Synthesis of the neuro-fuzzy regulator with genetic algorithm

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ABSTRACT

Real-acting objects are characterized by the presence of various types of random perturbations, which significantly reduce the quality of the control process, which determines the use of modern methods of intellectual technology to solve the problem of synthesis of control systems of structurally complex dynamic objects, allowing to compensate the influence of external factors with the properties of randomness and partial uncertainty. The article considers issues of synthesis of the automatic control system of dynamic objects by applying the theory of intelligent control. In this case, a neural network based on radial-basis functions is used at each discrete interval for neuro-fuzzy approximation of the control system, allowing real-time adjustment of the regulator parameters. The radial basis function is designed to approximate functions defined in the implicit form of pattern sets. The neuro-fuzzy regulator's parameter configuration is accomplished using a genetic algorithm, enabling more efficient computation to determine the regulator's set parameters. The regulator's parameters are represented as a vector, facilitating their application to multidimensional objects. To determine the optimal tuning parameters of the neuro-fuzzy regulator, characterized by high convergence and the possibility of determining global extrema, a genetic algorithm was used. The effectiveness of the neuro-fuzzy regulator is explained by the possibility of providing quality control of the dynamic object under random perturbations and uncertainty of input data.

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1. INTRODUCTION

Currently, for the synthesis of the control system of complex dynamic objects, various methods are used. Methods based on mathematical models, constructed using deterministic and random methods, are widely used in control systems for electric power systems (EPS). Such methods are based on assumptions about the accuracy, assignment and constraints of initial data, and the possible uncertainty of the "nondeterministic" is closed in a procrustean bed of interval estimates (normal distribution parameters) [1]. As a result of works carried out by many scientists and specialists all over the world over a dozen years, many methods, and algorithms for solving the problem of synthesis of control systems of electric power objects have been created. These include methods of classical [2], [3], heuristic [4]–[6] and artificial computational intelligence as ant algorithms [7], artificial neural networks [8], fuzzy logics [9], cuckoo search, bee algorithms [10], particle swarm optimization [11], and evolutionary algorithms [12]. Nowadays, many of them are used to solve production problems. Basically, these problem-solving methods involve the use of deterministic and stochastic input information. As it is known, in EPS, continuous technological processes are carried out continuously, and calculations and assessment of the state at the current moment of time are possible only in discrete modes of individual current values of their interval parameters, without considering the structure, which leads to confusing situation and frequent loss of possible solutions. This raises the problem of incompleteness and inaccuracy of initial data, which requires constant complication of mathematical models [13].

The use of intelligent methods is considered one of the effective approaches to improve the quality and efficiency of control of dynamic objects in the presence of various factors with random and probabilistic characteristics, as well as nonlinear properties. The complex and uncertain nature of the input data related to the object can be explained by the joint use of neural networks, fuzzy logic, and genetic algorithms. These adaptable tools are able to handle inaccurate, incomplete, or ambiguous information.

Using the hybrid approach in creating control systems, it is possible to significantly minimize the impact of uncertainty on the efficiency of dynamic control objects. This is achieved by compensating for the disadvantages of information and uncertainty. The presence of such controls in the control loop makes it necessary to create a control system in the class of discrete automatic control systems. At each discrete interval, a neural network based on radial-basis functions is used for neuro-fuzzy approximation of the control system, which allows real-time adjustment of the regulator parameters. The radial-basis function is specifically designed to estimate functions that are represented in the implicit form of a set of patterns. The neural network using these functions consists of one hidden layer, where only neurons in the hidden layer have a non-linear activation function [14], [15].

The study of scientific publications in the field of control systems of electric power objects [16]–[18] allowed us to conclude that traditional methods of active identification for adaptive modeling of the object are now widely available. Currently, scientific approaches related to the use of intelligent systems [19]–[21] have gained wide popularity in the theory of adaptive control. These systems successfully implement the experience and knowledge of experts (fuzzy regulators), as well as have the ability to self-learn (neuroregulators). Joint or combined application of these directions led to the emergence of a new scientific direction - hybrid or neuro-fuzzy networks (HN, NFN).

The article is devoted to the development of an algorithm for the synthesis of adaptive regulators on the basis of neuro-fuzzy network structures with genetic algorithms of training, capable to solve problems of management of complex nonlinear stochastic objects. In contrast to existing methods of regulator synthesis, the neuro-fuzzy regulator allows to significantly reduce the influence of various types of uncertainties of dynamic properties of the object and external influences. This will enhance the effectiveness of implementing automatic control systems (ACS) when there is insufficient prior knowledge about the control object's model.

The following is the order in which the material is presented: section 2 explains the method of solving the problem and reveals the essence of the proposed algorithm. Section 3 contains the simulation results that were used to verify the proposed neuro-fuzzy regulator (NFR). Section 4 concludes with a conclusion and recommendations for further use and development of the proposed approach.

2. METHOD

Suppose there is a control system for the operation modes of electric power objects. It is required to synthesize a regulator that provides asymptotic stability of the control system and the desired quality of operation of the object, using a genetic algorithm (GA). The procedure of synthesizing the structure of the regulator and finding its optimal parameters is carried out by the following algorithm.

Firstly, in step 1, a mathematical model of the control object (CO) is constructed. Next, in step 2, the choice of the architecture of the NFR, which consists of three parts in Figure 1 is carried out. In step 3 the formation of the fuzzy description of input and output parameters in the form of a term set of linguistic variables is carried out [22]. This includes defining the boundaries of the thermos $(x_1, x_2, \dots, x_n)$, the definition area of the term set $(T_1, T_2, \dots, Tn, [x_{min}, x_{max}])$, and the membership function of each of the thermos $(\mu\,(x))$ as illustrated in Figure 2.

In step 4, the formation of a fuzzy rule base is represented in the form of the Mamdani model [22],

$$\text{If } e(t) = T_i), \text{ then } u_p(t) = T_j) \tag{1}$$

where, T_{ij} – the terms of input and output variables, $i = 1, 2, \dots, n$; $j = 1, 2, \dots, m$ are the number of input and output variables.

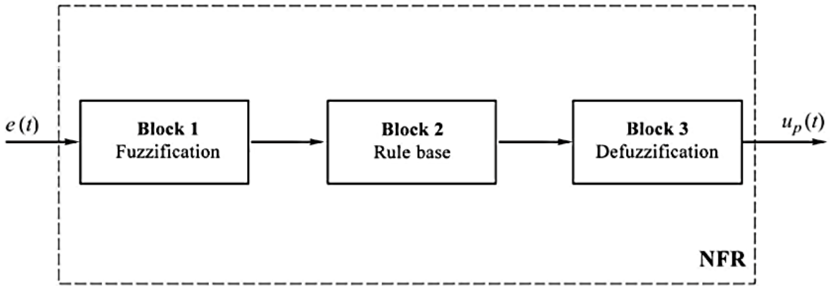

Figure 1. The structure of the NFR

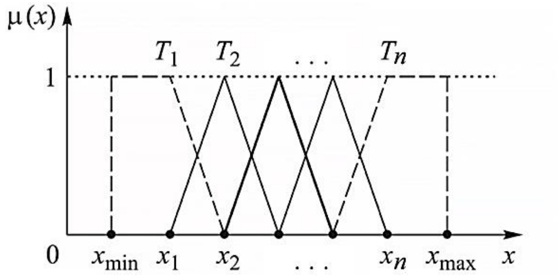

Figure 2. The term sets describe the input and output variables of the NFR

In step 5, to perform the defuzzification algorithm for the fuzzy inference result. The center of gravity method is used. In step 6, the adjustment of NFR parameters to obtain the optimal solution. We use a GA consisting of the following steps:

1) Randomly choosing the initial data, the initial population is formed.
2) The current population is determined.
3) Genetic operators are executed.
4) New chromosomes appear (return to step 2)
5) Stopping conditions are checked.
6) Found the optimal solution.

The formation of the initial population is carried out by defining the boundary between the input and output terms variables. The condition for stopping the work of the GA is the fulfillment of the integral quality criterion (IQC):

$$IQC = \int_0^T e^2(t)dt, \tag{2}$$

The procedure of the genetic algorithm is as follows: The initial population of chromosomes is formed by random selection of the values of the vectors G_j from the area $[0, CK_1^*] \times [0, CK_2^*] \times [0, CK_3^*] \times$ ..., which are configurable parameters of the NFR. Chromosomes are selected according to their survival rate when the selection method is applied, and arithmetic crossing and uniform mutation are used as genetic operators (including the use of generalized logical chains) [23]. To form a new generation, an elite strategy is used, when using each iteration of the algorithm in the population retains the best chromosome, i.e., the most adapted chromosome. The work of the GA shall stop when one of the following conditions is met:

1) Upon reaching the maximum number of generations K_{max};
2) If the fitness value $F_n(G^*)$ of the best chromosome G^* satisfies the condition $F_n(G^*) \geq \varepsilon$, where ε is the specified accuracy.
3) If the adaptability of the best chromosome does not change at a given number of iterations n_c.

The following algorithm is proposed for adjusting and determining the vector of the control parameters providing the solution to the problem:

1) Determination of source data: regulator parameter vector found by algorithm; constant C; population size N_{max}; the maximum number of K_{max} populations; probability of crossing chromosomes p_c, and chromosome mutation p_m; the accuracy of calculation ε; the number of iterations n_c at which the chromosome survival value does not change. We take the initial value of the number of iterations k to be zero [24].

2) Initialization. Calculates the maximum values of $g_1^{max} = (I = \overline{1, M})$ of the regulator parameters: $g_1^{max} = CK_1^*, g_1^{max} = CK_2^*, g_1^{max} = CK_3^*$. Randomly generated by N_{max} chromosomes, which form the initial population of $P(0)$ as follows: gene value g_{j1} $(j = 1, N_{max}, I = 1{,}3 \ldots)$ chromosomes G_j are randomly selected from segments $\lfloor 0, g_1^{max} \rfloor$. Thus, many vectors are formed $(K_1, K_2, K_3\ \ldots)$ belonging to the region $\lfloor 0, CK_1^* \rfloor \times \lfloor 0, CK_2^* \rfloor \times \lfloor 0, CK_3^* \rfloor \times \ldots$.
3) Assessment of fitness. For each chromosome G_j of the current *P(k)* population, the parameter values $(K_1, K_2, K_3\ \ldots)$ are selected from the corresponding genes and the appropriateness of the chromosome G_j is calculated.
4) Choosing the best chromosome. The chromosome G^* with the highest fitness value is selected, i.e., the parameter vector ensuring the minimum value of the quality indicator J is determined. If $F_n(G^*) = F_n$, then $i_c = i_c + 1$, otherwise $i_c = 1, F = F_n(G^*)$.
5) Check the stopping conditions. If one of the conditions is met: i) $k_c < K_{max}$; ii) $F_n(G^*) \geq \varepsilon$; and iii) $i_c = n_c$. Then paragraph 6 is passed, otherwise – to paragraph 10.
6) Selection. Formation of parent population $M(k)$ chromosomes.
7) Crossings. The cross operator applies to selected chromosomes of parent population $M(k)$.
8) Mutation. $P(k + 1)$ chromosomes are subject to mutation operator.
9) Transition to the next generation. The population $P(k + 1)$ includes the best chromosome G^*, assumes $k = k + 1$, and passes point 3.
10) Determines the vector of parameters $(K_1, K_2, K_3\ \ldots)$ of the regulator, ensuring the established regime of the transition process.
11) If at the found value of the vector (K_1, K_2, K_3, …) the condition $(K_1, K_2, K_3\ \ldots)$ is met, then the transition to paragraph 12 is made, otherwise - to paragraph 13.
12) The values $(K_1, K_2, K_3\ \ldots)$ shall be accepted as parameters of the regulator and shall be moved to paragraph 14.
13) To adjust the parameter vector $(K_1, K_2, K_3\ \ldots)$ GA is applied.
14) Stopping the algorithm and inferring the parameter vector $(K_1, K_2, K_3\ \ldots)$. Chromosomes are randomly generated to create populations within ranges of certain values.

To assess the suitability of the current population, use the chromosome fitness sign from (3) and (4).

$$\text{If } I_0 < I_{ij}, \text{ then } k_{ij} = 1\ (i = \overline{1{,}3}, j = \overline{1.3}). \tag{3}$$

Otherwise, we get $k_{ij} = 0$.
Let us define the survival rate as (4)

$$\text{If } k_{ij} = 1, \text{ then } \Delta_n = I_0 - I_{ij}, \text{ where } n = \overline{1{,}9}. \tag{4}$$

Otherwise, we get $\Delta_n = 0$.

The objective of calculating survival rates is to select the chromosome of the population with the highest survival rate according to the available suitability, and the survival rate can be calculated as (5),

$$B_n = (\Delta_n / \textstyle\sum_{n=1}^{9} \Delta_n) \cdot 100\%. \tag{5}$$

If you imagine a roulette wheel, which is divided into fractions in percentages of each chromosome, you should spin it twice for each of the pairs (father-mother). In this way, pairs of chromosome combinations are selected, which become candidate chromosomes for the next population. Beforehand, these chromosomes must undergo a crossing-over procedure before they are actually transferred to the new population.

Next, a crossing-over operation is performed, which is applied to chromosomes that have passed selection into the new population. In order to perform the crossover operation, the chromosome combinations must first be divided into input and output chromosomes. The right side of the descendant chromosome combination is the father chromosome, and the left side of the descendant chromosome represents the mother chromosome. The descendants of the chromosome are formed in a similar manner. In the next step, combinations of pairs are constructed based on the data already obtained, and then the suitability calculations of the obtained solutions are performed again. The algorithm will be performed until we find the minimum value of the integral criterion for all combinations of chromosomes and until the fitness feature k for all descendants equals 0.

In step 7, determine the optimal NFR parameters with GA for the corresponding input of $u(t)$. Step 8, introducing one formal neuron into NFR, which makes it possible to set the weight of each rule when constructing the resulting inference. The result is an NFR structure Figure 3 with the following parameters: x_0 –

the initial state of the neuron; $x_1, x_2, \dots, x_m$ – the output variables of the rule base; $a_1, a_2, \dots, a_m$ – the weight of the rules; Ne – the formal neuron; $f(g)$ – the activation function of the neuron; g – the activation function argument.

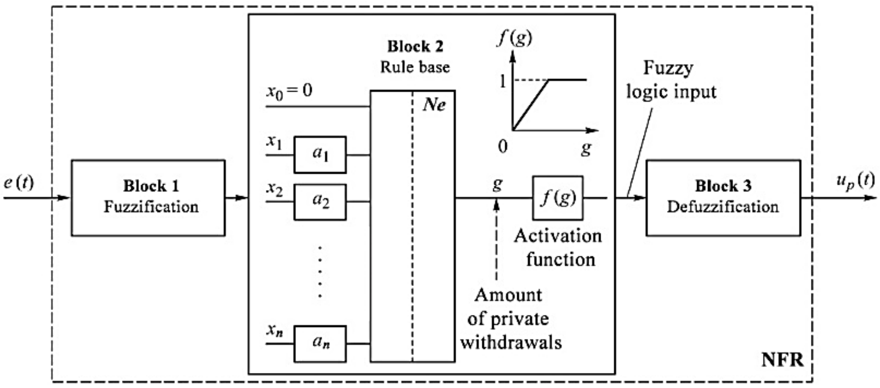

Figure 3. NFR Structure

In this case, the value of the activation function g is defined as (6) [22]:

$$g(x_k) = \sum_{j=1}^{m} a_j \mu_j(x_k), \ \forall x_k \in [x_{min}, x_{max}]. \quad (6)$$

Step 9, we will consider changes in the operating mode (load) of technological units of electric power facilities as a control object. The ranges of input and output parameters of the process are determined on the basis of the technological regulations, on the basis of which the terms of the sets are determined, each of which corresponds to one of the signal levels: *Z* - zero, *PS* - positive small, *NS* - negative small, *PL* - positive large, *NL* - negative large Figure 4 [25]–[27]. Figure 4 shows the term-multiples of input Figure 4(a) and output Figure 4(b) parameters of the NFR.

To form the rule base, the range values of input and output variables changes are taken into account. As input variables, the changes of the regulated parameter from the set value are taken, and the output parameters are the changes in the position of the actuator. In this case, the number of rules depends on the linguistic terms, taking into account a particular object. Table 1 shows an example of rule base formation. Let us find the average values within the variable change ranges. The rule base in the fuzzy logic inference system, taking into account the description of the input variable $\Delta\theta$ - the error signal, and the output parameter F - the control action Figure 4, is presented in Table 1 [28], [29].

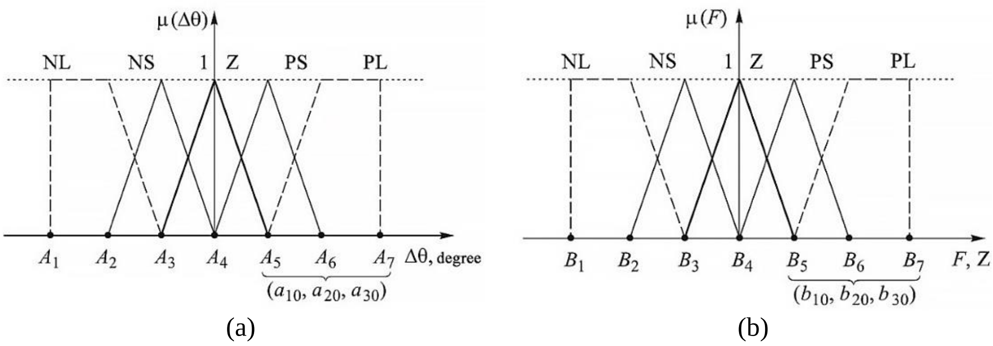

Figure 4. Terme-sets of input (a) and output (b) parameters of NFR

Table 1. Base of NFR rules

NFR input and output signals	Rule numbering				
	1	2	3	4	5
Δθ	NL	NS	Z	PS	PL
F	PL	PS	Z	NS	NL

3. RESULTS AND DISCUSSION

Let the dynamics of the object under study, i.e., the technological process occurring at the electric power facility (EPF), be described by the transfer function of the second order. To ensure the stability of the control system and the speed of the mathematical model of EPF, we apply a proportional-integral-differential (PID) regulator with adjustable coefficients K_d, K_i, K:

$$W_{PID-reg}(p) = K_d p + K_i \frac{1}{p} + K. \tag{7}$$

To solve the problem of synthesis of the mathematical model of a neuro-fuzzy PID regulator we chose a training sample, defined by giving the control object a single-step and harmonic action [30]–[32]. The training sample is presented in Table 2.

Table 2. The training sample

$\theta_{\text{set value}}$, deg	$\theta_{\text{set value}} \cdot 1(t)$		$\theta_{\text{set value}}\sin(\omega t)$, ω=1, 1/c
	F_{t0}, Z	$F_{\text{set up}}$, Z	$\lvert F_{\max}\rvert$, Z
95.6	727	-24.2	25.6
82.3	643	-21.7	22.3
75.6	576	-18.9	19.8
61.9	486	-16.1	17.1
53	401	-13.2	14.2
44.5	325	-11.1	11.3
31.5	241	-8.1	8.8
24.1	163	-5.9	5.9
11.01	85.3	-3.1	3.1
6.7	44.7	-1.9	1.9
0.7	4.6	-0.3	0.16

note: Having negative values of $\theta_{\text{set value}}$ the result will be symmetric

The ranges of possible values of the boundaries of linguistic terms of input and output parameters are determined by simulation results. The ranges of variation of the term sets are determined taking into account the modes of operation of the control objects, corresponding to the technological regulations of the control system functioning process. Let the ranges for the boundaries of linguistic terms be described by (8) and (9):

$$0 \le a_{10} \le 40; 40 \le a_{20} \le 80; 80 \le a_{30} < 120; \tag{8}$$

$$[0 \dots 5] \le b_{10} \le [-6{,}5 \dots 220];$$

$$[-6{,}5 \dots 220] \le b_{20} \le [-13 \dots 440];$$

$$[-13 \dots 440] \le b_{30} \le [-25 \dots 715]. \tag{9}$$

The process of NFR parameter optimization with the help of GA is presented in Table 3. The table shows that the value of the criterion decreased from 1.38 to 0.053. GA work stopped at the third step, when there was an increase in quality, the result could no longer be improved, and then the GA work stopped.

Table 3. Data from the output file of the software module implementing GA for NFR configuration

i	IQC	NFR input parameter term bounds							NFR output term bounds						
		A_1	A_2	A_3	A_4	A_5	A_6	A_7	B_1	B_2	B_3	B_4	B_5	B_6	B_7
0	1.3816	-78.0	-46.0	-16.0	0	16.0	46.0	78.0	-290.0	-180.0	-65.0	0	65.0	180.0	290.0
1	0.0531	-81.2	-59.7	-24.1	0	24.1	59.7	81.2	-205.8	-166.8	-22.4	0	22.4	166.8	205.8
2	0.0073	-71.9	-43.8	-1.1	0	1.1	43.8	71.9	-458.8	-213.9	-115.7	0	115.7	213.9	458.8
3	0.0073	-71.9	-43.8	-1.1	0	1.1	43.8	71.9	-458.8	-213.9	-115.7	0	115.7	213.9	458.8

note: *i* – - sequence of GA work steps; IQC – integral quality criterion

4. CONCLUSION

To check the validity of the proposed approach a simulation experiment was performed in conditions of a limited amount of data, i.e., the amount of training sample, taking into account that the size does not affect the quality of the algorithm it should be noted that in forming the ranges of the initial conditions of the term-numbers of fuzzy variables, two or three sample iterations were sufficient, after which the GA selects the optimal values. A GA developed in the absence of initial data (without a training sample) can also perform its task, only the ranges of term boundaries should be set wider without reference to the values of the training sample, in this case, the number of GA calculation steps increases by hundreds of times.

The results obtained indicate that the proposed neuro-fuzzy dynamic control system offers several advantages. Firstly, the adjustment of NFR parameters is based on GA, which enables more efficient computation and facilitates the identification of optimal regulator settings. Additionally, the regulator parameters are presented in vector form, which makes them suitable for use with multidimensional objects.

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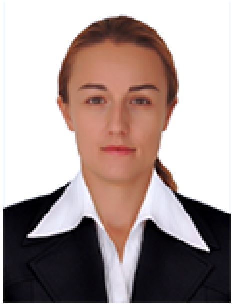

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