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NEURO-PID CONTROL FOR NONLINEAR PLANTS WITH VARIABLE PARAMETERS

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ABSTRACT

The synthesis technique of neuro-PID controller as three-channel structure in which each channel has piecewise-and-linear activation function which settings are configured by means of a genetic algorithm is considered in the article. The given examples of modeling show that the offered option of the organization of the controller can be successfully used in control of nonlinear objects with variable parameters for which linear PID-regulators cannot provide acceptable quality of control.

Keywords: neuro-PID controller, genetic algorithm, nonlinear time-varying plant.

1. INTRODUCTION

Nowadays, the most widespread type of industrial regulators is PID-regulators. About 90% of the regulators which are in commercial operation use PID algorithm. Simplicity of design and industrial use, clarity of functioning, ability to solve majority of practical problems and low cost secure so high popularity [1].

However, the existing methods of calculation of parameters of PID-regulators are oriented to linear systems as the regulator is a linear dynamic link here. If the object of control is significantly not linear or has the parameters that change in time, then it is difficult to achieve high quality control.

The simplicity and clarity of structure of PID-regulators stimulates the research connected with enhancement of their design by means of artificial neural networks (ANN) ([2-4] and others). So, in paper [2], it is offered to supplement a PID-regulator with a neural network regulator trained by means of back propagation algorithm. Signals of both regulators develop the way that allows receiving the nonlinear control law. In paper [3], the radial-and-basic neural network that helps change coefficients of the PID-regulator is used. Setup is carried out by means of genetic algorithm (GA). In [4], artificial neural network approximates the PID-regulator; for training, the algorithm of differential evolution is used. In [6], neural supervisor based on neural network of direct distribution manages PID-regulator coefficients.

In paper [5], the option of structure of 3-channel nonlinear regulator which is developed by means of genetic setup of the indistinct regulator of PID-type is considered. The configured settings in such regulator are parameters of transfer function of each channel.

In this paper, the potential of use of neuro-PID regulators to work with the objects having variable parameters are considered. As the working instrument of modeling the Matlab system with the Simulink expansion was used.

2. THE STRUCTURE OF NEURO-PID REGULATOR

The control law performed by PID-regulator follows the formula:

$$u(t) = k_{\mathrm{p}} e(t) + k_{\mathrm{i}} \int_0^t e(\tau) d\tau + k_{\mathrm{d}} \frac{de(t)}{dt}, \qquad (1)$$

where $e(t)$ – error of control, k_{P}, k_{i}, k_{d} – coefficients chosen in the course of design.

Having replaced a derivative and integral with the relations of final differences, it is possible to receive discrete representation of PID-regulator:

$$u(n) = k_p e(n) + k_i \Delta t \sum_{k=0}^{n} e(k) + \frac{k_d}{\Delta t}(e(n) - e(n-1)), \qquad (2)$$

where n – time point, Δt –sampling interval.

As appears from (1) and (2), PID-regulator can be presented in the form of a simple neural network containing only one neuron with three inputs and linear activation function (Figure-1). The law of control represents a hyperplane in 4D space. It is possible to assume that improvement of quality of control happens when replacing hyperplane with some hypersurface which is approximated by means of a neural network.

So, for example, in [2], to realize a nonlinear PID-regulator, the 2-layer artificial neural network of direct distribution containing 8 neurons of the hidden layer with sigmoid activation functions and one neuron of the output layer with linear activation function (Figure-1) is used.

Matrixes of weight coefficients W_1 and W_2 together give 32 adjusted parameters that makes the task of setup of weight coefficients quite difficult.

It is easy to notice that in the structure (Figure-1), each neuron of the hidden layer realizes a separate PID-regulator, and sigmoid activation function generally serves to restrict an output signal. The weights of the output layer make participation of each regulator in development of the general output signal fixed.

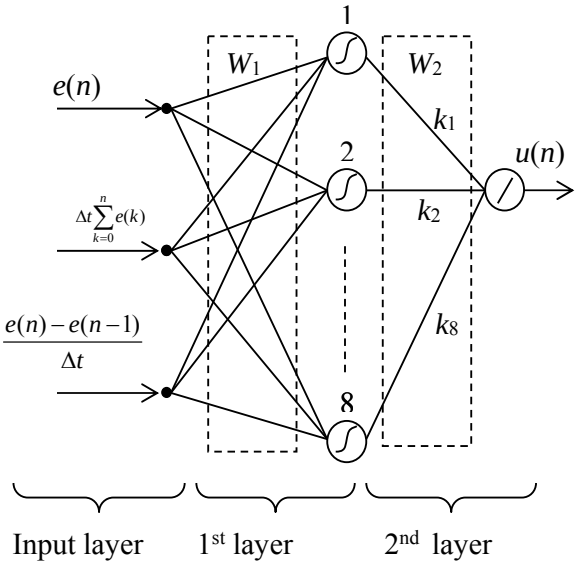

Figure-1. Realization of neuro-PID regulator.

Concerning this option of the description of neuro-PID regulator, it is possible to draw the following critical remarks:

- the meaning of 3-channel structure of the PID-regulator in which the channel of a mistake is responsible generally for increase time, whereas the channel of a derivative – for over-control and the channel of integral – for a static mistake, is lost;
- it is difficult to prove the amount of neurons of the first layer analytically, and for a specific object the configuration of neural network can be required;
- if we assume that all regulators (1st layer) work in the quasi-linear mode, then the 2-layer neural network can be transformed into single-layer by means of recalculation of weight coefficients.

Thus, when designing neuro-PID regulator, it is more profitable to use not a neural network with a big amount of neurons of the hidden layer, but a neural network with three neurons of the hidden layer which activation functions are adjusted in training process. This conclusion is also derived from the neural network description of the indistinct regulator of [5] PID-type.

If we are limited in (2) with two addends for integral, then the law of PID-control becomes the following:

$$u(n) = k_1 e(n) + k_2 (e(n) + e(n-1)) + k_3 (e(n) - e(n-1)), \quad (3)$$

where $k_1 = k_p$, $k_2 = k_i \Delta t$, $k_3 = k_d / \Delta t$.

If (3) is used, we can observe a neural network with two inputs and three neurons of the hidden layer (Figure-2).

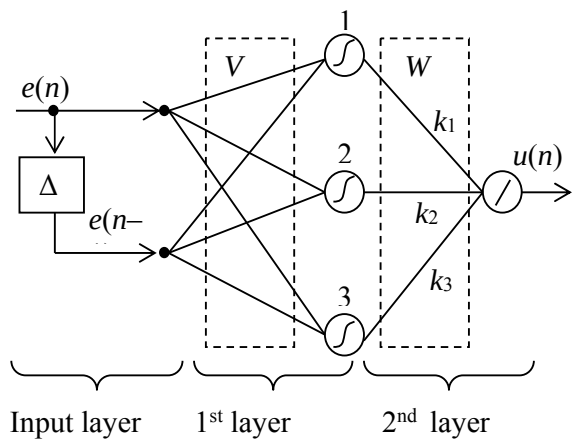

Figure-2. Discreet neuro-PID regulator.

The weight matrix of the output layer contains the regulator coefficients corresponding to channels of error, derivative and integral, and the weight matrix V can be considered set, proceeding from a way of approximation of the integral and derivative:

$$V = \begin{bmatrix} 1 & 1 & 1 \\ 0 & -1 & 1 \end{bmatrix}.$$

Thus, in the structure of the nonlinear PID-regulator (neuro-PID), only parameters of activation functions of neurons of the 1st layer are unknown.

Activation function of neurons can be chosen as piecewise-and-linear and odd-and-symmetric here (Figure-3, where the example for an error channel is shown).

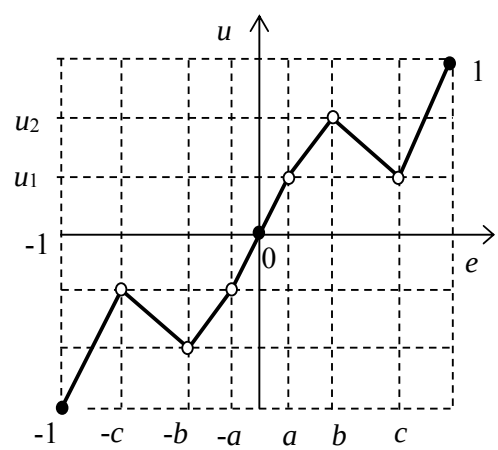

Figure-3. Option of the description of activation function.

The input signal is considered normalized therefore in the course of optimization it is required to choose the provision of three intermediate points: a, b and c.

To train the neuro-PID regulator, the genetic algorithm (GA) can be employed ([6, 7] and others). Parameters of the regulator are coded by P chromosome

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which, according to fig. 2 and 3, will have 12 genes (Figure-4).

P	*a*	*b*	*c*	*a*	*b*	*c*	*a*	*b*	*c*	*k*	*k*	*k*

Figure-4. Description of a chromosome in the course of genetic training.

When a more exact description of activation function is needed, the quantity of intermediate points can be increased. Addition of each new point increases chromosome length by 3 genes.

In Figure-5, the general scheme of genetic training is shown.

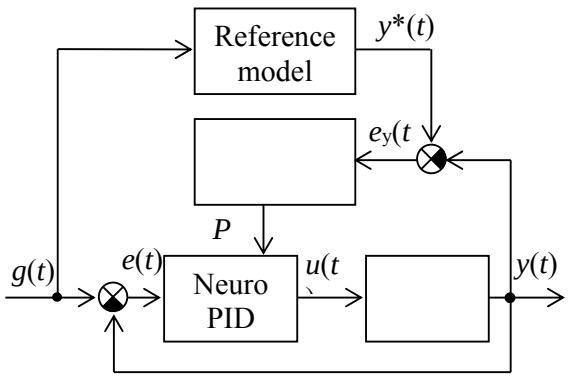

Figure-5. Genetic training of neuro-PID regulator.

In the course of the training, each option of parameters of the regulator will correspond to a certain transition process *y(t),* and the criterion function can be as in the following:

$$F(P)=\sum_{i=1}^{N}\left|e_y(t)\right| \quad \text{or} \quad F(P)=\sum_{i=1}^{N}e_y^2(t), \tag{4}$$

where N – number of considered time points during the transition process.

3. MODELING EXAMPLE

The considered approach to neuro-PID regulator design was used in the synthesis of control systems over non-linear objects with variable parameters. Also, the comparison with linear PID-regulator which settings were configured by means of GA was carried out. Let us review two examples of modeling.

Example 1. The non-linear system with variable parameters is described by the difference equation:

$$y(k)=\frac{a_0(k)y(k-1)+u(k-1)}{1+y^2(k-1)},$$

$$a_0(k)=1+0.5\sin\left(\frac{k\pi}{8}\right).$$

Figure-6 shows the result of modeling of the dynamics of a system in Matlab Simulink when rectangular impulses are introduced at input.

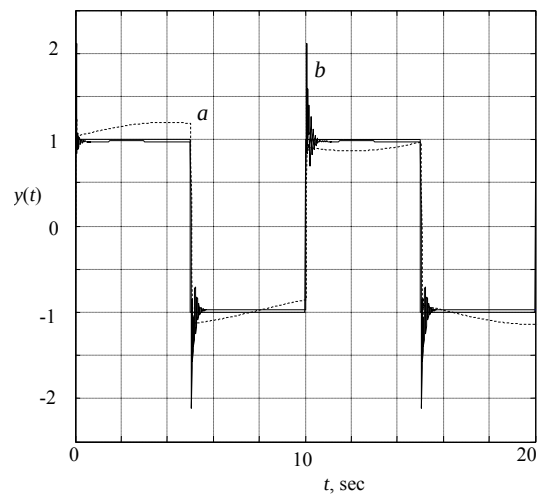

Figure-6. Transition processes in the system: *a* – open-looped system, *b* – system with linear PID-regulator.

After genetic training, the following structure of neuro-PID regulator (Figure-7) was received.

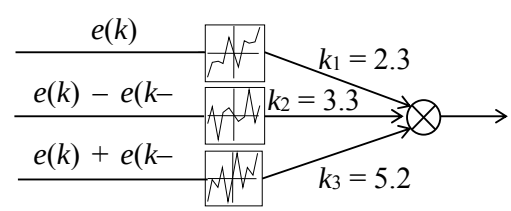

Figure-7. Neuro-PID regulator after training.

Figure-8 shows the result of work of neuro-PID regulator.

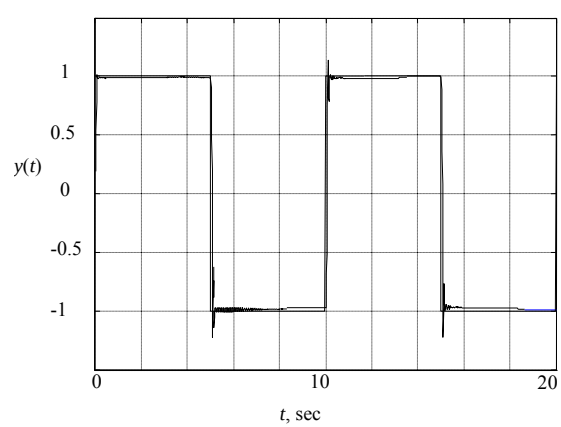

Figure-8. Transition processes in the system with a neuro-PID regulator.

The comparison of Figures 6 and 8 shows that the use of neuro-PID regulator allows considerable reducing of re-regulation and time of the transition process.

Example 2. Let us consider a problem of control over a nonlinear object - an oscillatory link with attenuation that depends on the size of the output signal:

$$T^2\ddot{y} + 2T\xi(y)\dot{y} + y = ku,$$
$$\xi(y) = (|y| - 0{,}5)^2.$$

Figure-9 shows the response of the system to a step-like input signal with random amplitude.

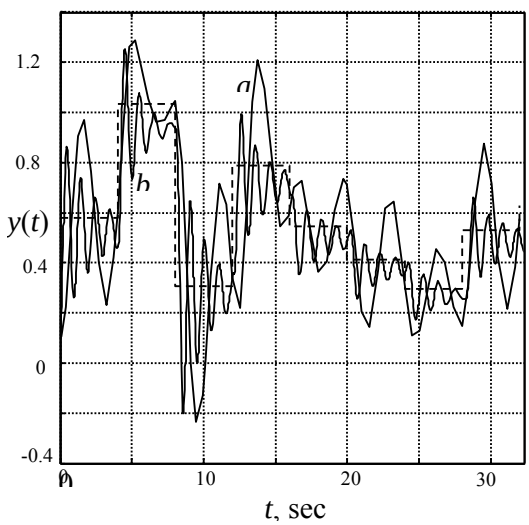

Figure-9. Transition processes in system: *a* – open-looped system, *b* - system with linear PID-regulator.

As Figure-9 shows, the linear PID-regulator is not capable of providing the acceptable quality of control.

The synthesized neuro-PID regulator is shown in Figure-10.

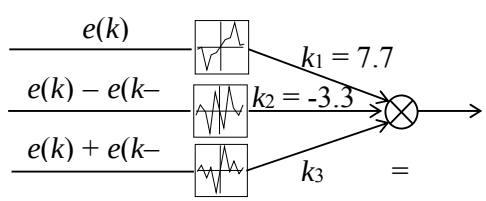

Figure-10. Structure of neuro-PID regulator.

Figure-11 shows high quality of performance of neuro-PID regulator.

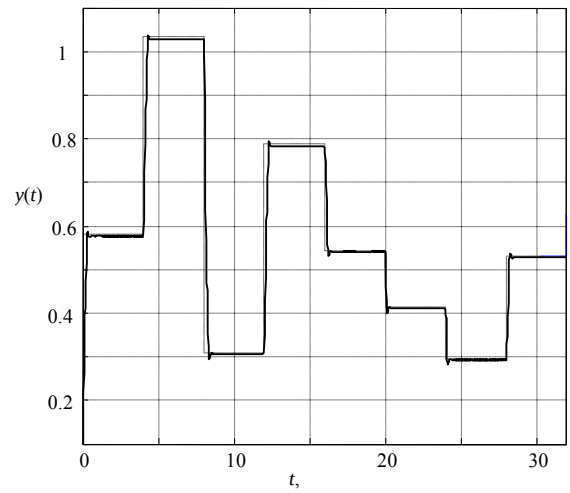

Figure-11. Transition processes in the system with neuro-PID regulator.

4. CONCLUSIONS

The considered here approach to designing of neuro-PID regulators by means of the genetic algorithm is notable for its simplicity and allows to control computing costs when parameters of the regulator are synthesized. The 3-channel structure of the regulator keeps the basic principle of PID-regulation; however, the control law becomes non-linear, and that allows increasing the quality of control.

As the given in the article results of computing experiments show, the neuro-PID regulator considerably exceeds the linear PID-regulator when control over objects with variable parameters is carried out.

Thus, the suggested option of design of non-linear regulators allows extending principles of PID-regulation to rather wide class of non-linear objects of control.

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