content with unsatisfactory quality indicators: G = 45% and transient control time: Tc =100 seconds.

Thus, the adaptive NFN successfully finds the optimal values of the ACS parameters with the PI controller controlling the complex process of fuel combustion in the SUB and reduces the content of harmful emissions into the atmosphere.

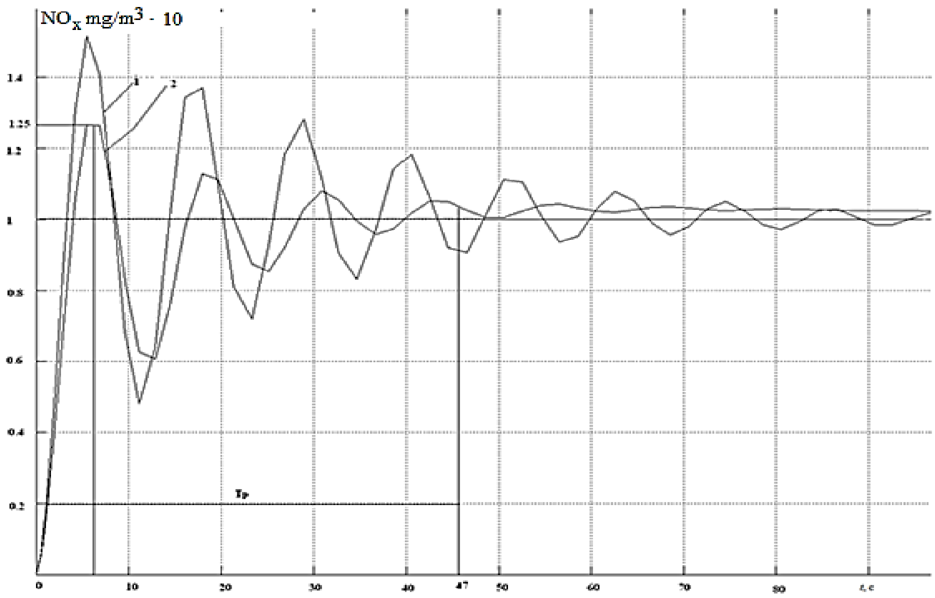


Figure 8: Processes of the neuro-fuzzy ACS of the process of regulating the NOx content in the output gases of the utilization steam generator: 1 – without adaptive settings, 2 – with adaptive settings at a 25% SUB load

The proposed method of setting is effective and can be recommended for implementation in ACS SUB c PID - controller. The use of the algorithm improves the process of adaptation of the ACS, because it does not require special methods of active identification of the parameters of the object that deteriorate the quality of management. For further testing of the proposed method, simulations were carried out at the SUB ACS on two more operating modes of the SUB (see Figure 9) for learning the neural network in order to reduce over-regulation of the transient process.

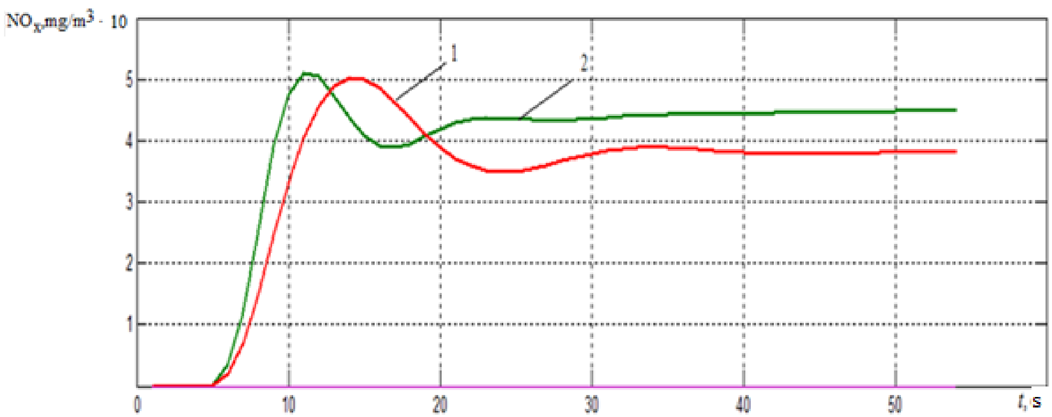


Figure 9: Processes of the neuro-fuzzy ACS of the process of regulating the NOx content in the exhaust gases of the utilization steam generator: 1 – at a steam load of 50%, 2 – at a steam load of 75% of the nominal

5. Conclusions

The analysis of the quality indicators (Figure 8) of the proposed intelligent system for controlling the fuel combustion process in order to reduce the NO_x content, when the ship is in the harmful emissions control zone, showed that the traditional ACS maintains the value of NO_x in the atmosphere at the level of 140 mg/m^3 , and the neuro-fuzzy adaptive control system manages to achieve the NOx index = 126 mg/m^3, i.e. 10% less; the time to reach the set value in the adaptive neural network ACS is 4 times less compared to the traditional ACS. Also, the analysis of the type of transient processes (see Figure 9) on other steam load regimes of the SUB demonstrates the compliance of the quality indicators with the expected values.

Thus, simulation modeling showed that the introduction of an improved system for controlling the content of nitrogen oxides in the flue gases of ship boilers will allow, according to preliminary calculations, to reduce the content of nitrogen oxides by up to 10% compared to a typical control system. According to the improvement, the introduction of a neuro-fuzzy expert system of PI adaptation into the control system of the liquid fuel combustion process is an alternative, in some cases, to expensive systems of chemical cleaning or recirculation of flue gases of ship power units.

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