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Comparative study of PI-controller and neurocontroller performances in optimal by settling time control problems

Abstract. When developing control systems, an important issue arises of choosing an operator, which forms the control function. The standard approach is to use a PI- or PID-controller, a more advanced approach involves ANNs training for this purpose. A comparative analysis of the PI- and neurocontroller performances makes it possible to establish the disadvantages and advantages of each of the compared controllers, which is an important scientific and applied problem. The purpose of the work was to conduct a comparative analysis of the performance of the PI-controller and the neurocontroller based on a set of evaluation indicators for plants of the second and third orders. Such a comparison was carried out by using an approach to the synthesis of both controllers, which involved the minimization of a complex objective function. The latter is obtained as a result of reducing the problem of optimal control with constraints to the problem of unconstrained optimization. The analysis showed that according to the settling time indicator (optimization criterion), the neurocontroller has an advantage of 6.1...96.2% for the modelled plants. At the same time, according to other indicators of the control quality, the PI-controller has an advantage. In addition, the synthesis of a neurocontroller in terms of finding the minimum of the objective function is a more difficult problem. For its solution, a bigger number of iterations of the VCT-PSO optimization algorithm is required. It is rationally to set more than 1000 iterations and swarm population in the range 30...50 particles. A comparative analysis by the settling time of the neurocontroller and PI-controller, which is tuned according to engineering methods, showed significant reserves for improving this indicator. Thus, if the requirements for settling time minimization are quite strict, then it is advisable to use a neurocontroller. The obtained results will make it possible to develop recommendations for the rational choice of the control operator when solving practical problems of the control systems synthesis

Keywords: plant; objective function; comparison; neurocontroller; control estimation indicators

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INTRODUCTION

State of technology development, particularly in the fields of electromechanics, electronics, and automation, involves the use of feedback control (regulation) systems. For their synthesis, engineers may use an extremely diverse range of mathematical methods. Quite often, the same control problem can be solved by using different approaches. PID-controllers are simple and very common (O'Dwyer, 2009). H_2 -controllers (Brand & Cole, 2021) are optimal in a sense of quadratic criterion. Fuzzy-controllers (Tong et al., 2020) and neurocontrollers (Ghahramani et al., 2020) implement a soft-computing approach for solution of control problems.

This is far from a complete list of types of controllers, that may be used to solve a specific control problem. At the same time, there is a need to determine which approach will be rational. In order to give an answer to this question, it is necessary to perform a comparative analysis of the qualitative indicators of the work of various controllers.

Certain steps in this direction have already been taken. For example, M. Dhandapani et al. (2024) reviewed the use of a PI- and a neuro-controller when charging the batteries of vehicles with electric traction ensures a stable voltage of the direct current link. However, suppression of higher harmonics is somewhat better performed by the neurocontroller.

According to A. Nouri et al. (2024), combined schemes of controllers make it possible to obtain a better effect when controlling the accumulation of electrical energy in photovoltaic energy technologies. In their work, it is proved that the ANN in combination with the linear-quadratic-regulator (LQR)-controller provides better performance and stability of the energy storage installation compared to the artificial neural network – proportional-integral (ANN-PI)-controller.

Interesting are the comparative studies of M. Yessief et al. (2022) on the use of PI-, fuzzy-, neuro-controllers, sliding controllers, and controllers in which the “backstepping” method is applied to control the parameters of wind turbines. The results of the comparison showed that the neurocontroller has the best values of response duration, static error, and accuracy when changing the set point among the compared controllers. The worst quality indicators correspond to the work of the PI-controller.

In a study by D.E. Beladjine et al. (2021), the authors

used PI- and neurocontrollers for the problem of control of the brushless motor rotation speed. The PI-controller showed a response time of 0.0523 s, and the neurocontroller – 0.0447 s. Such a difference can be significant in applications where precision and high speed of the actuator are required.

For a similar task in the study of H.S. Sridhar et al. (2020) used a slightly different approach. Here, for the control problem of a brushless motor, the performance of a PI-controller and a PI-controller configured by using ANN technology are compared. As these studies have shown, the operation of the last controller is not characterized by overshoot, it has a much higher speed and almost zero static error.

In these works, the authors usually focus on one plant (wind turbine, brushless motor, etc.). However, the involvement of a certain class of plants of different orders in the research will make it possible to obtain more general results. This is the approach implemented in this study.

Thus, the results of a comparative analysis of the work of one or another controller will make it possible to establish the disadvantages and advantages of each of them, which is an important scientific and applied problem to solve.

The aim of the work was to conduct a comparative analysis of the work of the PI-controller and the neurocontroller based on a set of evaluation indicators for plants of the second and third orders, since they are the most common in practice.

MATERIALS AND METHODS

The methodology of the research was as follows:

- 1) carry out the statement of the control problems of linear the second and third orders plants;
- 2) find solutions to control problems by using linear (PI-) and nonlinear (based on ANN) control operators;
- 3) conduct a comparative study of the results of the work of controllers for selected plants;
- 4) to establish the peculiarities of the application of controllers for the problem of optimal control of linear plants.

To ensure the general applicability of the technique, test plants described by Yu. Romasevych et al. (2019) were utilized. Their transfer functions are given in Table 1.

Table 1. Plants and their features

Plant transfer function	Features
$G_1(s) = \frac{1}{(s+1)^2}$	Systems with such transfer functions are very common in practice. These transfer functions have been used for a long time for the problems of testing the developed controllers.
$G_2(s) = \frac{1}{(s+1)^3}$	
$G_3(s) = \frac{1-0.1s}{(s+1)^3}$	These transfer functions have three identical poles and zero, which is in the right half-plane. The quality of control is determined by the parameter 0.1 in the numerator: when this value increases, the controls quality deteriorates.
$G_4(s) = \frac{e^{-s}}{(0.5s+1)^2}$	This transfer function has been used in many studies of PID-controllers. When the value 0.5 increases, the delay of the plant increases.

Source: compiled by the authors

For plants whose transfer functions were given in Table 1, it was necessary to synthesize optimal control operators. In this study, the settling time was taken as the optimality criterion:

$$t_s \rightarrow \min, \tag{1}$$

where t_s – settling time, i.e. time moment, when the following condition is met:

$$\frac{|r-x(t)|}{r} \leq \Delta, t \geq t_s, \tag{2}$$

where r – setpoint; x – process variable; Δ – relative acceptable deviation of process variable from the setpoint (according to the engineering requirements Δ was set $\Delta=0.05$).

In addition to the requirement to minimize criterion (1), the absence of overshoot was required:

$$\frac{\max(x(t))-r}{r} \leq 0, t \in [0, t_s]. \tag{3}$$

The main requirement for the synthesis of any controller operator is to ensure the stability of the closed-loop

$$Ter = \begin{cases} (|x(t) - r| + \sum_{i=1}^n |\dot{x}^i(t)|) \delta_{Ter}, & \text{if } |x(t) - r| > \Delta_x \vee |\dot{x}(t)| > \Delta_{\dot{x}} \vee \dots \vee |\dot{x}^n(t)| > \Delta_n; \\ 0, & \text{if } |x(t) - r| \leq \Delta_x \wedge |\dot{x}(t)| \leq \Delta_{\dot{x}} \wedge \dots \wedge |\dot{x}^n(t)| \leq \Delta_n; \end{cases}$$

$$Osh = \begin{cases} \frac{\max(x(t))-r}{r}, & \text{if } \frac{\max(x(t))-r}{r} > \delta_{Osh}; \\ 0, & \text{if } \frac{\max(x(t))-r}{r} \leq \delta_{Osh}; \end{cases} \tag{6}$$

where δ_{Ter} and δ_{Osh} – weighting coefficients that form the desired topology of the objective function and were set as follows: $\delta_{Ter} = 10^{10}$ $\delta_{Osh} = 10^4$ (these values were set in order to provide a “pit-in-pit” topology of the objective function. When optimizing the objective function (5), a solution that satisfies the condition $Ter=0$ was first found, and only then a solution for which $Osh=0$ was found. Consistent fulfillment of the specified conditions facilitates the process of finding the minimum of the function (5), $\Delta_x, \dots, \Delta_n$ – respectively, the limit values of the process variable and its higher derivatives by time, including the order of the plant (all these values were set equal to 10^{-3} ; this further ensures the achievement of the desired solutions of the problem and allows the conditions (4) to be approximately fulfilled).

Within the framework of the study, a mathematical operator – ANN was chosen to control the test linear plants the second and third orders (Table 2). This choice is due to the nonlinear properties of ANNs, which, as is known

control system. This requirement was written in the following form:

$$\begin{cases} \lim_{t \rightarrow \infty} x(t) = r; \\ \lim_{t \rightarrow \infty} \dot{x}(t) = 0; \\ \dots \\ \lim_{t \rightarrow \infty} \dot{x}^n(t) = 0, \end{cases} \tag{4}$$

where n – plant order. Here and further, the number above the symbol means the order of the time derivative.

In order to ensure that all conditions (1)-(4) are met, the objective function was considered:

$$Cr = Ter + Osh + t_s \rightarrow \min, \tag{5}$$

where Ter and Osh – the terminal criterion and the criterion responsible for the meeting of the condition of no overshoot (3), respectively.

The components of the objective function (5) Ter and Osh impose penalties when conditions (3) and (4) are not met, respectively. They were written as follows:

(Cybenko, 1989), form powerful approximation properties of ANNs. They, in turn, can be used to design a control operator that would meet the conditions of the control problem (1)-(4) – i.e. perform the required nonlinear mapping of input variables (state variables of the plant) into the output control function. In addition, for the synthesis of the operator that ensures the control conditions (1)-(4), a PI-controller was chosen. It is described by the following expression:

$$u = K_p(r - x(t)) + \int_0^t (r - x(t))dt, \tag{7}$$

where K_p and T_i – proportional and integral gains of the PI-controller, respectively, which are should be found as arguments on which the objective function (5) reaches a minimum. Features of the control operators used in the study (linear – PI-controller and nonlinear – neurocontroller) are shown in Table 2.

Table 2. Features of control operators

Plant transfer function	Inputs number	Outputs number	Neurocontroller			PI-controller	
			Number of neurons in the hidden layer	Neuron activation function	Parameters number (weights and biases)	Search domain	K_p search domain
$G_1(s)$	2	1	5	arctg	21	-1...1	0...20
$G_2(s)$	3				26		
$G_3(s)$	3				26		
$G_4(s)$	2				21		

Source: compiled by the authors

Since this research used the settling time criterion (1), the presence of constraints on the control function, which is formed at the output of the control operator, was a significant factor. It had a significant effect on the t_s value. Taking into account the constraints was also related to the possibility of technical implementation of the control strategy with the help of existing executive devices of the control system. In this study, for this the following expression was used:

$$\tilde{u} = \begin{cases} 5u, & \text{if } u_{\min} \leq 5u \leq u_{\max}; \\ u_{\min}, & \text{if } u_{\min} > 5u; \\ u_{\max}, & \text{if } 5u > u_{\max}, \end{cases} \quad (8)$$

where u_{\max} and u_{\min} – maximum and minimum control value, respectively ($u_{\max} = 2; u_{\min} = 0$). In expression (8), the empirical coefficient 5 is used in order to increase the value of control at the output of one or another controller and, thus, to increase the speed of the reaching of the setpoint r . The modified VCT-PSO particle swarm method (Romasevych et al., 2022) was used to minimize the objective function (5). Its characteristics are given in Table 3.

Table 3. Features of VCT-PSO algorithm

Feature	Numerical value
Iterations number	100
Swarm population	30
Coefficients values:	
• w	0.72
• c_1	1.19
• c_2	1.19
• RC	5

Source: compiled by the authors

The choose of the VCT-PSO algorithm was grounded by its strong search features. Indeed, it localized a global minimum for quit complex objective functions (Romasevych et al., 2022). Thus, one may hope, that this optimization algorithm will found the needed solutions of the stated problems.

RESULTS AND DISCUSSION

As a result of the application of the VCT-PSO algorithm, the K_p and T_i coefficients of the PI-controller, as well as the values of the weights and biases of the neurocontroller were obtained for all optimization problems. Moreover, for different problems, a different nature of the process of minimization of the objective functions (5) was observed.

Table 4. Values of the obtained controllers' parameters

Plant transfer function	Neurocontroller			PI-controller		
	Matrix weights of hidden layer	Vector of biases of hidden layer	Vector of weights of output layer	Bias of output layer	K_p	T_i
$G_1(s)$	$\begin{pmatrix} -0.687 & 0.688 \\ 0.570 & -0.367 \\ -0.237 & -0.566 \\ 0.207 & -0.598 \\ -0.960 & -0.984 \end{pmatrix}$	$\begin{pmatrix} 0.733 \\ -0.827 \\ 0.187 \\ 0.402 \\ 0.941 \end{pmatrix}$	$\begin{pmatrix} 0.256 \\ 1.000 \\ 0.866 \\ 0.899 \\ 0.962 \end{pmatrix}$	0.874	0.334	6.568

To evaluate it, the plot the convergence of the objective function (5) (in a logarithmic scale) was built (Fig. 1).

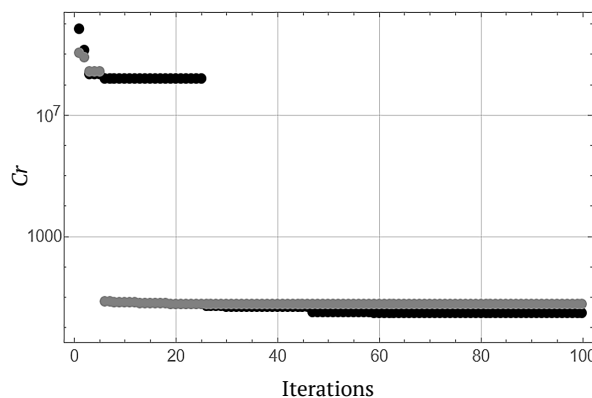


Figure 1. Plots of objective function (5) reducing in the problem of optimal PI-controllers (grey plot) and neurocontroller (black plot) for the plant with transfer function $G_2(s)$

Source: compiled by the authors

From Figure 1, it can be seen that for the case of using a PI-controller, the VCT-PSO algorithm already finds a solution on the sixth iteration that ensures the fulfillment of conditions (6). In the future, only the minimization of criterion (1) is performed. In contrast, finding a similar solution in the case of using a neurocontroller occurred at the twenty-sixth iteration. This is explained by the more complex topology of the objective function. Indeed, the number of arguments that must be determined in the process of neurocontroller training is 26, which is 13 times more than the number of PI-controller coefficients. In addition, since the neurocontroller is a nonlinear operator, the topology of the corresponding objective function (5) will be much more complicated.

The minimization of the objective function for other plants has a similar to that shown in Fig. 1 feature. The only difference lies in the number of iterations at which the components of the function (5) Ter and Osh are become zero. For cases with a smaller number of arguments of the Cr function (the number of parameters of the neurocontroller of second-order plants is equal to 21), there is a faster search of a solution in which the Ter and Osh components become zero. As a result of the conducted research, the numerical values of the coefficients of the PI-controller K_p and T_i , as well as the weights and biases of the neurocontroller (Table 4) were obtained for each plant (Table 1).

Continued Table 4.

Plant transfer function	Neurocontroller			PI-controller		
	Matrix weights of hidden layer	Vector of biases of hidden layer	Vector of weights of output layer	Bias of output layer	K_p	T_i
$G_2(s)$	$\begin{pmatrix} -0.400 & -0.146 & -0.581 \\ -0.018 & -0.398 & -0.111 \\ 0.347 & -0.114 & -0.912 \\ -0.590 & -0.659 & -0.068 \\ 0.043 & -0.405 & -0.879 \end{pmatrix}$	$\begin{pmatrix} 0.231 \\ 0.198 \\ -0.814 \\ 0.358 \\ 0.506 \end{pmatrix}$	$\begin{pmatrix} 0.238 \\ -0.01 \\ -0.284 \\ -0.221 \\ -0.259 \end{pmatrix}$	0.646	0.124	15.735
$G_3(s)$	$\begin{pmatrix} -0.766 & -0.239 & 0.471 \\ 0.232 & 0.027 & -0.973 \\ 0.521 & 0.962 & -0.989 \\ 0.863 & 0.675 & 0.319 \\ -0.506 & -0.405 & 0.985 \end{pmatrix}$	$\begin{pmatrix} 0.787 \\ 0.923 \\ -0.849 \\ -0.503 \\ -0.045 \end{pmatrix}$	$\begin{pmatrix} 0.946 \\ 0.201 \\ 0.301 \\ -0.677 \\ -0.790 \end{pmatrix}$	0.311	0.124	15.735
$G_4(s)$	$\begin{pmatrix} 0.447 & -0.166 \\ -0.991 & -0.511 \\ 0.978 & -0.068 \\ -0.212 & 0.112 \\ -0.382 & 0.007 \end{pmatrix}$	$\begin{pmatrix} 0.406 \\ 0.796 \\ -0.872 \\ 0.402 \\ -0.400 \end{pmatrix}$	$\begin{pmatrix} 0.211 \\ -0.212 \\ -0.682 \\ 0.788 \\ -0.833 \end{pmatrix}$	0.770	0.259	8.815

Source: compiled by the authors

The results of modelling the reaching the process variable $x(t)$ the set point $r=1$ (black curve) and the control function (gray curve) for various plots are shown in

Figure 2. Here, the graphical dependences on the left correspond to the control carried out with the help of a PI-controller, and on the right - a neurocontroller.

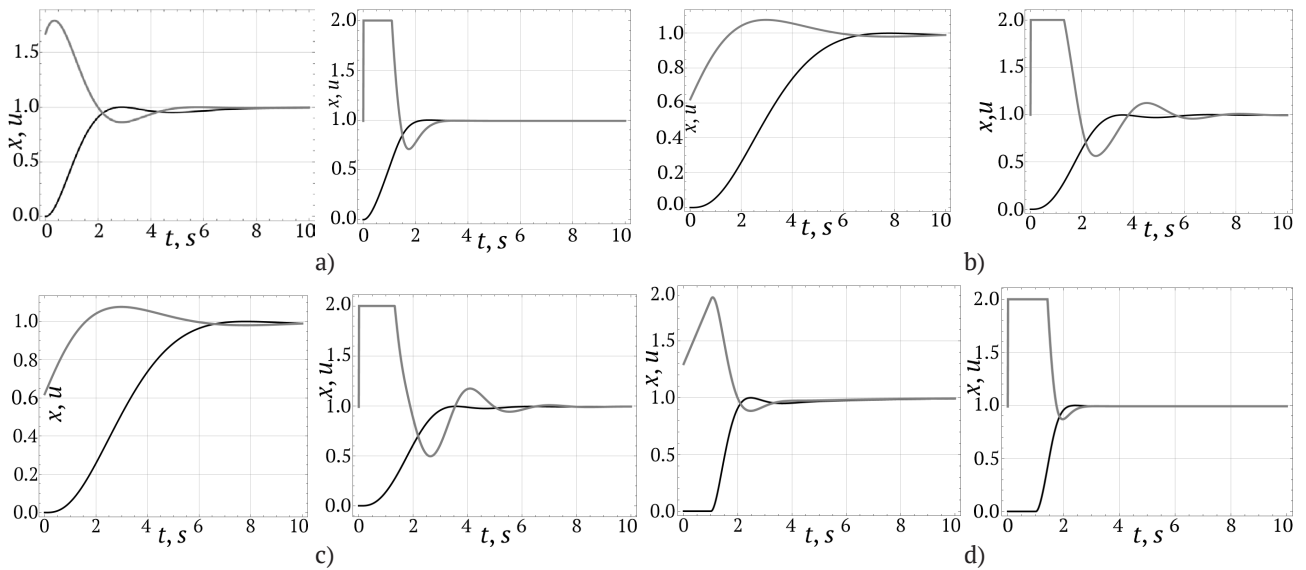


Figure 2. Plots of control function and process variable under PI-controller and neurocontroller application for the plants with transfer function

Note: a) $G_1(s)$; b) $G_2(s)$; c) $G_3(s)$; d) $G_4(s)$

Source: compiled by the authors

For the completeness of the analysis of the obtained results, the numerical values of the estimated indicators of

the control quality, corresponding to the application of the PI-controller and the neurocontroller (Table 5) were given.

Table 5. Values of quality control indicators

Plant transfer function	Settling time		Mean error value		Mean control value	
	PI-controller	neurocontroller	PI-controller	neurocontroller	PI-controller	neurocontroller
$G_1(s)$	2.19	1.79	0.511	0.544	1.432	1.636
$G_2(s)$	5.73	2.92	0.533	0.595	0.988	1.430
$G_3(s)$	5.73	2.95	0.533	0.606	0.988	1.393
$G_4(s)$	2.09	1.97	0.743	0.763	1.504	1.775

Source: compiled by the authors

The analysis of graphical dependencies (Fig. 2) shows that for all cases of transfer functions $G_1(s) \dots G_4(s)$ the use of a neurocontroller is associated with the reaching the u_{\max} constraint. This reduces the settling time t_s . In addition, from Figure 2a, 2d, it can be seen that after reaching the set point r , the process variable $x(t)$ does not change. The characteristics described above favorably distinguish the use of a neurocontroller from a PI-controller. For the cases, indicated in Figure 2b, 2c, the process variable $x(t)$ has only slight change.

A comparison of the qualitative indicators of control, which are given in Table 5, shows that the neurocontroller allows to significantly decrease the settling time. The relative value of such an increase in speed for all cases of transfer functions $G_1(s) \dots G_4(s)$ is within 6.1...96.2%. Larger values of the specified range refer to third-order plants, which are described by the transfer functions $G_2(s)$ and $G_3(s)$. Such an increase in the control performance (by settling time) occurred at the expense of a slight deterioration of other

control quality indicators. For example, the mean error value when using a neurocontroller increased by 2.7...13.7%, and the mean control value – by 18.0...44.7% (Table 5).

Comparing the obtained results on the indicator of the settling time with other studies of Yu. Romasevych et al. (2019), it may be concluded that the neurocontroller shows better efficiency by 21.8...71.2% than the PI-controller, the coefficients of which were found as a result of solving the optimization problem (1)-(4). A comparison of this indicator was also carried out with PI-controllers tuned by methods widely used in engineering practice. They are classical Ziegler-Nikols (Ziegler & Nichols, 1942) method and some of its recent variations: Kappa-Tau (Åström & Hägglund, 1995), AMIGO (Åström & Hägglund, 2004). Comparison was carried out based on other methods: Chien-Hrones-Rewick (Chien et al., 1952), Cohen-Coon (Cohen & Coon, 1953), Lambda (Eriksson, 2008). Skogestad (Skogestad, 2003), Tures-Luyben (Luyben, 1997) methods also were used for comparison purposes (Table 6).

Table 6. Increasing of control speed of neurocontroller comparing to PI-controllers tuned by engineering methods, times

Plant transfer function	Methods of PI-controller tuning							
	Ziegler-Nichols	Kappa-Tau	AMIGO	Chien-Hrones-Rewick	Cohen-Coon	Lambda Tuning	Skogestad	Tyres-Luyben
$G_1(s)$	1.68	2.57	3.18	3.35	3.24	7.37	2.18	-
$G_2(s)$	4.18	3.32	4.66	7.84	6.95	5.62	3.08	6.06
$G_3(s)$	5.29	3.56	4.92	9.08	8.14	5.59	2.03	7.93
$G_4(s)$	15.68	4.72	4.21	27.21	-	30.46	2.08	28.53

Source: compiled by the authors

The analysis of the data shown in Table 6 allows us to state that the neurocontroller provides significantly higher performance compared to the PI-controller, which is tuned by using engineering methods. It should be noted that although the specified engineering methods for tuning a PI-controller are quite common in practice, they do not always provide optimal control parameters. At the same time, the purpose of the conducted comparative analysis is to identify reserves for decreasing the settling time. As can be seen, no matter what approaches are used to tune the PI controller – engineering (Table 6) or optimization (Table 5) – in the case of switching to the use of a neurocontroller, such reserves exist.

From the data presented in Table 6 one may conclude, that there is a tendency – the higher a plant order, the bigger the decreasing of the settling time. The only exception is the tuning method developed by S. Skogestad (2003). Providing the comparative analysis of the settling time values referred to the mentioned tuning methods and neurocontroller performance some statements become obvious. The most of the commonly used tuning Ziegler-Nikols method (Ziegler & Nichols, 1942) shows good settling time value, but only for plant with transfer function $G_1(s)$. Indeed, the difference of this control quality indicator is only 68%. For the rest of the involved in the calculations plants

the difference is in magnitudes (especially for the plant with transfer function $G_4(s)$). Similar statements may be done for PI-controller performances, which are obtained by Chien-Hrones-Rewick (Chien et al., 1952), Lambda (Eriksson, 2008), Tures-Luyben (Luyben & Luyben, 1997) tuning approaches. For them settling time differs 27.21...30.46 times (Table 6).

Other domain of PI-controller tuning methods Kappa-Tau (Åström & Hägglund, 1995), AMIGO (Åström & Hägglund, 2004), Skogestad (Skogestad et al., 2003) indicates low influence by a plant order. The varying of the times of settling time increasing for these cases is quite low: for Kappa-Tau (Åström & Hägglund, 1995) is in the range 2.57...4.72; for AMIGO (Åström & Hägglund, 2004) – 3.18...4.21; for Skogestad (Skogestad, 2003) – 2.03...3.08.

Note, that all the numerical experiments (both for PI-controllers and for a neurocontroller) were carried out with plants, which described transfer functions given in Table 1. However, the important difference between neurocontroller performance and PI-controllers, which are tuned with mentioned methods, are in outputs (control function). Such improving of settling time indicator is connected with more flexibility of neurocontroller. It has dozens of adjustable parameters (degrees of freedom). Their proper tuning allows forming the needed control function. In general, it is

may be concluded that the developed (trained) neurocontroller has better settling time for all cases - an indicator that was used as an element of the optimal control statement (1)-(4). Such an advantage was obviously achieved due to the fact that the neurocontroller is a non-linear control operator that can do the optimal control strategy quite well. Unlike a PI-controller, it has a much larger number of degrees of freedom (weights and biases). Their purposeful change makes it possible to obtain a significant improvement of one or another quality control indicator. At the same time, in order to fully realize the approximation properties of the neurocontroller, it is necessary to have a powerful optimization algorithm, which can ensure the minimization of the appropriately constructed objective function on multiple degrees of freedom of the neurocontroller. Therefore, the solution of the problem of optimal control (by settling time) largely depends on the applied optimizer. It is likely that this conclusion can be extended to a number of other optimization criteria and other plants. However, this thesis is not asserted - within the framework of this study, it remains only a hypothesis that will be proven or disproved in further research by the authors.

CONCLUSIONS

This study presents the results of a comparative analysis of the work of the PI-controller and the neurocontroller for four test plants of second- and third-order. Optimization approaches for tuning PI-controller and training the ANN for control problems (the ANN acts as a control operator) makes it possible to obtain a significant increase in the speed of control. This thesis is based on a comparison of the performance of optimally tuned controllers and PI-controllers that are tuned by using engineering methods. The use of a neurocontroller makes it possible to increase the speed of operation in the range of 6.1...96.2% for the plants, which are described by the transfer functions $G_1(s) \dots G_4(s)$. To a greater extent, the improvement of this

indicator is associated with the third order plants. At the same time, it is necessary to note a certain increase in other undesirable indicators (the mean error value by 2.7...13.7%, the mean control value - by 18.0...44.7%). Therefore, the optimization of the settling time is associated with a certain decrease in other qualitative indicators of control, which quite naturally leads to the idea of using complex optimization criteria. The latter will be used in further research by the authors. The use of ANNs for the control problem requires a justified choice of the optimization algorithm. Within the framework of this work, the VCT-PSO algorithm made it possible to solve all optimization problems, and therefore it may be recommended it for solving problems of this kind. Cases of more complex problems (larger number of ANN parameters, higher orders of control plants, their nonlinearity, etc.) will require careful adjustment of the parameters of the VCT-PSO method (the number of particles in the swarm - 30...50, the number of iterations - more than 1000).

In addition to the above, it may be indicated other prospects for further research in this direction: the use of more complex models of neurocontrollers for delayed and unstable plants; taking into account other significant constraints that affect the dynamics of control (for example, constraints on the rate of change of the control function, which is caused by the electromagnetic and mechanical inertia of the executive device of the control system); optimization of other control modes (for example, neutralization of external disturbances).

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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**Порівняльний аналіз роботи ПІ-регуляторів та нейрорегуляторів
у задачах оптимального за швидкодією регулювання**

Анотація. При розробці систем автоматичного регулювання важливе питання вибору оператора для керуючого впливу на об'єкт можна вирішити за допомогою стандартних ПІ- чи ПІД-регуляторів або навчання штучної нейронної мережі, що потребує порівняльного аналізу їхніх переваг і недоліків. Мета роботи полягала у проведенні порівняльного аналізу роботи ПІ-регулятора та нейрорегулятора за комплексом оціночних показників для об'єктів регулювання другого та третього порядків. Таке порівняння проводилось із застосуванням єдиного підходу щодо синтезу обох регуляторів, який передбачав мінімізацію складної цільової функції. Остання отримана у результаті зведення задачі оптимального регулювання із обмеженнями до задачі безумовної оптимізації. Результати аналізу показали, що за показником швидкодії (критерій оптимізації) нейрорегулятор на модельованих об'єктах регулювання має перевагу на 6,1...96,2 %. Разом з тим, за іншими показниками якості регулювання переважає ПІ-регулятор. Синтез нейрорегулятора у плані відшукування мінімуму цільової функції є складнішою задачею, для вирішення якої необхідна більша кількість ітерацій оптимізаційного алгоритма VCT-PSO. При цьому раціонально задавати кількість ітерацій більше 1000 та розмірність рою 30...50 частинок. Порівняльний аналіз швидкодії нейрорегулятора та ПІ-регуляторів, які налаштовані за інженерними методиками показав значні резерви покращення цього показника. Таким чином, якщо вимоги максимізації швидкодії регулювання є досить жорсткими, то доцільно застосовувати нейрорегулятор. Отримані результати дадуть змогу виконати раціональний вибір оператора регулювання при вирішенні практичних задач синтезу систем регулювання

Ключові слова: об'єкт регулювання; цільова функція; порівняння; нейрорегулятор; оціночні показники регулювання