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CONTROL SYSTEM SYNTHESIS WITH SELF-ADAPTING REGULATOR BY INTERACTIVE ADAPTATION METHOD

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Abstract: *The research results on the creation of a self-adapting control system for a nonlinear dynamic object based on the theory of intelligent control using interactive adaptation methods have been presented. The lack of an accurate description and the nonlinearity of the dynamic properties of the object under study, the presence of mutual influence of cross communication channels in the control circuits, as well as the influence of various types of uncertainties associated with the lack of a priori information about the process, significantly complicate the solution of the problem of synthesis of highly efficient control systems for dynamic objects, which necessitates the hybrid application of neural network methods and fuzzy technology involving methods of traditional automatic control theory. In order to solve these problems, it is proposed to use self-adapting neural network regulators capable of selecting the structure and adjusting the parameters of the regulators taking into account changes in both the properties of the object under study and external disturbing influences. The architecture of the proposed neural network has been presented in the form of a multilayer neural network. Training and correction of the parameters of the weight connections of the neural network have been implemented by the method of interactive adaptation, carried out implicitly. Self-adaptation of neuroregulator parameters was provided taking into account the rate of change of technological parameters of the control object. An adaptive fuzzy algorithm for the synthesis of self-adaptation of a control system for technological objects based on a dynamic model with robust properties has been developed.*

Keywords: *adaptation, dynamic object, learning, neural-network, neural-network regulation, neurocontroller, weight coefficient.*

Аннотация: *Интерфаол адаптация усулидан фойдаланган ҳолда интеллектуал бошқариш назарияси усуллари асосида ночизиқли динамик объектларни бошқариш тизимини яратиш бўйича тадқиқот натижалари келтирилган. Тадқиқ этилаётган объектнинг динамик хоссаларини ифодаланишини аниқмаслиги ва ночизиқлиги, алоқа каналларининг ўзаро кесишишининг мавжудлиги, ҳамда жараён тўғрисидаги априор маълумотларнинг ноаниқлиги билан боғлиқ бўлган турли омиллар динамик объектларни юқори сифатли бошқариш тизимларини синтезлаш масаласини ечишни мураккаблаштиради. Бу масалани ечиш учун анъанавий автоматик бошқариш назарияси ҳамда нейрон тармоқ ва норавшан технологиялар усулларини биргаликда қўллаш таклиф этилган. Ушбу масалани ечиш учун тадқиқот объекти хоссалари ва ташқи халақит таъсирларини ўзгаришини ҳисобга олиш асосида ростлагичлар структурасини танлаш ва параметрларини созлашни амалга ошириш имконини берувчи ўзи мослашувчан нейрон тармоқли ростлагичларни қўллаш таклиф этилган. Нейрон тармоғининг архитектураси кўп қатламли нейрон тармоғи шаклида ифодаланган. Бунда нейрон тармоғининг вазн коэффициентларини ўқитиш ва параметрларига тузатишлар киритиш учун интерфаол адаптациялаш усули қўлланилган. Нейроростлагич параметрларини ўзи мослашиши бошқариш объекти технологик параметрларини ўзгариш тезлигини ҳисобга олиш орқали таъминланган. Робаст хоссали динамик моделлар асосида технологик объектларни ўзи мослашувчан бошқариш тизимини адаптив ноқатъий синтезлаш алгоритми ишлаб чиқилган.*

Таянч сўзлар: *адаптация, динамик объект, ўқитиш, нейрон тармоқли ростлаш, нейроконтроллер, вазн коэффициенти.*

Аннотация: *Приведены результаты исследований по созданию самоадаптирующейся системы управления нелинейным динамическим объектом на основе теории интеллектуального управления с использованием методов интерактивной адаптации. Отсутствие точного описания и нелинейность динамических свойств исследуемого объекта, наличие взаимовлияния перекрестных каналов связи в контурах регулирования, а также влияние различных типов неопределенностей, связанных с отсутствием априорной информации о процессе, существенно усложняют решение задачи синтеза высокоэффективных систем управления динамическими объектами, что обуславливает* *необходимость гибридного применения методов нейронной сети и нечеткой технологии с привлечением методов традиционной теории автоматического управления. В работе для решения этих задач предложено использовать самоадаптирующиеся нейросетевые регуляторы, способные осуществлять выбор структуры и корректировать параметры регуляторов с учётом изменений как свойств исследуемого объекта, так и внешних возмущающих воздействий. Архитектура предлагаемой нейронной сети представлена в виде многослойной нейронной сети. Обучение и коррекция параметров весовых связей нейронной сети реализованы методом интерактивной адаптации, осуществляемой неявным образом. Самоприспосабливание параметров нейрорегулятора обеспечивается с учетом скорости изменения технологических параметров объекта управления. Разработан адаптивно-нечеткий алгоритм синтеза самоадаптации системы управления технологическими объектами на основе динамической модели с робастными свойствами.*

Ключевые слова: *адаптация, динамический объект, обучение, нейросетевое регулирование, нейроконтроллер, весовой коэффициент.*

Introduction

Particular attention has recently intensified to the problem of synthesizing mathematical models and control algorithms of various technological processes that have insufficient information about the various signals and interference affecting it, on account of the development of principles and algorithms for control systems.

The experience of creating automatic control systems for complex technological objects, in conditions of great uncertainty and incomplete knowledge about the object, the fuzzy descriptions showed the inefficiency of using only formal classical methods of control theory.

In this regard, it is necessary to investigate and develop alternative algorithms and control schemes, for example, intelligent control systems. Such systems have the ability to understand and learn about the control object, disturbances, the external environment, and working conditions. At this stage, artificial neural-networks, due to their abilities for self-adapting and self-learning, are considered as promising means for intelligent systems [1-4].

Currently, more and more «intelligent» properties are emerging in technical devices that ensure high quality control, adaptation to changes in object parameters and reflection of external disturbances. In general, there is a tendency to create systems that have the ability to adapt or self-study, as well as to obtain a model of a complex object that takes into account its dynamic parameters.

At the present stage of development of high-quality control systems requires the application of new intelligent approaches that allow the most effective use of all recent achievements in the fields of hardware and software.

The most relevant in the field of building control systems is the development of universal methods for automated synthesis of system parameters.

Neural-networks have entered practice wherever you need to solve the problems of prediction, classification or control. System self-learning refers to a set of methods and algorithms for setting up and functioning of control system with an unknown dynamic object. The system synthesis procedure includes the following steps: identification of the control object; initial setting of the regulator; adaptation of regulator parameters during control [5-9].

These steps define the basic functional elements and algorithms necessary to build a self-adapting system.

The self-adapting neural-network approach is equally suitable for linear and complex nonlinear dependencies. It is especially effective in analyzing data when it is necessary to find out whether there are dependencies between these variables.

With the development of new technologies in production, the requirements for control systems for speed, reliability of operation and accuracy characteristics grow.

To ensure these characteristics, as well as high quality indicators of the control system, including its adaptive properties with a significant variation in the parameters of the object and environmental conditions, the use of non-trivial control laws is required [10-12].

The concept of integrated application of neural-networks is reflected in the construction of self-adapting systems for automatic control of complex technical objects. The study of self-adapting neural-fuzzy control systems for use in the field of control showed the possibility of building based on them reliable models of complex non-linear objects and regulators implementing various control laws, including non-linear and close to optimal ones.

An important feature of the proposed synthesis schemes of models and regulators built on the basis of self-adapting neural-fuzzy control systems is that they involve a training procedure at a preliminary stage or during the control process.

In some cases, the use of these laws is limited by hardware implementation capabilities and time when calculating control effects on computing devices in the control loop. In this case, self-adapting neural-network technology is used.

Self-adapting neural-fuzzy control systems have accumulated the basic properties and structural features of their biological prototypes and are a collection of interconnected simple computational elements (neurons). The main properties of these structures include: the possibility of their training; synthesis by examples; high fault tolerance; high computational power due to parallel operation of individual elements.

These properties allow you to successfully use the self-adapting neural-fuzzy control systems to control complex dynamic objects.

The most investigated direction in this area is the construction of a linear model, which involves choosing a model structure based on a priori object information.

Model parameters are defined during the identification of object parameters. The obtained values can be used to adjust the regulator or to correct its parameters during control using analytical or numerical algorithms.

However, the use of a linear model for complex dynamic objects is almost always incorrect due to the presence of significant non-linearities (and most often dynamic). For such objects, it is impractical to consider the problem of parametric identification, since there are difficulties in determining the nonlinear structure of the model and, most significantly, at present there are no general rules (algorithms) for adjusting the regulator according to the known parameters of the nonlinear model.

Therefore, for complex dynamic objects, it is proposed to build a model on the selected nonlinear basis and use multilayer self-adapting neural- fuzzy control systems for this.

Many real multi-link control objects are characterized by significant nonlinearity and stochasticity of behaviour, a wide field of parameter change in its operating conditions.

To achieve a high quality of control indicators for such objects, it needs to have customization elements in the control system, which allows the system to adjust parameters when changing object properties [13-16].

One possible solution in constructing self-adapting control systems is the use of neural-network theory.

The main advantages of self-adapting neural-fuzzy control systems technologies compared to traditional control systems have been identified:

1. Self-adapting neural-fuzzy control systems allow solving non-standard problems in a standard way. It is possible that a specialized computer will better solve one class of problems. However, one neurocomputer is more versatile and has the ability to solve several classes of problems, while it is not necessary to design a specialized computer for the control system every time, since the neurocomputer will do everything itself.

2. Instead of programming, training is used. The self-adapting neural-fuzzy control systems are learning. You only need to form training sets.

3. Self-adapting neural-fuzzy control systems are most effective in those areas where an analogue of human intuition is needed for recognizing images (recognition of faces, reading handwritten texts, etc.), preparing analytical forecasts, translating from one natural language to another, etc. It is for such problems that it is usually difficult to propose a formal algorithm.

4. Self-adapting neural-fuzzy control systems allow forming effective software for computers with a high degree of parallelization of processing. It is very rare to use parallel systems effectively.

With the help of self-adapting neural- fuzzy control systems technologies, it is possible to ensure that all elements simultaneously and without unnecessary duplication perform the task.

5. Self-adapting neural-fuzzy control systems technologies are «democratic», these are also easy to use and approach any control systems, so anyone with no experience can work with them.

This article discusses the problem of building a self-adapting neural-fuzzy control system for multidimensional dynamic objects.

A multivariate statistically controlled series of objects, for which the number of controlled parameters is equal to the number of control effects, acts as a control object [17-21].

Proposed self-adapting neural-fuzzy control system is designed so that error vector after comparison elements is supplied to input of neural-network.

Then, depending on the error signal, the weighting factors are corrected at each discrete time t. The vector of control signals from the output of the self-adapting neural-fuzzy control systems is supplied to the input of the control object.

Research Methods and the Received Results

A self-adapting neural-network for controlling multi-linked objects is a multilayer neural-network with one intermediate layer, which contains N_0 neurons in the input layer and N_2 neurons in the output layer, moreover $N_2=N_0=n$, where n – number of controlled variables.

The network is characterized by the number of neurons N_1 in the interior layer. The input layer consists of error signal receiving nodes, and the output layer consists of source-neurons of control signal.

At the first stage superposition of input signals of neuron is calculated:

$$z_i^l = \sum_{j=1}^{N_{l-1}} w_{ij}^l o_j^{l-1},$$

where w_{ij}^l – weight coefficient that is a tunable parameter and characterizes the connection of the j-th neuron (l-1) of the layer with the i-th neuron of the l-th layer; w_j^{l-1} – output scalar.

Then the value of z is converted into the output value of the neuron:

$$o_j^{l-1} = f(z_i^l).$$

The nonlinear transformation is given by the activation function, which is often determined by the sigmoid function, i.e.:

$$f(z) = \frac{1}{1-exp(-z)}.$$

An important property of this activation function is the ease of defining a derivative of this function:

$$f(z_i^l) = f(z)(1-f(z)).$$

With the accepted designations, the mathematical description of the training of the self-adapting neural-fuzzy control systems is written in the form of a system of equations:

$$\left.\begin{array}{l} u_j(t) = o_j^2, \qquad j=\overline{1,n}; \\ o_j^l = f(z_i^l), \qquad i=\overline{1,N_l}, l=\overline{1,2}; \\ z_i^l = \sum_{j=0}^{l-1} w_{ij}^l o_j^{l-1}, \qquad i=\overline{1,N_l}, l=\overline{1,2}; \\ o_j^0 = e_j(t), \qquad j=\overline{1,n}; \\ o_j^0 = o_0^1 = 1 \end{array}\right\}$$

With the operation of a self-adapting neural- fuzzy control system, the settings of the system – the weights of the self-adapting neural- fuzzy control systems – change so that the value of E=$\|e\|\to 0$. Value E is determined by equation:

$$E = \frac{1}{2}\sum_{i=1}^{n} \alpha_i e_i^2, \qquad j=\overline{1,n},$$

where α_i - coefficients determining the weight of each control channel in the total error E.

Correction of self-adapting neural- fuzzy control systems weight coefficients w_{ij}^{l} (self-adapting neural- fuzzy control systems training) is carried out using the interactive adaptation method.

The essence of which is that the error that is required for training is calculated implicitly.

Using the interactive adaptation method, the system is divided into *N*-subsystems, each of which has an integrable output signal yn and an integrable input signal xn, the relation between them is presented in the form of a functional relationship:

$$F_n: X_n \to Y_n, \qquad n = \overline{1,n}.$$

The relationship of the *i*-th link of the system has the form:

$$y_i(t) = F_i[x_n(t)], \qquad i = \overline{1,n}.$$

Let the interaction between the links and the external signal $u_i(t)$ be linear and described by the equation:

$$x_i(t) = u_i(t) + \sum_{j \in J_i} w_{ij} y_i(t), \qquad i \in n,$$

where $J_i = \{K : y_i = i\}$ - set of connected inputs of the *i*-th link; w_{ij} - weights of the connections.

In this case, the ratio of the input and output of the *i*-th link is described by the following equation:

$$y_i(t) = F_i\left[u_i(t) + \sum_{j \in J_i} w_{ij} y_i(t)\right], \qquad i \in n.$$

The purpose of the training is to adjust the bond weights w_{ij} so as to minimize the loss function $E\ (y_1,\ \dots,\ y_n,\ u_1,\ \dots,\ u_n)$, which is a system error function.

The training of self-adapting neural-fuzzy control systems is to minimize the error of the control system. This is done by adjusting the link weights of the w_{ij} self-adapting neural-fuzzy control systems.

In this case, the weights of the links w_{ij} are adjusted according to the following rule:

$$\dot{w}_{ij} = F'^{input}_{posts}[x_{ij}^{input}] \cdot \left(\frac{y_{ij}^{output}}{y_{ij}^{input}}\right) \sum w_{ij} u_{ij} -$$

$$-\gamma \cdot F'^{input}_{posts}[x_{ij}^{\text{вх}}] \cdot y_{ij}^{output} \cdot \frac{\partial E}{\partial y_{ij}^{input}},$$

where $\gamma > 0$ - coefficient determining the learning rate; $F'^{input}_{posts}[x_{ij}^{input}]$ - derivative of Fresher; E - loss function (error).

Provided that equation has a single solution for w_{ij}, where the loss function $E\ (y_1,\ \dots,\ y_n,\ u_1,\ \dots,\ u_n)$ will monotonically decrease in time and the following equality will be satisfied:

$$\dot{w}_{ij} = -\gamma \cdot \frac{\partial E}{\partial y_{ij}^{input}}.$$

With this approach, the self-adapting neural-fuzzy control systems can be decomposed into constituent elements, represented as an elementary self-adapting neural-fuzzy control system (Fig. 1).

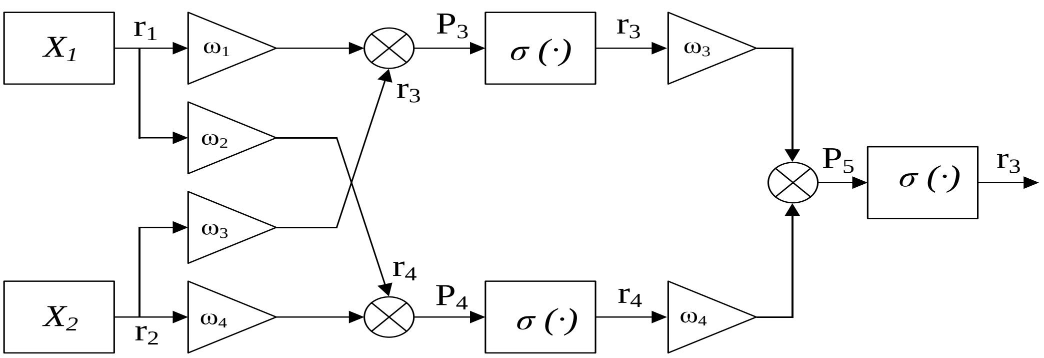

Fig. 1. ***Block diagram of the elementary self-adapting neural-fuzzy control system.***

Mathematically, the self-adapting neural-fuzzy control system learning algorithm is presented in the form:

$$Pn = \sum_{s \in Dn} \omega_s \cdot r_{press};$$

$r_n = \sigma(pn),$

where n – neuron index; Dn – set of input synapses of neuron n; pres and post – presynaptic and postsynaptic neuron corresponding to synapse s; ω_s – weight of the synapse s; p_n – membrane potential of neuron n; r_n – frequency of neuron n excitation; σ – activation function of the sigmoid type, which is presented in the form:

$$\sigma(x) = \frac{1}{1+e^{-x}}.$$

In this case, the weight of synapses is determined by the equation:

$$\dot{\omega}_s = r_{pres}(\phi_{posts}\sigma(-P_{posts}) + \gamma \cdot f_{posts}),$$

$$\phi_n = \sum_{s \in A_n} \omega_s \cdot \dot{\omega}_s,$$

where γ – direct feedback coefficient for all neurons; φ_n – direct reverse error signal.

It should be noted that this training method is equivalent to an algorithm for backward propagation of an error, but for transmitting an error from the output of the network to its input, the use of a self-adapting neural-fuzzy control system with backward propagation is not required.

Proposed solution allows organizing automatic control system based on self-adapting neural-network technologies in various microprocessor software and technical systems. It shows the operability of this solution and confirms the merits of self-adapting neural-fuzzy control systems technologies.

Conclusion

The self-adapting neural-fuzzy control systems can be successfully applied to control both stationary and non-stationary multidimensional objects. The proposed algorithm for synthesis of a self-adapting neural-fuzzy control system of technological equipment allows reducing the number of iterations in the process of training the algorithm of fuzzy-logical output, accelerate the process of training the system due to the use of a fast-acting algorithm of fuzzy-logical output, reduce the error of the results of training a neuro-fuzzy network from 8 to 1%. The use of this control system contributes to:

- reduction of system self-configuration time;
- adaptive adjustment capabilities to change dynamic properties of the control object;
- relative ease of using the algorithm and narrowing a number of adjustment parameters.

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