Identification and adaptive control based Hopfield neural networks

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Abstract. The principles of adaptive supervisory control of a linear system are considered. The control algorithm assumes an alternation of the stages of plant identification and adjustment of the regulator coefficients using artificial Hopfield neural networks. For identification, the plant model in the form of a discrete transfer function is used. The input of the neural network receives signals from the input and output of the plant and their delayed values, and the outputs of the neural network are the coefficients of the model. To determine the weights and displacements of a neural network, the Lyapunov function is introduced, which describes the energy of the network as a function of the output error of the model. The identification stage precedes the step of adjusting the regulator coefficients. Supervisor based on the Hopfield neural network uses the obtained estimates of the model parameters, its outputs are the PID-controller coefficients. To adjust the weights and displacements of the neural network supervisor, we also consider the energy function, the minimization of which means the convergence of the outputs of the control system and the given reference model.The computational experiments performed showed a good quality of the adaptive system operation when controlling a linear plant with unknown parameters. The considered algorithms of identification and adaptation can be used to control a wide range of linear plants with variable parameters.

1. Introduction

Neural networks (NN) are an effective tool for solving many technical problems [1], including modelling, optimization, classification, recognition, management, forecasting, etc. There are different topologies of the NN, but on the basis of the presence of feedback, there are two class: static and dynamic NN.

In practice, static feedforward NN (multi-layer perceptrons) are widely used, which are trained using the algorithm of back propagation. These static NN can be converted into dynamic ones by supplying the delayed values of the output of the NN to its input. This approach allows solving the task of identifying a dynamic plant, considering the accumulated data sets from its input and output [2]. In [3, 4], the feedforward NN is used to implement the PID controller. In [5], a feedforward NN was used to estimate the delay at the output of an object with a delay.

The Hopfield NN are dynamic neural networks [6, 7]. The Hopfield NN traditionally used in the tasks of organizing associative memory and optimization. The identification with the help of Hopfield NN differs in that it allows us to obtain estimates of the parameters of the mathematical model of the controlled plant. For example, in [8] the problem of identifying the parameters of a mathematical pendulum was considered. In the paper [9], the Hopfield NN with nonlinear activation functions is considered to optimize the parameters of the PID controller. The dynamic plant model is described by the equations of state. The parameters of a neural network are calculated as a combination of state variables and input signals. It is noted that it is possible to increase the speed of the system and reduce the static error in comparison with the traditional control scheme.

In this paper, we consider the problem of identification and adaptive control of a linear dynamical object using the dynamic Hopfield NN. The technique for determining the parameters of the NN based on the use of Lyapunov functions is given, which makes it possible to minimize the error of the system state. The problem of identification of the model of the object is considered as auxiliary for determining the parameters of the regulator, which ensures the closeness of the output of the plant and the given reference model.

2. Hopfield neural network

The recurrent Hopfield NN it has one layer of neurons, where the outputs of each of them are feedback to the inputs of the others (Figure 1, where *AN* is an artificial neuron, I_i and u_i are the displacement and output signal of the *i*-th neuron, w_{ij} is the coupling weight *i* and *j* neurons).

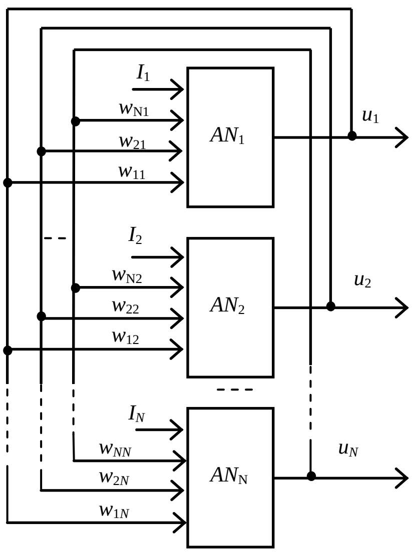

Figure 1. Structure of the Hopfield neural network.

The output of the *j*-th neuron is described by the equations:

$$\begin{cases} \dfrac{dx_i}{dt} = \sum\limits_j w_{ij} u_j - I_i; \\ u_i = \varphi(x_i), \end{cases} \tag{1}$$

where φ is the activation function of the neuron.

Stability of the NN is guaranteed if its parameters are chosen in such a way that there exists a Lyapunov function, i.e. a function that would always decrease when the network state changes. The form of this function is dictated by a specific task. To justify the fact that a positive-definite function is a Lyapunov function, one must prove that its derivative is negative definite.

Let $E(X)$ be a function positive for any values of the parameters X. The dynamics of the NN should be realized in such a way that the function $E(X)$ has a negative derivative.

$$\frac{dE(X)}{dt} = \frac{\partial E(X)}{\partial x_i}\frac{dx_i}{dt}, \qquad i = \overline{1,n}. \tag{2}$$

Let the dynamics of NN be determined by the expression:

$$\frac{du_j}{dt} = -\frac{\partial E}{\partial x_j}; \tag{3}$$

Then it follows from (2) and (3):

$$\frac{dE(x_j)}{dt} = -\frac{du_j}{dt}\frac{dx_i}{dt}, \qquad j = \overline{1,n}. \tag{4}$$

According to (1),

$$u_j = \varphi(x_j) \quad \Rightarrow \quad x_j = \varphi^{-1}(u_j). \tag{5}$$

Then

$$\frac{dx_j}{dt} = \frac{\partial \varphi^{-1}(u_j)}{\partial u_j}\frac{\partial u_j}{dt}, \qquad j = \overline{1,n}. \tag{6}$$

Substituting (6) into (4), we obtain

$$\frac{dE(x_j)}{dt} = -\left(\frac{du_j}{dt}\right)^2 \frac{\partial \varphi^{-1}(u_j)}{\partial u_j} \tag{7}$$

The derivative (7) is always negative if the activation function φ is chosen in such a way that the partial derivative is always positive. This condition is ensured for a continuously differentiable monotonically increasing function (linear function, hyperbolic tangent, and so on). Thus, condition (3) ensures the minimization of $E(X)$ in the course of the Hopfield NN operation.

3. Identification of a linear dynamic plant

The task of identification is to determine the structure and parameters of the mathematical model of the plant from experimental observations. Let us consider the traditional formulation of the problem of parametric identification of a linear dynamical plant.

At the input of the investigated plant, a certain test action g(t) is applied, the output signal $y(t)$ is the reaction of the plant. The error in the output of the model $e(t) = y(t) - y_m(t)$ should be minimized by adjusting the parameters of the $P(t)$ model, which are the outputs of the neural network (Figure 2).

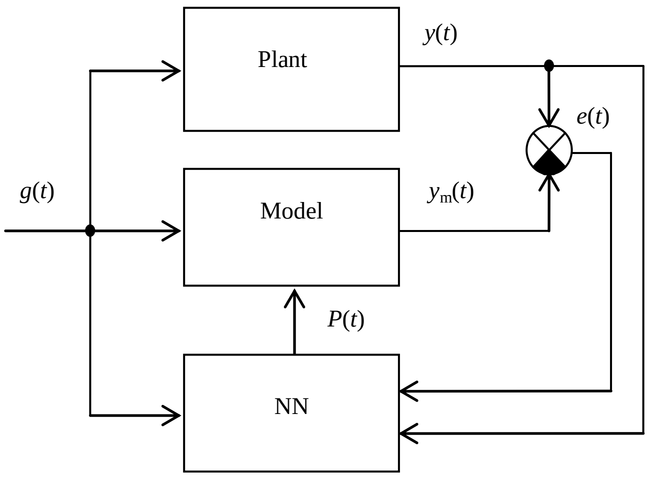

Figure 2. Neural network identification scheme.

A linear dynamic plant can be described by a discrete transfer function of the form:

$$W(z) = \frac{Y(z)}{G(z)} = \frac{b_0 + b_1 z^{-1} + \ldots + b_m z^{-m}}{1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_n z^{-n}}. \tag{8}$$

The problem of identification is reduced to the search for unknown coefficients b_0, b_1, ... b_m and a_1, a_2, ... a_n.

In practice, the method of least squares and its modifications is often used to solve the problem of parametric identification [10]. The use of the Hopfield NN for identification makes it possible to abandon analytical calculations in favor of recurrent optimization using experimental data.

For the sake of simplicity, let us consider a dynamic plant of the second order, for which an equation is obtained from (8):

$$Y(z)\left(1 + a_1 z^{-1} + a_2 z^{-2} + \ldots + a_n z^{-n}\right) = G(z)\left(b_0 + b_1 z^{-1} + \ldots + b_m z^{-m}\right) \tag{9}$$

We transform (9) into a difference equation that serves as a model of a linear plant:

$$y(k) = b_0 g(k) + b_1 g(k-1) + \ldots + b_m g(k-m) - a_1 y(k-1) - a_2 y(k-2) - \ldots - a_n y(k-n). \tag{10}$$

where k is the time moment.

For identification, it is necessary to consider several consecutive moments of time in which (10) is fixed.The number of equations must be greater than or equal to the number of model parameters of the plant. A system of equations can be associated with an energy function describing a simulation error:

$$E = \sum_{i=1}^{n+m} \left(b_0 g(i) + \ldots + b_m g(i-m) - y(i-1)a_1 - \ldots - y(i-n)a_n - y(i)\right)^2. \tag{11}$$

Minimization (12) means choosing the values b_1, b_2 and a_1, a_2, under which the dynamics of the model is closest to the dynamics of the plant.

It is obvious that $E > 0$ at all points, except for the equilibrium point, where it is reset.

The dynamics of the NN must be realized in such a way that the function (11) becomes a Lyapunov function.

$$\frac{dE}{dt} = \frac{\partial E}{\partial a_1}\frac{da_1}{dt} + \ldots + \frac{\partial E}{\partial a_n}\frac{da_n}{dt} + \ldots + \frac{\partial E}{\partial b_1}\frac{db_1}{dt} + \ldots + \frac{\partial E}{\partial b_m}\frac{db_m}{dt}.$$

The number of neurons should correspond to the number of unknown parameters.

Let u_i be the output of the i-th neuron. Then in order for E to be a Lyapunov function, it is necessary that conditions (3) are satisfied:

$$\begin{cases} \dfrac{du_1}{dt} = -\dfrac{\partial E}{\partial a_1}; \\ \dfrac{du_2}{dt} = -\dfrac{\partial E}{\partial a_2}; \\ \quad \ldots \\ \dfrac{du_n}{dt} = -\dfrac{\partial E}{\partial a_n}; \\ \dfrac{du_{n+1}}{dt} = -\dfrac{\partial E}{\partial b_1}; \\ \quad \ldots \\ \dfrac{du_{n+m}}{dt} = -\dfrac{\partial E}{\partial b_m}. \end{cases} \tag{13}$$

After substituting (11) into (13) and performing transformations, one can obtain a set of weights W and displacements V of the neural net.

4. An example of neural network identification

Consider the identification of a second-order discrete transfer function:

$$W(z) = \frac{Y(z)}{G(z)} = \frac{b_0 + b_1 z^{-1}}{1 + a_1 z^{-1} + a_2 z^{-2}}. \tag{14}$$

To search for unknown parameters a_1, a_2, b_1, b_2, we consider the system of equations:

$$\begin{cases} b_1 g(i) + b_2 g(i-1) - y(i-1)a_1 - y(i-2)a_2 = y(i), \\ b_1 g(i-1) + b_2 g(i-2) - y(i-2)a_1 - y(i-3)a_2 = y(i-1), \\ b_1 g(i-2) + b_2 g(i-3) - y(i-3)a_1 - y(i-4)a_2 = y(i-2), \\ b_1 g(i-3) + b_2 g(i-4) - y(i-4)a_1 - y(i-5)a_2 = y(i-3). \end{cases} \tag{15}$$

The energy function describing the simulation error can be associated with system (15):

$$E = \sum_{i=1}^{4} \left(b_1 g(i) + b_2 g(i-1) - y(i-1)a_1 - y(i-2)a_2 - y(i)\right)^2. \tag{16}$$

Then

$$\frac{dE}{dt} = \frac{\partial E(a_1)}{\partial a_1}\frac{da_1}{dt} + \frac{\partial E(a_2)}{\partial a_2}\frac{da_2}{dt} + \frac{\partial E(a_1)}{\partial b_1}\frac{db_1}{dt} + \frac{\partial E(b_2)}{\partial b_2}\frac{db_2}{dt}.$$

The system (13) is transformed to the form:

$$\begin{cases} \dfrac{du_1}{dt} = -\dfrac{\partial E}{\partial a_1}; \\ \dfrac{du_2}{dt} = -\dfrac{\partial E}{\partial a_2}; \\ \dfrac{du_3}{dt} = -\dfrac{\partial E}{\partial b_1}; \\ \dfrac{du_4}{dt} = -\dfrac{\partial E}{\partial b_2}. \end{cases} \tag{17}$$

After substituting (16) into (17) and performing the transformations, we obtain a set of weights W and displacements V of Hopfield neural network (where $g_1 = g(i)$, $g2 = g(i-1)$, etc.).

$$W_1 = \begin{bmatrix} g_1^2 + g_2^2 + g_3^2 + g_4^2 & g_1g_2 + g_2g_3 + g_3g_4 + g_4g_5 \\ g_1g_2 + g_2g_3 + g_3g_4 + g_4g_5 & g_2^2 + g_3^2 + g_4^2 + g_5^2 \\ -y_2g_1 - y_3g_2 - y_4g_3 - y_5g_4 & -y_2g_2 - y_3g_3 - y_4g_4 - y_5g_5 \\ -y_3g_1 - y_4g_2 - y_5g_3 - y_6g_4 & -y_3g_2 - y_4g_3 - y_5g_4 - y_6g_5 \end{bmatrix};$$

$$W_2 = \begin{bmatrix} -g_1y_2 - g_2y_3 - g_3y_4 - g_4y_5 & -g_1y_3 - g_2y_4 - g_3y_5 - g_4y_6 \\ -g_2y_2 - g_3y_3 - g_4y_4 - g_5y_5 & -g_2y_3 - g_3y_4 - g_4y_5 - g_5y_6 \\ y_2^2 + y_3^2 + y_4^2 + y_5^2 & y_2y_3 + y_3y_4 + y_4y_5 + y_5y_6 \\ y_2y_3 + y_3y_4 + y_4y_5 + y_5y_6 & y_3^2 + y_4^2 + y_5^2 + y_6^2 \end{bmatrix};$$

$$W = [W_1;\ W_2]. \tag{18}$$

$$V = \begin{bmatrix} -g_1y_1 - g_2y_2 - g_3y_3 - g_4y_4 \\ -g_2y_1 - g_3y_2 - g_4y_3 - g_5y_4 \\ y_1y_2 + y_2y_3 + y_3y_4 + y_4y_5 \\ y_1y_3 + y_2y_4 + y_3y_5 + y_4y_6 \end{bmatrix}. \tag{19}$$

In Figure 4 and 5 show the results of modeling the identification process at Δt = 0.05 s. The transient processes of the plant and the model practically coincide (Figure 4). Estimates of the coefficients of the model gradually approach constant values: b_1 = 0.375; b_2 = 0.1198; a_1 = –0.4881; b_2 = –0.3572 (Figure 5).

In Figures 6 and 7 show the results of identification with an abrupt change in the parameters of the plant (at t = 50 sec.). The neural network reacts quickly to the changed modeling conditions.

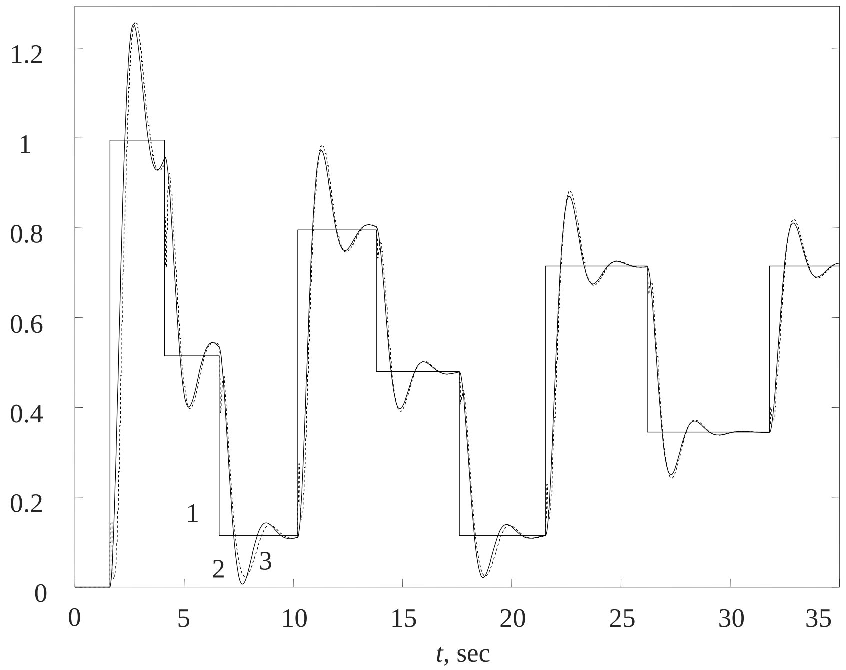

Figure 4. Reaction to the input signal (1) of the plant (2) and model (3).

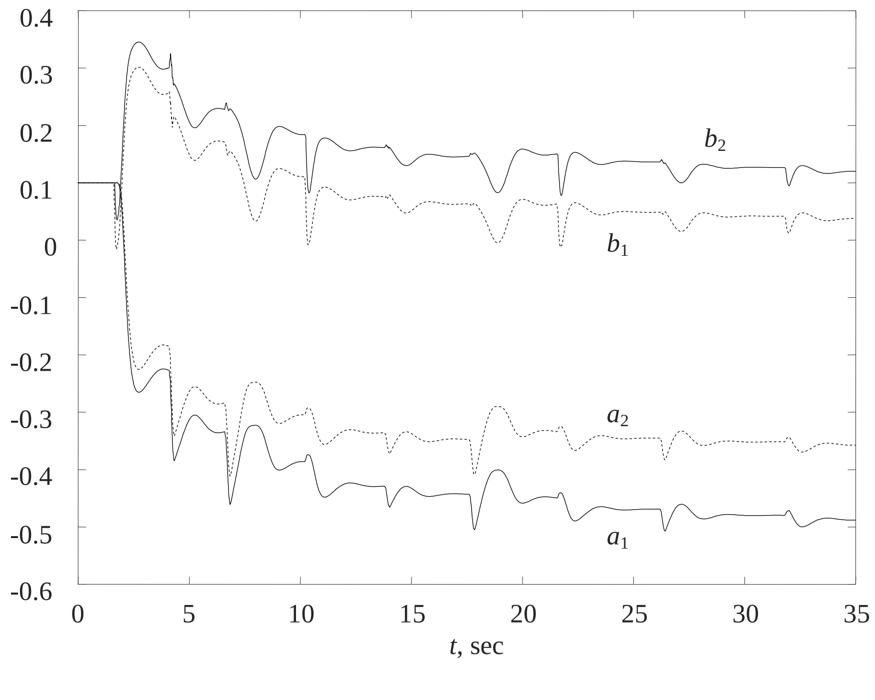

Figure 5. Changing the estimates of coefficients in the identification process.

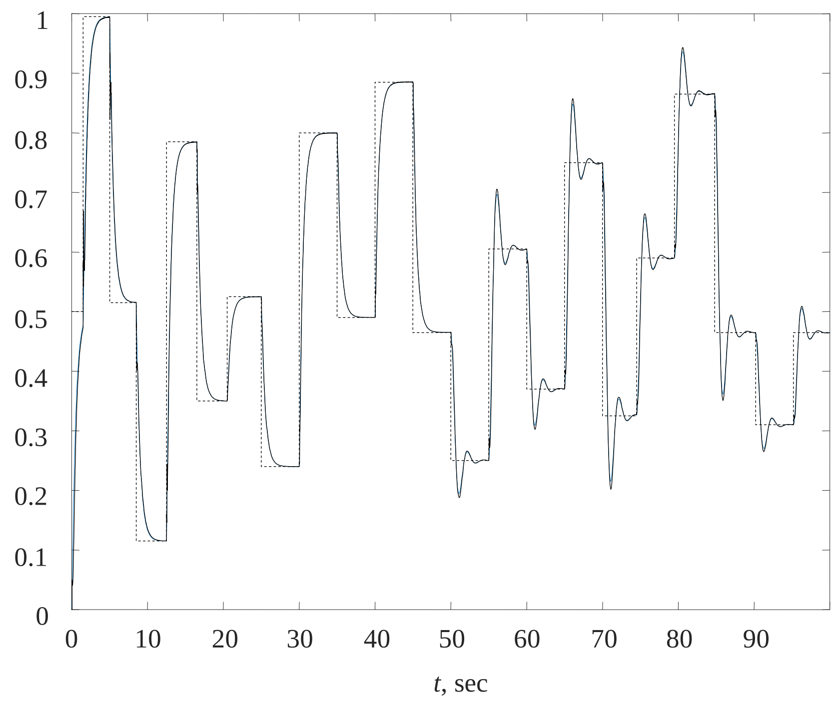

Figure 6. Switching the plant in the process of identification.

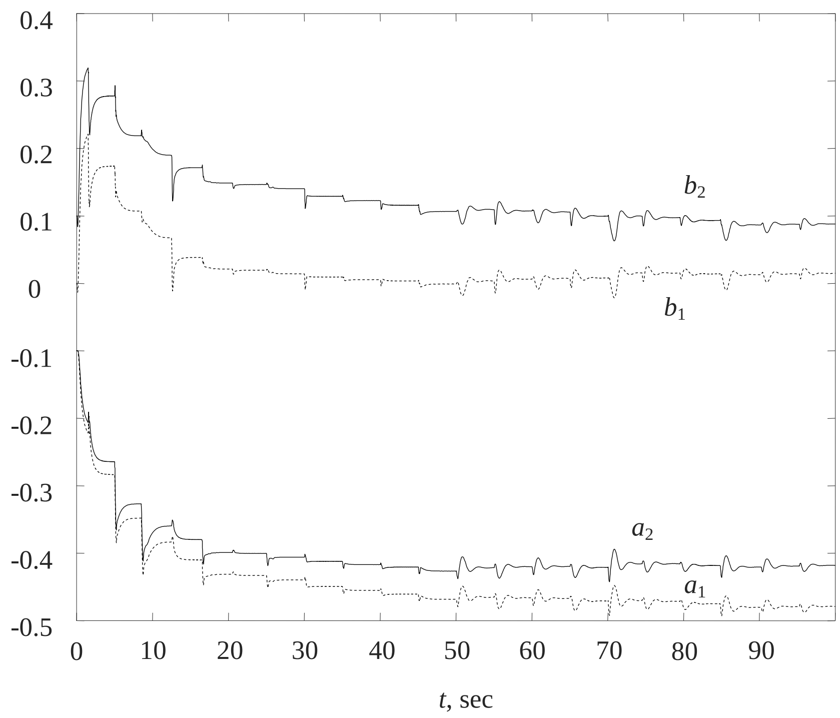

Figure 7. Changing ratings when switching an plant.

5. Adaptive supervisory control

The algorithm of neural network identification can be used to organize the neural network supervisor of the PID controller. The supervisory control method assumes the design of a two-level system in which the PID controller is located at the lower level, and at the upper level - an intelligent unit that controls the parameters of the lower level controller. Suffice it for a long time that the variants of implementing the su-primor with the help of fuzzy logic rules are known [11, 12]. The drawback of this approach is that the rules are heuristic, which does not guarantee the accuracy and stability of the control of the object with variable parameters.

The supervisor can be implemented on the basis of a feedforward NN [13] or radial-basis NN [14, 15]. However, in this case, the NN must be previously trained in off-line mode.

The use of Hopfield NN allows to justify the choice of supervisor parameters by means of the Lyapunov function description, which provides minimization of neural network energy in online mode.

The principle of supervisory control is explained in Figure 8, where the neural network identifier and the neural network supervisor are implemented on the basis of the Hopfield NN.

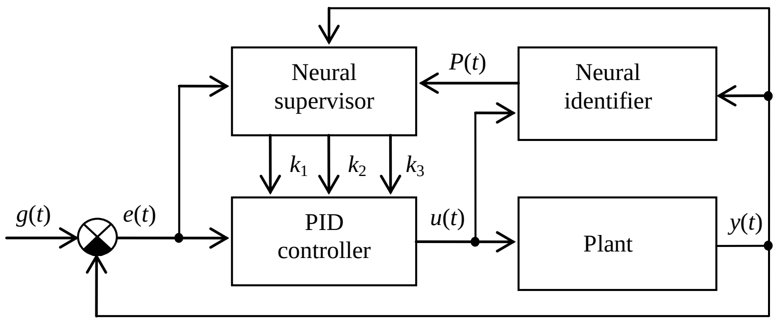

Figure 8. Adaptive control system with supervisor.

The problem of adaptive control assumes the fulfillment of the hypothesis of quasi-stationary - the parameters of the plant must change more slowly than the processes of adaptation take place. The identification step precedes the step of changing the controller parameters.

The neural network identifier continuously evaluates the parameters $P(t)$ of the difference model of the form (10), obtaining the values of the signals from the input and output of the control plant ($u(t)$ and $y(t)$). The purpose of the neural network supervisor is to adjust the PID controller coefficients k_1, k_2 and k_3 so that $y(t) \approx g(t)$. Instead of the driving influence $g(t)$, the signal of the reference model can be used.

The basic equation of the PID controller is as follows:

$$u(t) = k_1 e(t) + k_2 \int_0^t e(t)dt + k_3 \frac{de(t)}{dt} \tag{20}$$

For the numerical solution (20), the following substitutions are made:

$$\frac{de(t)}{dt} = \frac{e_k - e_{k-1}}{\Delta t}, \qquad \int_0^t e(t)dt \approx \Delta t \sum_{i=1}^{N} e_{k-i}$$

where N is the number of times, k is the current time, and Δt is the data update period.

Then (20) can be represented in the form:

$$u_k = k_1 e_k + k_2 \Delta t \sum_{i=1}^{N} e_{k-i} + k_3 \frac{e_k - e_{k-1}}{\Delta t}, \tag{21}$$

Expression (21) can be simplified by considering the control signal at the previous time:

$$u_{k-1} = k_1 e_{k-1} + k_2 \Delta t \sum_{i=1}^{N} e_{k-i-1} + k_3 \frac{e_{k-1} - e_{k-2}}{\Delta t}. \tag{22}$$

Subtracting (22) from (21), we obtain

$$u_k = u_{k-1} + \left(k_1 + \frac{k_2}{\Delta t}\right)e_k + \left(-k_1 - 2\frac{k_2}{\Delta t} + k_3\Delta t\right)e_{k-1} + \frac{k_3}{\Delta t}e_{k-2}.$$

Introducing the notation *x*, *y*, *z* for new coefficients, we obtain in the difference form:

$$u(k) = u(k-1) + xe(k) + ye(k-1) + ze(k-2). \tag{23}$$

Let the control plant be described by a transfer function of the form (14). Then to determine the unknown coefficients *x*, *y*, *z*, we can consider a system of three equations (where $w(t)$ is the output of the reference model):

$$\begin{cases} b_1u(k) + b_2u(k-1) - y(k-1)a_1 - y(k-2)a_2 = w(k), \\ b_1u(k-1) + b_2u(k-2) - y(k-2)a_1 - y(k-3)a_2 = w(k-1), \\ b_1u(k-2) + b_2u(k-3) - y(k-3)a_1 - y(k-4)a_2 = w(k-2). \end{cases}$$

The energy function of the Hopfield NN takes the form:

$$E = \sum_{k=1}^{3}\left(b_1u(k) + b_2u(k-1) - y(k-1)a_1 - y(k-2)a_2 - w(k)\right)^2. \tag{24}$$

We represent (24) in the form:

$$E = s_1^2 + s_2^2 + s_3^2. \tag{25}$$

Then the output of the Hopfield NN neurons describes the system:

$$\begin{cases} \dfrac{dx}{dt} = -\dfrac{\partial E}{\partial x} = -2\left(\dfrac{\partial s_1}{\partial x}s_1 + \dfrac{\partial s_2}{\partial x}s_2 + \dfrac{\partial s_3}{\partial x}s_3\right); \\ \dfrac{dy}{dt} = -\dfrac{\partial E}{\partial y} = -2\left(\dfrac{\partial s_1}{\partial y}s_1 + \dfrac{\partial s_2}{\partial y}s_2 + \dfrac{\partial s_3}{\partial y}s_3\right); \\ \dfrac{dz}{dt} = -\dfrac{\partial E}{\partial z} = -2\left(\dfrac{\partial s_1}{\partial z}s_1 + \dfrac{\partial s_2}{\partial z}s_2 + \dfrac{\partial s_3}{\partial z}s_3\right); \end{cases} \tag{26}$$

6. Simulation of the supervisory system

We will use the model with the coefficients obtained in the example above. To adjust the controller, a reference model is set in the form of a transfer function, which corresponds to a weakly oscillatory transient process:

$$W(s) = \frac{1}{0.2s^2 + 0.5s + 1}.$$

In Figure 11 shows the response of the reference model and the system with the supervisory PID controller to the stepped input signal. The output signals are almost identical.

In Figure 12 shows the change in the PID regulator coefficients during the transient process (for given initial values *x* = *y* = *z* = 0.5).

As the simulation showed, the output of the neural network supervisor responds to a change in the level of the input signal with constant estimates of the plant parameters (Figures 13 and 14).

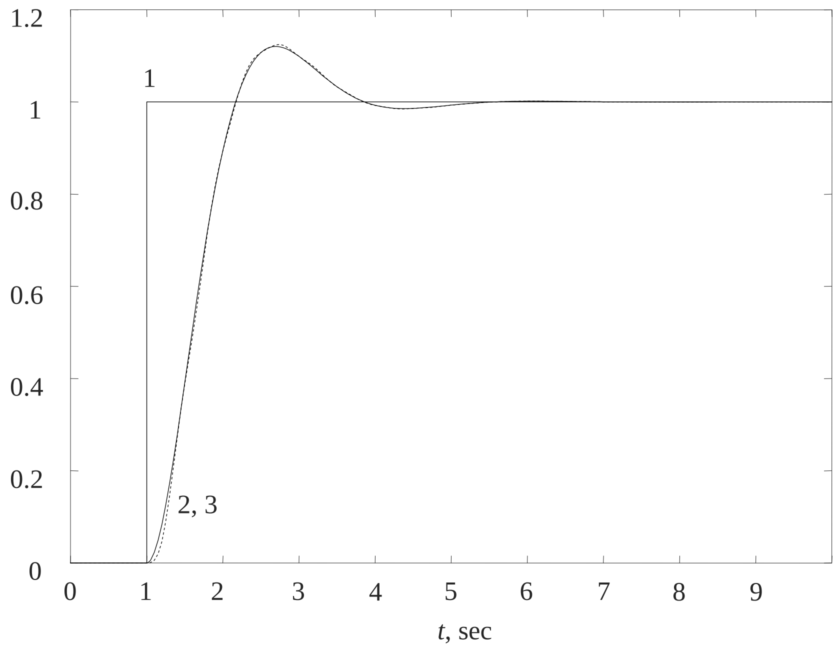

Figure 11. Reaction to step input signal (1): PID system (2), reference model (3, dotted line).

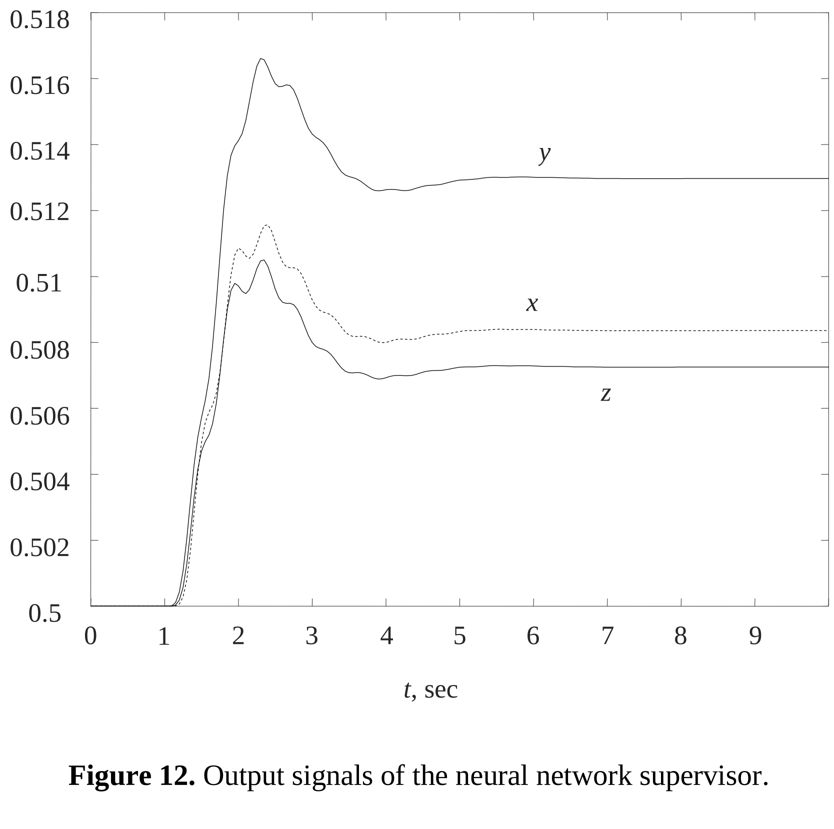

Figure 12. Output signals of the neural network supervisor.

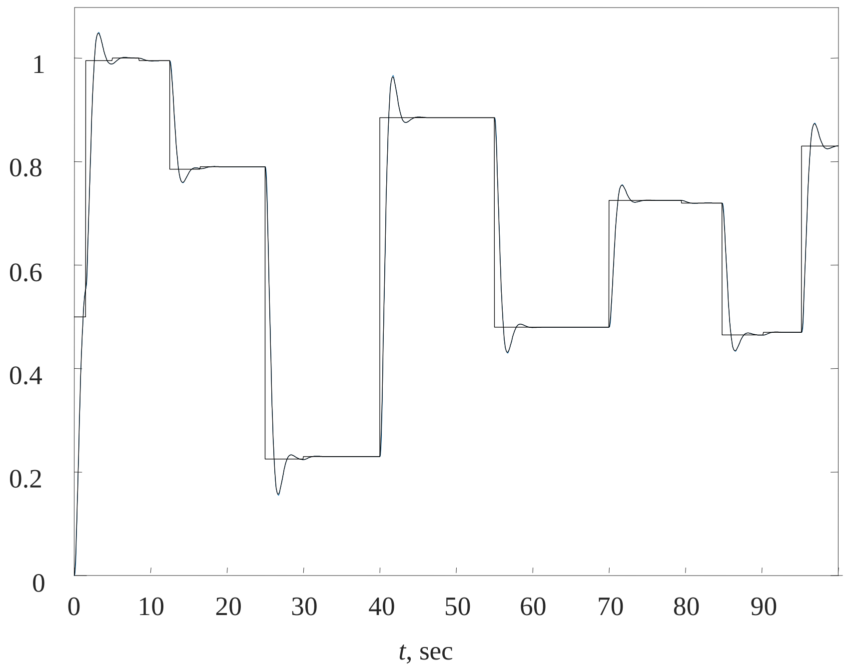

Figure 13. Reaction to stepwise action of variable amplitude.

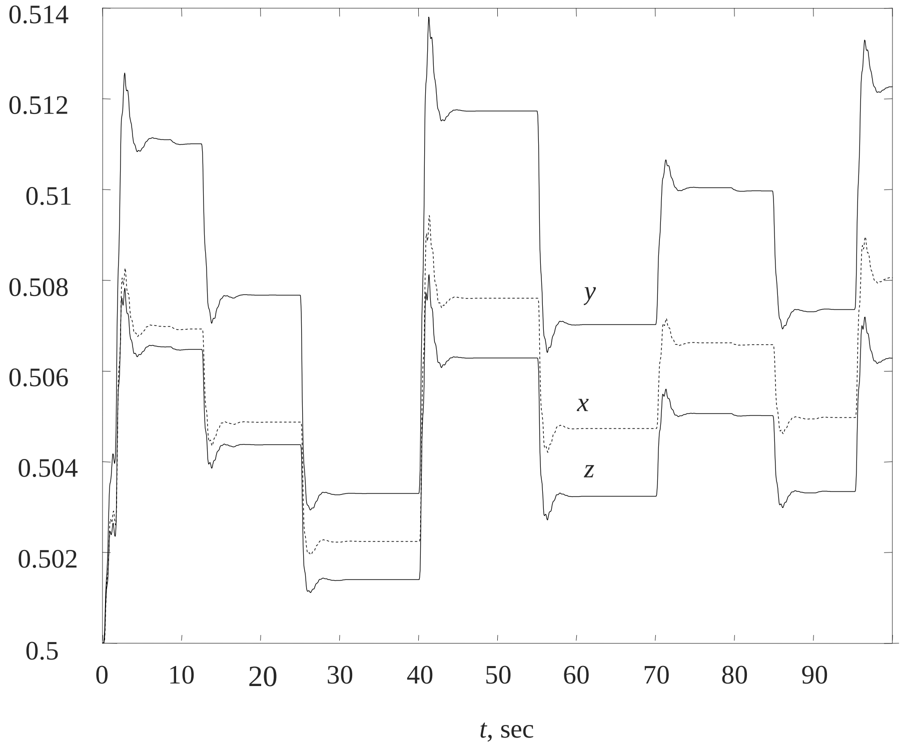

Figure 14. Change in estimations of regulator coefficients.

The oscillations of the coefficients are caused by the fact that the weights and displacements of the Hopfield NN vary dynamically during the transient process. Small oscillations of the regulator coefficients provide practically zero level of steady error (Figure 15).

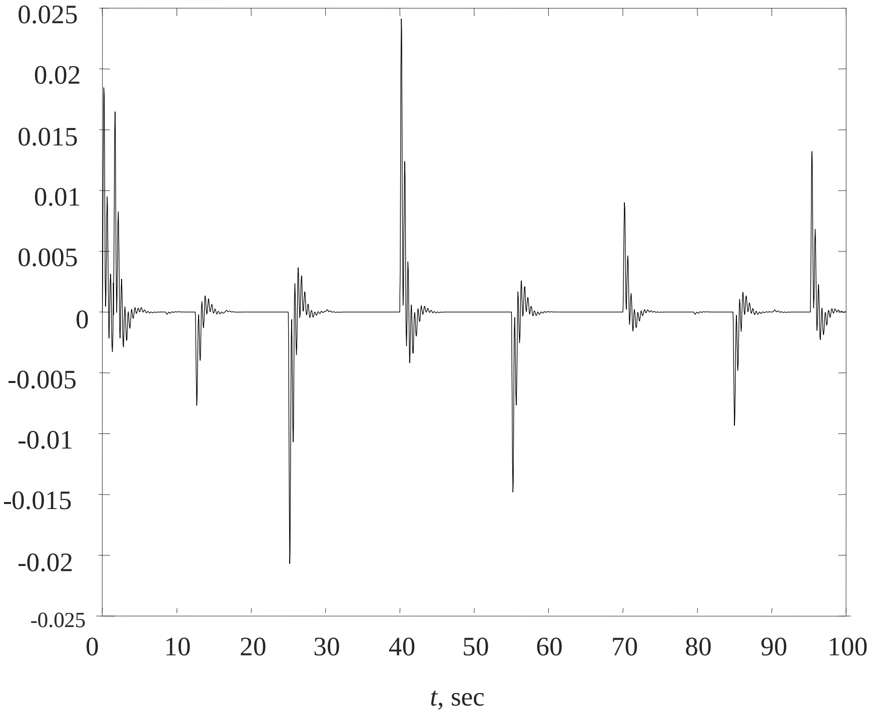

Figure 15. Changing the output error.

Simulation showed that the system with the neural supervisor easily tracks the change in the dynamics of the reference model.

In Figure 16 shows the results of the experiment with a change in the reference model in the form of an oscillatory link to the aperiodic link (at t = 40 sec). Transient processes almost coincide.

In Fig. 17 shows the variation of the regulator coefficients.

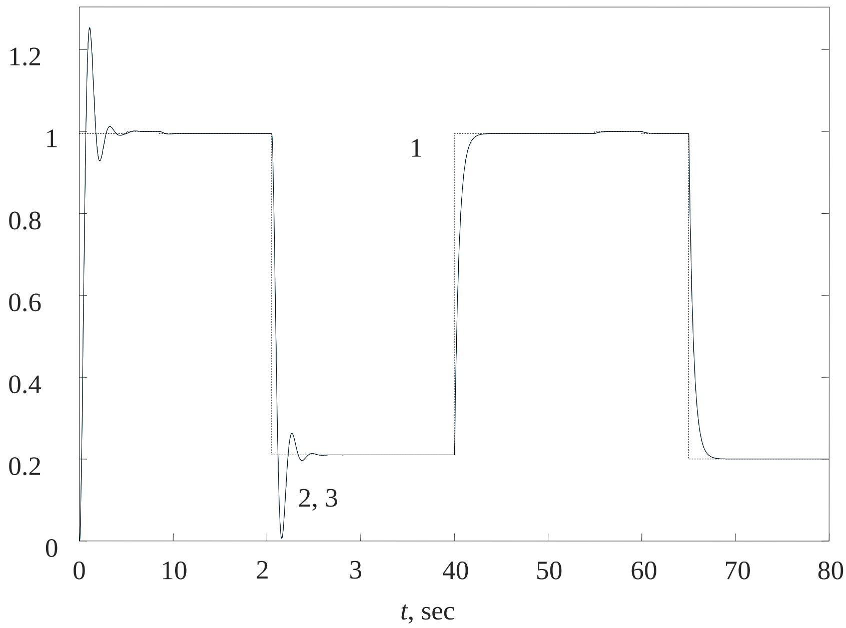

Figure 16. Reaction of the system with the change of the reference model: 1 - setting action, 2, 3 - output of the plant and the etalon model.

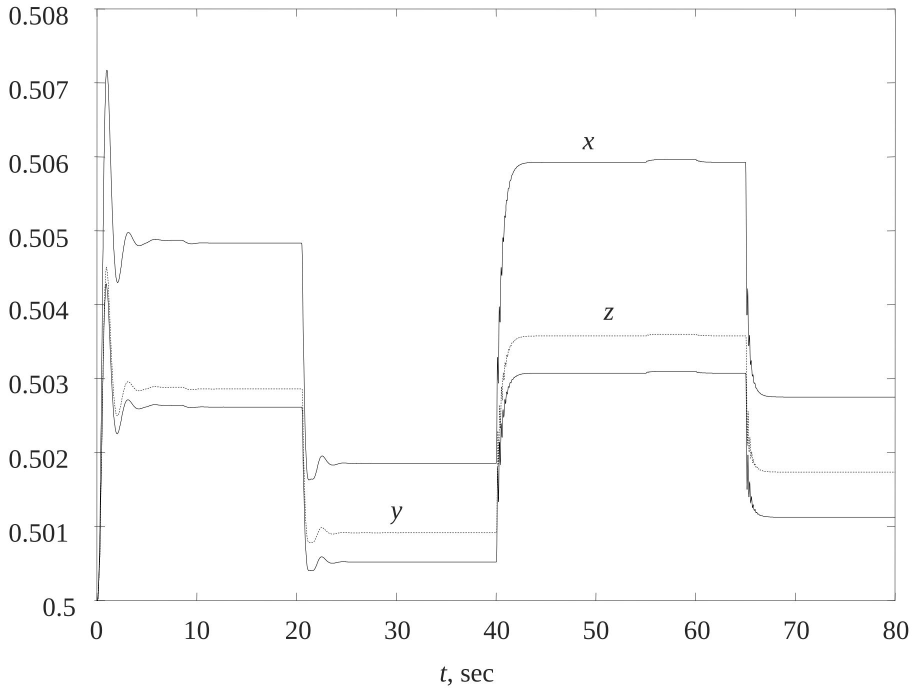

Figure 17. Output signals of the supervisor when changing the reference model.

7. Conclusion

The technique of organization of adaptive supervisory control of a linear plant, considered in the article, is based on the use of the Hopfield NN. The number of neurons of this single-layer NN should correspond to the number of unknown variables in the problem under consideration. The weights and displacements of the Hopfield NN must be chosen in such a way that the outputs of the neurons tend to take constant values minimizing some function of the network energy. For the construction of the energy function, variants of Lyapunov functions that describe the error in the output of the model during identification and the error of the output of the system with respect to the reference model, with adaptive control, are considered.

The advantage of the proposed approach is that the identifier based on the Hopfield NN allows continuous evaluation of the model parameters. The adaptation of the controller can be performed periodically or in a situation where the deviations of the current estimates exceed a predetermined threshold. In addition, the adaptive controller can monitor the variable dynamics of the reference model. The examples of modeling presented in the article show a good quality of solving the problems of identification and control of the regulator coefficients. A neural network supervisor based on Hopfield NN is an alternative to fuzzy supervisors of PID controllers with heuristic tuning rules, as well as classical adaptation schemes [16].

The computational experiments carried out assumed that the identification stage and the adjustment stage of the regulator occur sequentially. The variant of continuous interaction of the NN of identification and adaptation NN requires additional investigation. It also requires a study of the ratio of the amount of real-time calculations required by the described approach and adaptive algorithms based on the recursive least-squares method.

In general, this approach can be useful in the development of adaptive control systems by a wide class of linear dynamic plant with variable parameters.

8. References

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