Neural network optimizer of proportional-integral-differential controller parameters

Isamiddin Siddikov, Gulruxsor Nashvandova, Gulchekhra Alimova
Department of Information Processing and Management System, Faculty of Electronics and Automation, Tashkent State Technical University named after Islam Karimov, Tashkent, Uzbekistan

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ABSTRACT

Wide application of proportional-integral-differential (PID)-regulator in industry requires constant improvement of methods of its parameters adjustment. The paper deals with the issues of optimization of PID-regulator parameters with the use of neural network technology methods. A methodology for choosing the architecture (structure) of neural network optimizer is proposed, which consists in determining the number of layers, the number of neurons in each layer, as well as the form and type of activation function. Algorithms of neural network training based on the application of the method of minimizing the mismatch between the regulated value and the target value are developed. The method of back propagation of gradients is proposed to select the optimal training rate of neurons of the neural network. The neural network optimizer, which is a superstructure of the linear PID controller, allows increasing the regulation accuracy from 0.23 to 0.09, thus reducing the power consumption from 65% to 53%. The results of the conducted experiments allow us to conclude that the created neural superstructure may well become a prototype of an automatic voltage regulator (AVR)-type industrial controller for tuning the parameters of the PID controller.

Corresponding Author:

Gulruxsor Nashvandova
Department of Information Processing and Management System, Faculty of Electronics and Automation,
Tashkent State Technical University named after Islam Karimov
Tashkent, Uzbekistan
Email: gnashvandova@gmail.com

1. INTRODUCTION

Most of the real operating control objects are considered in the works [1]–[3], and possess the properties of nonlinearity, the parameters of which dynamically change in the process of functioning of the object. Widely used linear proportional integral differential (PID) controllers [4], [5], in practice, do not allow to provide the desired behavior of the system when changing the operating mode of the object, as well as in the presence of a priori and current parametric uncertainties of information about the process [6]–[8]. This is because the optimal coefficients of linear regulators are determined only for a particular object state. However, when the state of the object changes, there is a need to reconfigure the parameters of linear regulators, which leads to a decrease in the quality of control and an increase in energy costs. This is especially characteristic of objects with high energy intensity. At present, such scientists as Siddikov *et al.* [9]–[12], actively research to improve control systems of technological processes based on energy-saving technologies with the use of modern control methods. One of the ways to solve this problem is the creation of adaptive-intelligent control systems of technological processes that have the properties of automation of determining the optimal tuning parameters of the PID controller, both in the design process and in operation.

Currently, there are a large number of methods for determining the optimal tuning parameters of process control system regulators are proposed. These methods include the Ziegler-Nichols method [13], frequency method [14], and SIEMENS adaptive PID controller [15], based on identification approaches and methods of intelligent technologies [16], [17]. Application of these methods, for operative determination of regulators' tuning parameters at the change of operating modes of the control object (CO), causes some difficulties and faces certain difficulties in identification of the control object with inertial properties [18], [19]. Methods for solving optimization problems based on evolutionary algorithms such as genetic algorithms [20], and particle swarm [21]–[23] are iterative, requiring an accurate model of the control object, which is a difficult problem.

One of the ways to solve these problems is to use neural network methodology, since these methods have the properties of adaptation and learning ability to give the desired behavior to control systems, due to the possibility of using nonlinear control laws, as well as the property of adaptation to neural network control systems [24], [25]. The main advantage of neural network (NN) is the possibility of operative retraining depending on production situations. This article developed a methodology for correction of coefficients of the adaptive PID controller using a neural network optimizer. In addition, the authors of the article propose the formation of a database of situation rules designed to reconfigure the parameters of the regulator depending on the situation.

The following is the order of presentation: section 2 explains the method of solving the problem and reveals the essence of the neural network optimizer of PID controller parameters. Section 3 contains the results of the analysis of the proposed method of synthesis of the neural network optimizer. Section 4 concludes with a conclusion and recommendations for further use and development of the proposed approach.

2. METHOD

An important step in using a neural network to control dynamic objects is the choice of its structure. Provided that the inner layer uses a nonlinear activation function of the sigmoidal function type [26], it is sufficient to take a two-layer neural network (one inner input layer and an output layer) in the architecture, allowing for high accuracy of approximation of any function for many variables. The functional diagram of the proposed neural network optimizer having a superstructural linear PID controller [27], which is a superstructure of the controller and designed to calculate its parameters, is shown in Figure 1.

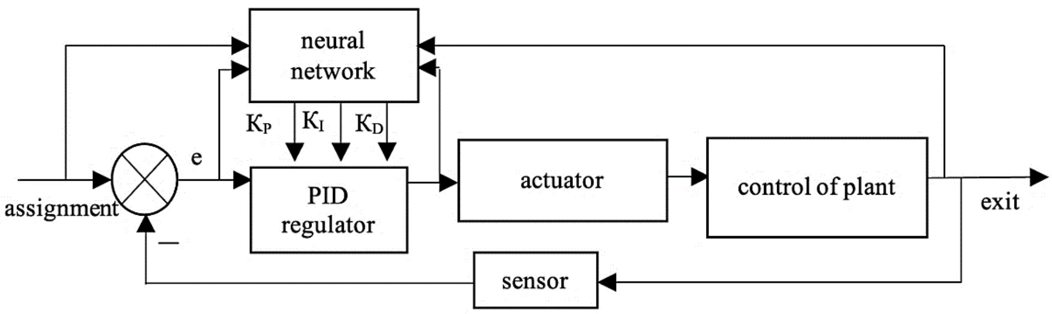

Figure 1. Control scheme with neural network optimizer of regulator parameters

Here, the determination of optimal tuning parameters of the PID controller K_P, K_I and K_D is carried out using neural networks. The task of the control system is to monitor the operating mode in order, on the one hand, to ensure the minimum transient process and, on the other hand, to reduce the losses of consumed energy. At the same time, the control system should provide the required quality of transients in terms of accuracy, overshoot, and number of oscillations, taking into account the nonlinear properties of the control object, without making significant changes in the structure of the control system. The number of adjustable parameters of the PID controller will be equal to 3.

When using the neural network optimizer, the neural network structure is initially formed, the input parameters of which are the control task - $r(t)$, the mismatch signal - $e(t)$, the output of the linear regulator - $u(t)$ and the control object - $y(t)$, and the tuning parameter of the regulator is taken as the output variables. Then, the neural network optimizer is represented as a function of several variables characterizing the relationship between the regulator tuning parameters K_P, K_I and K_D with the input parameters of the optimizer. At the same time, the neural network optimizer approximates these dependencies to determine the tuning parameters of the PID controller.

When using a neural network to describe the control process, an important task is to determine the number of layers of the neural network, as well as the number of neurons in the input and output layers of the network, taking into account the principle of operation of the control law used [28]. When using PID control law in control problems, the dependence of the regulator output signal on the input signals is described in the form:

$$U(s) = \left(K_P + \frac{K_1}{S} + K_D S\right) Y(s) \tag{1}$$

In this case, the transfer function of the linear regulator has the form:

$$W_c(s) = \frac{U(s)}{Y(s)} = K_P + \frac{K_1}{S} + K_D S \tag{2}$$

Since the performance of the PID controller is estimated by the neural network discretely, with a step Δt, therefore, to determine the number of neurons of the input layer of the PID control law, it is represented in discrete form using the ratio $s = (\frac{z-1}{z})/\,\Delta t$. Then, the transfer function of the PID controller is represented in the form:

$$W_c(z) = K_P + \frac{K_I \Delta t z}{z-1} + K_D \frac{z-1}{\Delta t z} = \frac{z}{z-1}\left(K_P\left(\frac{z-1}{z}\right) + K_I \Delta t + \frac{K_D}{\Delta t}\left(\frac{z-1}{z}\right)^2\right) = \frac{z}{z-1}\left(K_D/\Delta t z^2 - (2K_D/\Delta t + K_P)1/z + (K_P + K_I\Delta t + K_D/\Delta t)\right) \tag{3}$$

Introducing the notations $a_1 = (K_P + K_I\Delta t + K_D/\Delta t), a_2 = -(2K_D/\Delta t + K_P), a_3 = K_D/\Delta t$, we obtain the difference equation for the kth control step:

$$u(t_k) = a_1 e(t_k) + a_2 e(t_k - \Delta t) + a_3 e(t_k - 2\Delta t) + u(t_k - \Delta t) \tag{4}$$

From this, we can see that when forming the control signal, the PID controller has information about the error signal at the current moment (clock back, two clock cycles back) and about the control signal (clock back). In our case, the number of NN inputs will be equal to 4. Here there is another important point that must be taken into account for tuning the parameters of the controller, it is related to the need to know not only about the error signal at the current moment but also about the current value of the task. In the case when at different values of the set point and the same error signals, the controller parameters have different values, then for a particular type of transient process - the set point should be considered unchanged at the considered moment. Taking this into account, (4) will take the form:

$$u(t_k) = (a_1 + a_2 + a_3)r - a_1 y(t_k) - a_2 y(t_k - \Delta t) - a_3 y(t_k - \Delta t) + u(t_k - \Delta t). \tag{5}$$

Hence, we can see that the number of inputs of the neural network is 5: the task, the output of the co at the current moment, a clock back, two clock back, and the value of the control action at the previous moment. The number of neurons in the output layer will be equal to 3, each of which corresponds to the adjustable parameters of the PID controller K_P, K_I and K_D. In the output layer we use the activation function with a sigmoidal form:

$$f(s) = \frac{1}{(1+e^{-as})}, \alpha = const \tag{6}$$

To determine the number of neurons in the hidden layer of the neural network, the training sample size is taken into account. To solve this problem, we can use the formulas proposed by Ziegler-Nichols [29]:

$$N_{hid} \geq 2N + 1 \tag{7}$$

where N is the number of inputs of the neural network.

On the other hand, it is necessary to take into account the fact that the measured quantities are subject to interference. Therefore, the object characteristic is averaged over at least three points. Hence, we can conclude that when averaging the signal over three points, 15 measurements are required. In general, for a neural network optimizer, the number of neurons in the inner layer can be determined by (8):

$$N_{hid} = (2N+1) + N_{av} + N_{delay} - 1, \tag{8}$$

where N is the number of inputs of the neural network; N_{av} is the number of averaged output data from the object; N_{delay} is the number of delayed signals from the output of the object, which are the input of the neural network.

Based on this, the structure of neural network optimizer for PID controller is proposed in Figure 2. The following notations are given in the structure: x_1 is task; x_2 is signal from the object output delayed by one clock cycle; x_3 is output signal from the control object delayed by Δt, x_4 is output signal from the object delayed by $2\Delta t$; x_5 is signal from the regulator output. These signals are normalized in the interval [0;1]. The values of the inner layer neurons and the output of the neural network optimizer are determined as:

$$S_j^{(1)} = \sum_{j=1}^{5} \omega_{ji}^{(1)} \cdot x_i + b_j^{(1)},$$

$$O_j^{(1)} = f^{(1)}\left(S_j^{(1)}\right) \left(j = \overline{1,15}\right),$$

$$S_k^{(2)} = \sum_{j=5}^{15} \omega_{kj}^{(2)} \cdot O_j^{(1)} + b_k^{(2)},$$

$$O_k^{(2)} = f^{(2)}\left(S_k^{(2)}\right) (k = \overline{1,3}),$$

where $\omega_{ji}^{(1)}$ is the weight coefficient of the connections between the neuron of the inner and input layer; $\omega_{ji}^{(2)}$ is the weight coefficient of the connections between the neuron of the output and inner layer; x^i are the input signals of the neural network; $b_j^{(1)}, b_k^{(2)}$ are the linear displacement of the neuron of the inner and output layer, respectively; $O_j^{(1)}, O_k^{(2)}$ are output signals of neurons of the inner and output layer; $S_j^{(1)}, S_k^{(2)}$ are total neuron values for the inner and output layer; $f^{(1)}$ is hyperbolic activation function; $f^{(2)}$ is linear activation function.

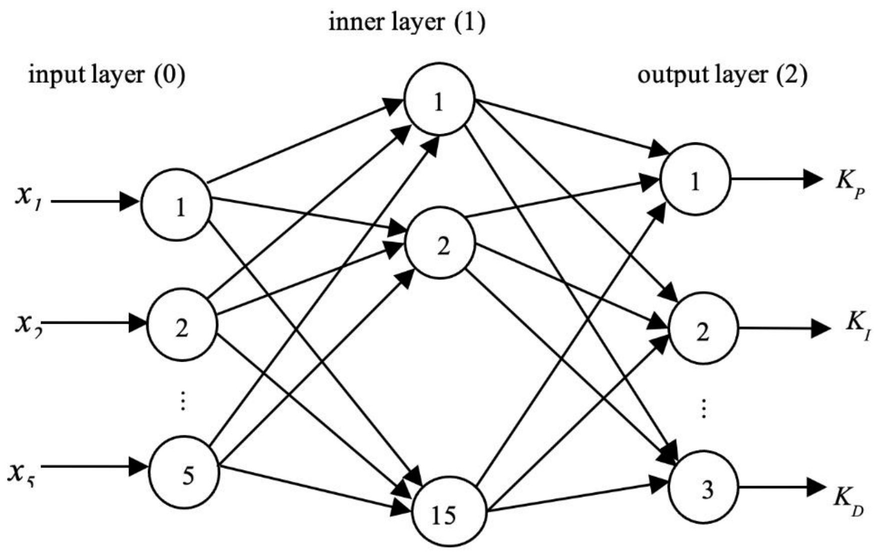

Figure 2. Structure of neural network of PID controller neural network optimizer

The next stage is the training of the neural network. To solve the problem of training a neural network optimizer, the paper proposes a backpropagation gradient algorithm [30], which allows for minimizing the target function of the training process. The mathematical model of training, for the proposed neural network, consists of the following procedures:

$$E(t) = \frac{1}{2}(r(t) - y(t))^2 \rightarrow min,$$

$$e_2(t) = r(t) - y(t), e_1(t) = e_2(t) - e_2(t-1), e_3(t) = e_2(t) - 2e_2(t-1) + e_2(t-2),$$

$$\delta_j^{(2)} = e_k \frac{dO_k^{(2)}}{ds_k^{(2)}}, k = \overline{1.3},$$

$$\delta_j^{(1)} = \sum_{k=1}^{3} \delta_j^{(2)} \omega_{kj}^{(2)} \frac{dO_j^{(1)}}{ds_j^{(1)}}, j = \overline{1.15},$$

$$\Delta\omega_{kj}^{(2)}(t) = \eta_k^{(2)} \delta_k^{(2)} O_j^{(1)} + \alpha\omega_{kj}^{(2)}(t-1) + \beta\omega_{kj}^{(2)}(t-2),$$

$$\Delta b_{kj}^{(2)}(t) = \eta_k^{(2)} \delta_k^{(2)} + \alpha\Delta b_k^{(2)}(t-1) + \beta\Delta b_k^{(2)}(t-2),$$

$$\Delta\omega_{ji}^{(1)}(t) = \eta^{(1)} \delta_j^{(1)} O_i^{(0)} + \alpha\Delta\omega_{ji}^{(1)}(t-1) + \beta\Delta\omega_{ji}^{(1)}(t-2),$$

$$\Delta b_j^{(1)}(t) = \eta^{(1)} \delta_j^{(1)} + \alpha\Delta b_j^{(1)}(t-1) + \beta\Delta b_j^{(1)}(t-2),$$

$$\omega_{kj}^{(2)}(t+1) = \omega_{kj}^{(2)}(t) + \Delta\omega_{kj}^{(2)}(t),$$

$$b_k^{(2)}(t+1) = b_k^{(2)}(t) + \Delta b_k^{(2)}(t),$$

$$\omega_{ji}^{(1)}(t+1) = \omega_{ji}^{(1)}(t) + \Delta\omega_{kj}^{(1)}(t),$$

$$b_j^{(1)}(t+1) = b_j^{(1)}(t) + \Delta b_j^{(1)}(t),$$

where $r(t)$ is the input influence; $y(t)$ is the output signal of the control object; $\eta^{(1)}, \eta_k^{(2)}$ are the learning rates of the neurons of the inner and output layers of the neural network; α and β are the convergence learning rate coefficients; $\delta_j^{(1)}, \delta_j^{(2)}$ is the total error of the neuron of the inner and output layers; e_k is the error value of the neurons of the output layer.

In the known works [31]–[35], the learning rate of neurons of the inner layer of the neural network was taken the same, and it does not change during the functioning of the system, which leads to undesirable situations. To solve this problem, in this paper, it is proposed to choose the learning rate differently as the adjustable parameters of the controller have different values. Therefore, for each adjustable parameter of the regulator, it is necessary to choose different learning rates, with the possibility of changing (adjusting) them during the operation of the system. To determine the necessary value of the learning rate, a rule base is compiled.

The rule base of the neural network optimizer contains information about the need to train the neural network (when the task is changed), knowledge and learning rate of the neurons of the output layer of the neural network, as well as the direction of changes (increase and decrease) in the value of the regulator parameters. The direction of changes in these parameters is determined by the sign of correction of weight coefficients between the neurons of the inner and output layers of the neural network, and the laws of the learning rate of the neurons of the output layer, represented by (9):

$$\Delta\omega_{kj}^{(2)}(t) = -\eta_k^{(2)} \delta_k^{(2)} O_j^{(1)},$$

$$\omega_{kj}^{(2)}(t+1) = \omega_{kj}^{(2)}(t) + \Delta\omega_{kj}^{(2)}(t),$$

$$\delta_k^{(2)} = e_k, \tag{9}$$

where $\eta_k{}^{(2)}$ is the learning rate of neurons of the output layer of the neural network; $\delta_k^{(2)}$ is total error of the output layer neuron; e_k is error of neurons of each output channel of the neural network (output parameters of the network); $O_j^{(1)}$ is output signal of the inner layer neuron; and $\omega_{kj}^{(2)}$ is neuron weight coefficients between the inner and output layers of the neural network.

The rule for changing the neuron learning rate is usually embedded in the neural network rule base. The choice of the discretization step (Δt) is made for each specific object, taking into account its dynamic properties. Since the accuracy of neural network operation depends on the value of Δt, in general case Δt is chosen based on the time of transient process regulation: $\Delta t = t_P/N$, where N is the number of neurons of the inner layer of the neural network, t_P is the regulation time. It should be noted that the proposed control system with a neural network optimizer also allows us to promptly respond to the drift of the object characteristics when changing the task and modes of its operation.

3. RESULTS AND DISCUSSION

A neural network optimizer, built as a superstructure of the PID regulator, was used to control the technological parameters of the natural gas drying process. The research was carried out under the same conditions as the experiment. Natural gas with a temperature of 25 ºC and pressure of 1,894 kPa was supplied to the dryer. The process was considered complete if the transient process was established in the vicinity of 5% relative to the set one. The experimental results showed that the application of a neural network optimizer in controlling the drying process allowed to increase the completeness, which led to a decrease in zeolite consumption from 95% to 62%, by increasing the accuracy of control from 0.23 to 0.09 as shown in Table 1. As a result of the conducted experiments, it can be concluded that the created neural network optimizer can become a prototype of an industrial PID controller when tuning its parameters.

Table 1. The results of the experiment showed

Quality assessment	Classic PID controller	PID controller with neural network optimizer
Control accuracy	0.23%	0.09%
Zeolite consumption	95%	62%
Power consumption	65%	53%

A simulation experiment was conducted to test the effectiveness of the proposed approach to synthesizing a control system with a neural network optimizer. To do this, a jump signal proportional to the value of the controlled parameter of the object was supplied to the input. The experiment results showed that the synthesized control system with a neural network optimizer made it possible to achieve a 4% overshoot and reduce the duration of the transient process by 23% relative to a conventional PID controller. At that time, the classic PID controller gives a 12% overshoot. The found optimal values of the tuning parameters of the PID controller with a neural network optimizer, for the case under consideration, are equal to $K_P = 2.5, K_I = 1.6 \cdot 10^{-2}$. At the same time, the optimal parameters of the classic PID controller have the following values: $K_P = 0.9, K_I = 6.976 \cdot 10^{-4}$.

4. CONCLUSION

Based on the obtained results, we can draw the following conclusions about the architecture of the neural network, for linear regulators, it is enough to have three layers, and the number of neurons in the input layer of the neural network is determined by analyzing the dynamics of the linear regulator, and the number of output neurons depends on the number of adjustable parameters of the regulator. In this case, to choose the number of neurons in the inner layer of the neural network, it is necessary to take into account the number of input neurons and the number of averaged points of the controlled parameters of the object. For neural network training the method of backpropagation of gradient is proposed, which is characterized by high convergence and accuracy. The obtained results allow us to conclude that the use of a neural network optimizer of parameters of linear regulators taking into account nonlinear properties of EI allowed to increase in the accuracy of regulation from 0.23 to 0.09, which allowed to reduce zeolite costs from 65% to 53% and reduce power losses by 12%. The proposed improvements made in the scheme of realization of the PID-neuro regulator allowed to provision of stable operation of the NS and its trainability in the control loop in real-time. In addition, when changing the parameters of the object, such a trained (and constantly operationally updated) NS can reconfigure the parameters of the PID-neuro-regulator during the transient process and provide the required quality of the transient process. The main changes of the proposed approach for neural network control of a dynamic object are to develop a methodology for changing the speed and direction of training of the neural network, as well as the rules of training the output neurons of the neural network, which are the parameters of the PID-regulator.

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BIOGRAPHIES OF AUTHORS

Isamiddin Siddikov received his degree in electrical engineering with a degree in automation and telemechanic in 1976 from the Tashkent Polytechnic Institute, Tashkent, Uzbekistan. In 1989 he defended his Ph.D. thesis in the specialty of control in technical systems. In 2016 he defended his doctoral thesis in the specialty “Intellectualization of control processes for dynamic objects and technological processes.” He is currently a professor at the Tashkent State Technical University named after Islam Karimov. Under his leadership, 17 PhDs were trained. His research interests include the intellectualization of control processes for non-linear continuous-discrete dynamic objects, and the developed methods, and models used in the field of automation of electric power facilities, oil and gas, chemical-technological industries, and the light industry. In addition, he is a reviewer of leading scientific journals such as Vestnik TSTU, and Chemical Technology. Control and management”, “Technical science and innovation”. He is the author or co-author of more than 150 refereed journals and conference articles, 7 monographs and 4 textbooks, 28 scientific articles indexed in the Scopus database (Elsevier). He can be contacted at email: isamiddin54@gmail.com.

Gulruxsor Nashvandova received a bachelor’s degree in vocational education (radio electronic devices and systems) from Tashkent State Technical University in 2015, and a master's degree in radio technical devices and communications in 2017. Currently, she is a doctoral student at the Department of Information Processing and Management Systems, Faculty of Electronics and Automation, Tashkent State Technical University. The main goal of his research activities is based on logical control of technological parameters of the natural gas treatment process. In this direction, she has written and published many scientific articles in domestic and foreign scientific journals, including journals indexed in Scopus and Web of Science scientific databases. She can be contacted at email: gnashvandova@gmail.com.

Gulchekhra Alimova in 2000, she received a bachelor's degree from the Tashkent Institute of Textiles and Light Industry in the field of Textile Products Technology, in 2009 he received a master's degree in the specialization of technological processes and production automation and control, and in 2022, 05.01.08 - a Ph.D. in the specialization of technological processes and production automation and control degree. Currently, he is working as a Ph.D. senior lecturer at the Department of Information Processing and Control Systems, Faculty of Electronics and Automation, Tolshkent State Technical University. Her scientific interests are based on the main goal of his scientific activity: the adaptive-neural control system of cotton fiber spinning. In this direction, he has written and published many scientific articles in domestic and foreign scientific journals, including journals indexed in Scopus and Web of Science scientific databases. She can be contacted at email: alimova250979@mail.ru.