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Neural network control of a nonlinear dynamic plant with a predictive model

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ABSTRACT

The paper considered the possibilities of applications of neural network technologies to control a dynamic plant with nonlinear properties. To give the control system the desired dynamic property, the use of a neural network predictive controller is proposed. The model of the control plant is in the form of a multilayer forward-directional neural network, which allows us to construct a controller using generalized equation methods with prediction. A neural network control algorithm with prediction based on minimizing the quadratic quality functional is proposed. The algorithm makes it possible to minimize the root mean square error of regulation and the control signal rate of change. To determine the sequences of optimal control impacts, the application of the Newton-Raphson method is proposed. To reduce computational costs when receiving control signals, the decomposition of the original matrix, represented as a Hess matrix, is carried out. To predict the behavior of a control plant, a formula is proposed for calculating the gradient of a neural network, discrepant by the possibility of its use in the real-time mode of the control. The proposed algorithm of the neural network control with predictive allows higher quality control of complex nonlinear dynamic plants in the real-time mode.

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1. INTRODUCTION

The majority of actually operating dynamic plants are characterized by functioning in conditions of uncertainty, which are characterized by complexly and badly studied connections between process variables, the presence of disturbing and random interference, as well as nonlinear elements, which significantly complicates the use of linear adaptive control algorithms for solving assigned problems [1]–[3]. Traditional adaptive control methods usually require that the order of the system is known and does not change during its operation [4]–[6]. The currently applied systems for adaptive stabilization of parameters of dynamic plants do not provide the control process, the range of regulation of variables, as well as the smoothness of changes in controlled values, which significantly reduces the quality indicators of the control system built based on classical adaptive control methods. These algorithms are not effective enough due to the nonlinearity of the plant and also have a probabilistic nature due to the presence of external and internal factors. In this regard, the paper proposes an algorithm for the self-organization (adaptation) of neuro-fuzzy networks, which allows you to configure not only the parameters but also the structure of the network in the process of process control during the operation of the plant [1]. Modern research and development are aimed at obtaining high-quality control through the use of modern “intelligent” technologies [7]–[10].

The most suitable in such cases is the application of neural network methods with an approximating nonlinear function. In neural control systems, the analytical control law and model of the plant are represented in the form of a neural network [1]–[3]. The approximating properties of neural networks of nonlinear functions allow both structured and unstructured methods for controlling complex nonlinear dynamic plants. A distinctive feature of this approach is the simplicity of the neurocontroller included in the control loop. However, this method has a significant disadvantage associated with the choice of architecture of initial parameters and neural networks. Currently, there are many methods based on the use of inverse neurocontrol and regulation with associative memory models [11]–[15]. Among them, the most effective is proactive control, based on a predictive model of the control plant [1]. The paper issue has been considered of synthesizing a predictive neural network control system designed to give the control system the desired dynamic characteristics.

The order of presentation of the material is given section 2 explains the method for solving the problem and reveals the essence of the proposed algorithm. Section 3 contains simulation results that were used to test the proposed neural network control of a nonlinear dynamic plant with a predictive model. Section 4 concludes with a conclusion and recommendations for further use and development of the proposed approach.

2. METHOD

One of the promising areas for improving the quality of control of nonlinear dynamic plants is the application of intelligent technology methods for designing controllers. The most suitable mathematical apparatus in such cases is the application of neural network methods, which have the opportunity to approximate a nonlinear function. In neural control systems, the law of analytical control and the model of a dynamic plant are represented in the form of a neural network [1]–[3]. Through the approximating properties of a neural network of nonlinear functions, they allow the use of both structured and unstructured methods for controlling complex nonlinear dynamic plants under conditions of parametric uncertainty.

To overcome the above difficulties, the work proposes an algorithm for the synthesis of a neural network control system with a predictive property, based on the use of a predictive model of the control plant, based on the combined use of a multilayer neural network with the Newton-Raphson optimization method [3], which allows considering the limitations of the variable states of the control plant in the mode real-time operation. A distinctive feature of the algorithm is the possibility of application in the control of non-stationary plants and plants with variable delay. It should be noted that generalized control with the prediction of dynamic plants has the properties of robustness in concerning the uncertainty of the values of the plant’s parameters and the interference that arises when obtaining information about the state of the plant [16]–[20]. The structural scheme of a neural control system with predictive properties is presented in Figure 1, which consists of four blocks: plant of control, reference model, neural network models of the plant and algorithm of optimization. The optimization algorithm includes an algorithm that minimizes the quality of functional and neural network block. The principle of operation of the proposed neural network system for controlling a dynamic plant is as follows: the driving signal $f(n)$ is fed to the reference model, which represents the desired behaviour of the control plant. Further, the reference model generates a signal $y_m(n)$, which is fed to the optimization algorithm block. To calculate the values of the optimal control signal, the input signal is filed through a switch to the input of the control plant, where, based on the predicted value of the plant's output signal $y_n(n)$ determines the optimized control signal for the subsequent tact $u(n+1)$.

Calculation of optimal control signals generated by a neurocontroller with predictive properties consists of the following steps:

- A signal is generated according to the setting trajectory in the reference process model.
- Predicting the behavior of the control plant based on the current value of the control signal and the neural network model of the plant at each control tact.
- Checking the execution of quality criteria, that is ensuring execution minimum quality of the plant behavior is met at the found values of the control signal.
- The found optimal control signal is transmitted to the control plant.
- These procedures are repeated for each control tact.

The effectiveness of this algorithm depends mainly on the computational costs (calculation accuracy, convergence and performance) for solving optimization problems. Analysis of optimization methods showed [21]–[23] that the most effective method, when the time constants of the plant are large, is the Newton-Raphson method [3], which allows high convergence of the required large computational costs. In addition, the effectiveness of a predictive control algorithm is significantly influenced by the presence of an adequate model of the plant [24]. To solve this problem, the work suggested the application of a neural network to describe the dynamics of a plant, thanks to which it is possible to solve problems with nonlinear dynamics of the plant. In this case, the neural network has a three-layer architecture. The number of neurons in a neural network depends on the input and output variables. With this approach, the quadratic quality functional is represented in the following form [25]:

$$F = \sum_{i=N_1}^{N_2} [y_m(n+i) - y_n(n+i)]^2 + \sum_{i=1}^{N_u} \lambda(i)[\Delta u(n+i)]^2 \longrightarrow min, \tag{1}$$

where $N_{1,}N_2$ are prediction boundary, N_u is control range, y_m is desired behavior of the plant, y_n is predicted output of the neural network, λ is punitive function, and $\Delta u(n+i)$ is variable value of control.

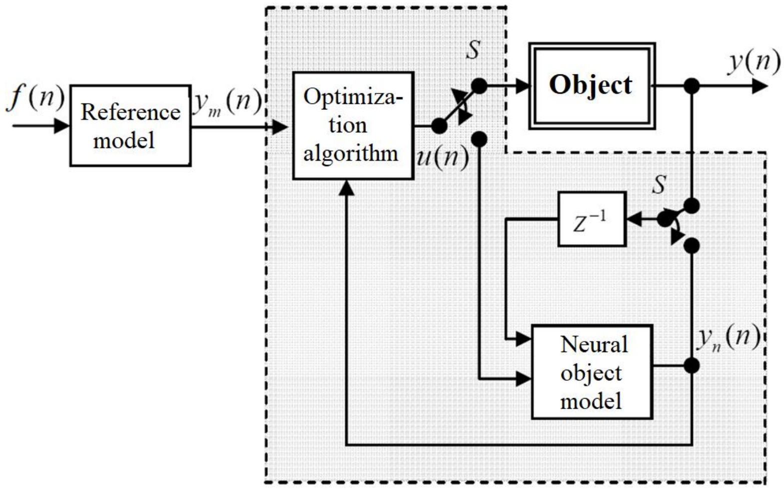


Figure 1. Scheme of a generalized neural network control system with a predictive model

The quality functional contains four desired adjustable parameters of the neural network controller of the control system – $N_{1,}N_2, N_u, \lambda$. Parameters N_1 and N_2, indicate the limits of change in signal error N_u, which is the range of change of the control signal. The main constraint on the values of N_u and N_1 is that they must be less than or equal to the value of N_2 [1]. The penalty λ is introduced to ensure a balance between the first and second terms.

At the each tact, the values of the control signal are determined by the formula [26], [27].

$$U(k+1) = U(k) - \left(\frac{\partial^2 F}{\partial U^2}(k)\right)^{-1} \frac{\partial F}{\partial U}(k), \tag{2}$$

where:

$$\frac{\partial F}{\partial U}(k) = \begin{bmatrix} \frac{\partial F}{\partial u(n+1)} \\ \vdots \\ \frac{\partial F}{\partial u(n+N_u)} \end{bmatrix}, \tag{2a}$$

$$\frac{\partial^2 F}{\partial U^2}(k) = \begin{bmatrix} \frac{\partial^2 F}{\partial u(n+1)^2} & \cdots & \frac{\partial^2 F}{\partial u(n+1)\partial u(n+N_u)} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 F}{\partial u(n+N_u)\partial u(n+1)} & \cdots & \frac{\partial^2 F}{\partial u(n+N_u)} \end{bmatrix}. \tag{2b}$$

To determine the vector $U(k+1)$, we write (2) in the form of a system of linear equations:

$$\frac{\partial^2 F}{\partial U^2}(k)\big(U(k+1)-U(k)\big) = -\frac{\partial F}{\partial U}(k), \tag{3}$$

where $\frac{\partial^2 F}{\partial U^2}(k) = A; -\frac{\partial F}{\partial U}(k) = b; \big(U(k+1)-U(k)\big) = x.$

The solution to (3) is the vector x, in which $U(k+1)$ is obtained from the relation $U(k+1) = U(k) + x$. The calculations continue until the value of each component $U(k+1)$ becomes less than the specified accuracy. To solution of a system of equations, it is necessary to calculate the values of each element (2a) and (2b). The element (2a) with index h is defined as follows:

$$\frac{\partial F}{\partial u(n+h)} = -2\sum_{i=N_1}^{N_2}[y_m(n+i) - y_n(n+i)]\frac{\partial y_n(n+i)}{\partial u(n+h)} + 2\sum_{i=1}^{N_u}\lambda(i)[\Delta u(n+i)]\frac{\partial \Delta u(n+i)}{\partial u(n+h)},$$
$$h = 1, \dots, N_u$$

The element with indexes m, h (2b) is defined as follows:

$$\frac{\partial^2 F}{\partial u(n+m)\partial u(n+h)} =$$
$$= 2\sum_{i=N_1}^{N_2}\left\{\frac{\partial y_n(n+i)}{\partial u(n+m)}\frac{\partial y_n(n+i)}{\partial u(n+h)} + \frac{\partial^2 y_n(n+i)}{\partial u(n+m)\partial u(n+h)}[y_m(n+i) - y_n(n+i)]\right\} +$$
$$+2\sum_{i=1}^{N_u}\lambda(i)\left\{\frac{\partial \Delta u(n+i)}{\partial u(n+m)}\frac{\partial \Delta u(n+i)}{\partial u(n+h)} + \Delta u(n+i)\frac{\partial^2 \Delta u(n+i)}{\partial u(n+m)\partial u(n+h)}\right\},$$
$$\mathrm{h} = 1, \dots, \mathrm{N_u},\ m = 1, \dots, N_u.$$

To calculate the output of the control plant $y_n(n+j)$ and its derivatives, the work proposes the use of a neural network [1]–[3]. To predict the behavior of a plant, the output value of the plant model from the current point in time is used, calculated by (4) and (5):

$$y_n(n+k) = \textstyle\sum_{i=1}^{S^{L-1}}\{w_i f_i\big(net_i(n+k)\big)\} + b, \tag{4}$$

$$n_i(n+k) = \sum_{i=0}^{n_d} w_{i,j+1}\begin{cases} u(n+k-j), k-N_u < i \\ u(n+N_u), k-N_u \geq i\end{cases} + \sum_{j=1}^{min(k,d_d)}\Big(w_{i,n_d+j+1}y_n(n+k-j)\Big) +$$
$$+\textstyle\sum_{j=k+1}^{d_d} w_{i,n_d+j+1}y_n(n+k-j) + b_i. \tag{5}$$

To minimize the quality functional of the control system in mode real-time, we perform the differentiation operation $y_n(n+k)$ from (5) by $u(n+h)$ [1].

$$\frac{\partial y_n(n+k)}{\partial u(n+h)} = \textstyle\sum_{i=1}^{S^{L-1}} w_i \frac{\partial f_i(net_i(n+k))}{\partial u(n+h)}. \tag{6}$$

To differentiate a complex function $\frac{\partial f_i(net_i(n+k))}{\partial u(n+h)}$ applies to split the equation into two parts:

$$\frac{\partial f_i(net_i(n+k))}{\partial u(n+h)} = \frac{\partial f_i(net_i(n+k))}{\partial net_i(n+k)}\frac{\partial net_i(n+k)}{\partial u(n+h)}. \frac{\partial f_i\big(net_i(n+k)\big)}{\partial u(n+h)} = \frac{\partial f_i\big(net_i(n+k)\big)}{\partial net_i(n+k)}\frac{\partial net_i(n+k)}{\partial u(n+h)}. \tag{7}$$

In this case, the derivative of the output function is determined by (8):

$$\frac{\partial net_i(n+k)}{\partial u(n+h)} = \sum_{j=0}^{n_d} w_{i,j+1}\begin{cases}\delta(k-j,h), k-N_u < i \\ \delta(N_u,h), k-N_u \geq i\end{cases} +$$
$$+\textstyle\sum_{j=1}^{min(k,d_d)}\left(w_{i,n_d+j+1}\frac{y_n(n+k-j)}{\partial u(n+h)}\delta_1(k-j-1)\right) \tag{8}$$

To obtain the values of the elements of the matrix (2b), we are differentiating the (6), (7) and (8) by the required controls $u(n+m)$ and obtain:

$$\frac{\partial^2 y_n(n+k)}{\partial u(n+h)\partial u(n+m)} = \sum_{i=1}^{S^{L-1}} w_i \frac{\partial^2 f_i(net_i(n+k))}{\partial u(n+h)\partial u(n+m)}, \tag{9}$$

$$\frac{\partial^2 f_i(net_i(n+k))}{\partial u(n+h)\partial u(n+m)} = \frac{\partial f_i(net_i(n+k))}{\partial net_i(n+k)} \frac{\partial^2 f_i(net_i(n+k))}{\partial u(n+h)\partial u(n+m)} + \frac{\partial^2 f_i(net_i(n+k))}{\partial net_i(n+k)^2} \frac{\partial net_i(n+k)}{\partial u(n+h)} \frac{\partial net_i(n+k)}{\partial u(n+m)},$$

$$\frac{\partial^2 net_i(n+k)}{\partial u(n+h)\partial u(n+m)} = \sum_{i=1}^{min(k,d_d)} w_{i,n_d+j+1} \frac{\partial^2 y_n(n+k-j)}{\partial u(n+h)\partial u(n+m)} \delta_1(k-j-1). \tag{10}$$

For obtain the last equation, is differentiated two times (2b). The proposed neural network control algorithm with predictive properties, based on optimization solutions to problems using the Newton-Raphson method for minimizing the quality functional, makes it possible to obtain high-quality control of complex nonlinear dynamic control plants and allows the possibility control systems to apply this algorithm in mode real-time.

3. RESULTS AND DISCUSSION

As an example, consider a neural network control system. In this case, the nonlinearity of a nonlinear dynamic plant is compensated for through the use of a neural network. The neural network system for controlling the dynamic plants includes a block of a neural network controller, a block for signal generation unit with randomly varying amplitude, a block of graph plotting and a block of control plant, as shown in Figure 2. The model of the control plant is presented in Figure 3.

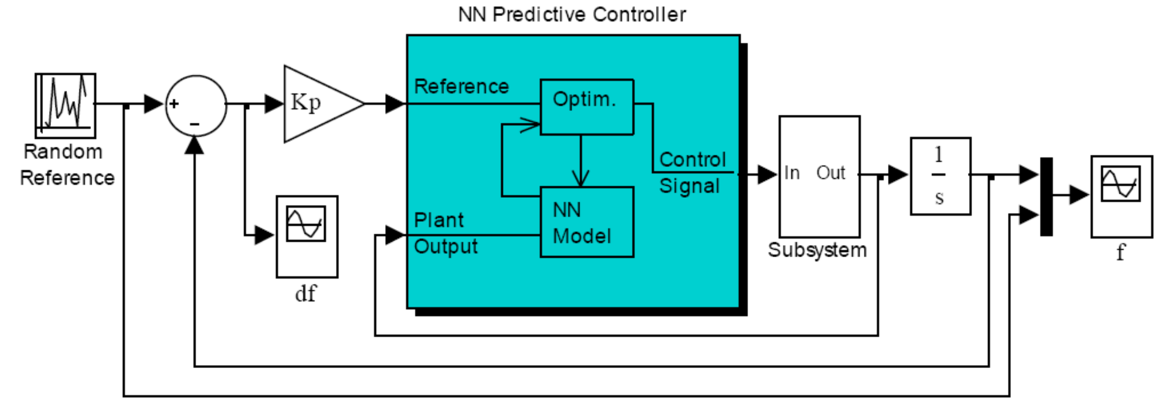


Figure 2. Predictive neural network system of control dynamic plant

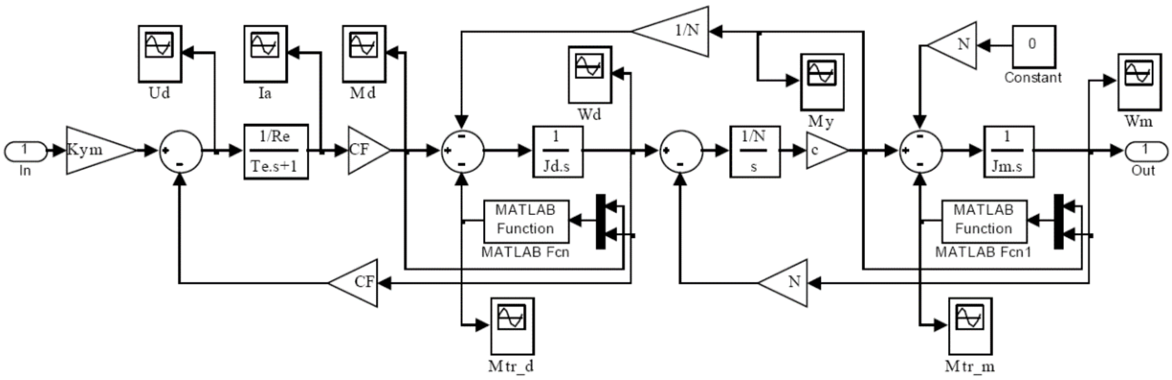
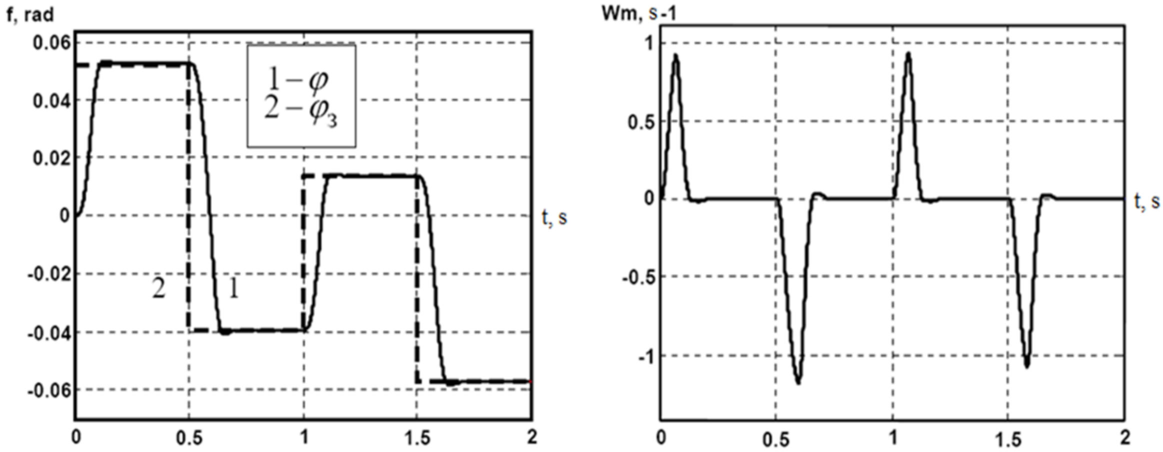


Figure 3. Model of control plant

To solve the problem of synthesizing a neuro controller with predictive properties, it is first necessary to construct a neural network model of the control plant applying the results of modelling the dynamics of the plant. As well as the model of the plant is used to configure the parameters of a neural network controller with predictive control properties, it is first necessary to determine the structure and parameters of the neural network, and then the procedure of her training is performed. To solve this problem, a training sequence of signals is generated, formed in the form of a series of random step signals supplied to the input of the controlled plant, as shown in Figure 4(a).

In the Subsystem block, the behavior of the control plant predicting is carried out and then the optimization of problems is solved. The results of modelling a neural network synthesized control system are shown in Figure 4(b). It is clear from the graphs that transient processes have high dynamic characteristics. In this case, the parameters were set within the limits of +1 and -1.



(a) (b)

Figure 4. Graphs of transient processes of the neural network control system: (a) training sequence of signals in the form of random step signals input and (b) results of the modelling

4. CONCLUSION

To ensure high dynamic characteristics of a control system for a nonlinear dynamic plant, it is proposed to use a neural network controller with predictive properties. For this, neural network control with prediction has been proposed. The effectiveness of implementing neural network control with prediction using a perceptron such as a nonlinear model of the control plant is shown.

To synthesize a neurocontroller with predictive properties, it is proposed to use a method for solving optimization problems with the combined use method of the Newton-Raphson with automatic step selection. The results of simulation modelling of the system are presented. Analysis of transient processes revealed that the synthesized neurocontroller with predictive properties provides high dynamic characteristics of the controlled system.

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