UDC 519.714+519.715+681.518

Pervushina N. A., Donovskiy D. E., Khakimova A. N.

Development of synthetic methodology of neuro-fuzzy controller adjusted by genetic algorithm

The paper focuses on a synthetic methodology of a neuro-fuzzy controller adjusted by genetic algorithm for a dynamic control object. An algorithm for controller synthesis and a genetic algorithm for adjusting the controller's parameters have been developed. The methodology has been tested on the classical problem of stabilising a vertical pendulum on a mobile trolley. The results obtained confirm the efficiency of the methodology and allow for the conclusion that the neuro-fuzzy controller when appropriately adjusted ensures high quality of the stabilisation system, even if there are random disturbances on the dynamic object.

Keywords: fuzzy controller, neuro-fuzzy controller, genetic algorithm, formal neuron, stabilisation system.

Introduction

In our time, the need for solving vital tasks of automatic control of dynamic objects, in particular, unmanned aerial vehicles, when they are acted upon by various random disturbances ever more often demands for application of smart methods of mathematical simulation, such as fuzzy logic, genetic algorithms (GA), and neural networks. Combining neural networks, GA, and fuzzy algorithms makes it possible to solve problems of different levels of complexity and fuzziness (as per initial data), but most importantly, they provide a multi-tool for processing of inaccurate, incomplete, or fuzzy information [1].

The application of smart methods in constructing control systems enables to considerably reduce the influence of fuzziness on control system quality, as well as compensate for the lack of a priori information at the systems design stage [2].

This paper introduces a methodology for developing a neuro-fuzzy controller (NFC) with its parameters being adjusted by GA. The NFC and suitability of GA for its adjustment were tested on a classical model problem of stabilising a dynamic object, the latter being represented by a vertical pendulum on a mobile trolley.

Problem statement

The subject considered here is a closed-loop system of dynamic object control (Fig. 1) – a stabilisation system (SS) [3].

For the synthesis of a mathematical model of NFC, adjusted by GA, in an SS having a structure as given in Fig. 1, the following algorithm is proposed.

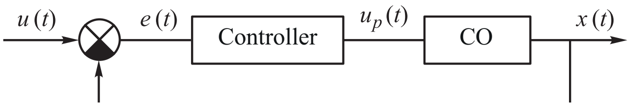

Fig. 1. Closed control circuit with controller in direct circuit: CO – dynamic control object; $u(t)$ – control input; $e(t)$ – control error (mismatch), $e(t)=u(t)-x(t)$; $u_p(t)$ – control signal from controller output; $x(t)$ – SS output value

Synthesis algorithm for a mathematical model of NFC adjusted by GA

Stage 1. Building a mathematical model of CO and solving the controller synthesis task by the classical method. It is necessary to first select controller structure (P, PI, PID controllers [3], etc.) and then calculate or select its coefficients.

Stage 2. Testing the constructed SS (Stage 1) within a range of possible operating modes, and verifying stability. Obtaining a learning sample for implementation of fuzzy controller (FC) synthesis procedure.

Stage 3. Taking a decision on FC structure (in the most elementary case, it will be a "single input – single output" structure). Selecting linguistic description for the FC input variable(s) and output variable (fuzzification [4]). Fig. 2 shows the "single input – single output" FC structure. The structure features three functional blocks necessary for FC operation.

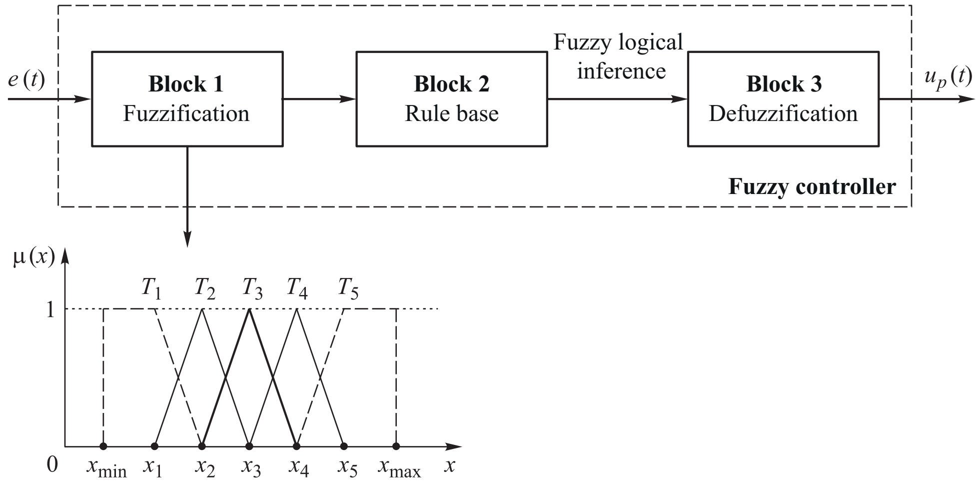

Fig. 2. Fuzzy controller structure and term set for description of FC input and output variables: $\propto(x)$ – membership function of each of the terms (granules); $T_1, T_2, \supset, T_5$, $[x_{min}, x_{max}]$ – term set definition region, $x_1, x_2, \supset, x_5$ – term boundaries (determined as per learning sample data)

The “Fuzzification” block contains fuzzy description of the input $e(t)$ and output $u_p(t)$ parameter in the form of a term set of linguistic variables. Each parameter will be collectively designated as x, and a term set example is given in Fig. 2. A degree of information granularity (the number of terms) is determined by estimator, proceeding from the problem solving specifics.

Stage 4. Based on the learning sample data (Table 1), schemes of logical inferences are compiled in the fuzzy rule base in accordance with the linguistic description of Stage 3. A general view of logical inferences is as follows:

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

where T_i – term of input variable;

$i = 1, 2, \ldots, n$ – number of input variable terms;

T_j – term of output variable, $j = 1, 2, \ldots, m$ (number of output variable terms).

Stage 5. Selecting the type of fuzzy inference result defuzzification. The most frequently used is the centre-of-gravity method [4].

Stage 6. Testing SS with FC. An inference on stability is made. If the SS with FC turns out to be unstable, the boundaries of terms $x_1, x_2, \ldots, x_{n(m)}$ are corrected until obtaining a stable SS.

Stage 7. Developing GA for adjusting FC parameters within the framework of a standard process for obtaining an optimal solution [1]:

1) generating an initial population;

Table 1

Learning sample

Registered signals of SS loop	Signal values registered at time moment t				
SS error, $e(t)$	$e_1(t)$	$e_2(t)$	$\cdots$	$e_i(t)$	$\cdots$
Control signal, $u_p(t)$	$u_{p1}(t)$	$u_{p2}(t)$	$\cdots$	$u_{pi}(t)$	$\cdots$

Note. t – initial moment of time and/or time corresponding to SS steady-state operation mode onset.

2) current population emerging;

3) genetic operators functioning;

4) new chromosomes emerging (transition to Stage 2);

5) checking termination conditions;

6) stopping evolution;

7) optimal solution.

Generation of the initial population is performed at Stage 3: term boundaries of the input and output variables. The condition of GA operation stopping within the framework of SS functioning is suggested to be selected in the form of an integral performance criterion [3]:

$$\text{IPC} = \int_0^T e^2(t)dt. \qquad (2)$$

Stage 8. Testing the GA of FC parameters adjustment (term boundaries). For that purpose, test control of $u(t)$ at the SS input is selected, and the FC parameters are adjusted within their specified variation ranges relative to the boundary values set at Stage 6. The testing result must demonstrate GA operation correctness, i. e. consistent approximation to an optimal solution – set of FC parameters.

Stage 9. Adjusting FC parameters by means of GA for the set type of $u(t)$ input.

Stage 10. Entering one formal neuron into FC, enabling to set the weight of each rule when constructing a resulting inference. As a result, the NFC structure emerges. The procedure for constructing a resulting inference for a base of five rules is schematically shown in Fig. 3.

The activation function argument g is found from the formula

$$g(x_k) = \sum_{j=1}^{m} a_j \mu_j(x_k), \quad \forall x_k \in [x_{\min}, x_{\max}]. \qquad (3)$$

Stage 11. NFC testing under unit weights of rules $a_j = 1$ $(j = \overline{1,5})$. If testing results coincide with the results of Stage 9, then a_j are selected in an interval from 0 to 1 in such a way that, as per criterion (2), the result of SS operation for a given type of $u(t)$ input is better than at Stage 9, or an inference is made about impossibility of further improvement of SS performance quality.

Solving the problem of synthesis of a mathematical model of NFC adjusted by GA

The algorithm proposed in the paper has been successfully tested in solving the problem of stabilising a vertical pendulum on a mobile trolley.

The task of stabilising a vertical pendulum is a classical problem in the automatic control domain, widely used as a reference standard for testing control algorithms. Due to simplicity of parameter interpretation and non-linearity of the problem, it is frequently used as a test object, on which functioning of various controllers is demonstrated.

The authors of the paper also used the problem described above to test functioning of NFC with adjustment by GA when solving the problem of stabilising position of an unsteady dynamic object (a vertical pendulum).

A vertical pendulum is represented in the form of a light rigid rod having length $2l$ and point mass m at its end, with its base secured in the centre of a trolley with mass M. The viscous friction coefficient during movement of the trolley is b; $\vec{F}$ – force applied to the trolley (steering); x – trolley coordinate; θ – angle of pendulum deflection from the vertical [5, 6].

The equations of vertical pendulum motion on the trolley are as follows

$$(M + m)\ddot{x} + b\dot{x} - ml\ddot{\theta}\cos\theta + ml\dot{\theta}\sin\theta = F; \qquad (4)$$

$$l\ddot{\theta} - g\sin\theta = \ddot{x}\cos\theta. \qquad (5)$$

Since the goal of SS is to hold pendulum

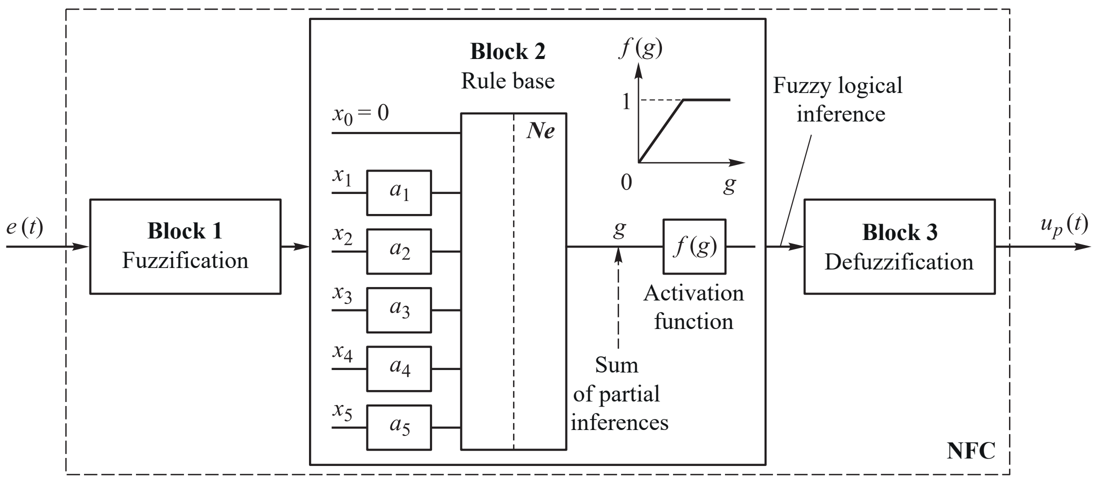

Fig. 3. NFC structure: x_0 – neuron initial state; x_1, ⊃ , x_5 – rule base output variables; a_1, ⊃ , a_5 – rule weights; Ne – formal neuron; $f(g)$ – neuron activation function; g – activation function argument

in the vertical position, these non-linear equations can be linearised in the area of point $\theta = 0$, $\dot{\theta} = 0$, $\ddot{\theta} = 0$ and a mathematical model of CO can be built by the angle of pendulum deflection θ in the form of transfer function:

$$W_F^{\theta}(p) = \frac{B_1 p}{p^3 + A_2 p^2 + A_1 p + A_0}, \qquad (6)$$

where $B_1 = \frac{1}{lM}$, 1/(m·kg);

$A_2 = \frac{b}{M}$, m·kg;

$A_1 = -\frac{g(m+M)}{lM}$, 1/s^2;

$A_0 = -\frac{gb}{lM}$, m/(s^2·kg).

A CO with transfer function (6) is unstable by the Hurwitz criterion, as among the characteristic equation coefficients (denominator in formula (6)) there are negative values [3]. To ensure CO stability, let us build a stabilisation system with unity feedback and PID controller in a direct control circuit (see Fig. 1). In this case: $u(t) = \theta_{set}$ (specified value of pendulum deflection angle at stabilisation), $e(t) = \Delta\theta$ (deflection from θ_{set}), $u_p(t) = F$ (force applied to the trolley), $x(t) = \theta$ (actual pendulum deflection angle).

Stability and high-speed response of the CO mathematical model (6) is ensured by PID controller with coefficients K_d, K_i and K:

$$W_{\text{PID contr}}(p) = K + K_d p + K_i \frac{1}{p}. \qquad (7)$$

Using the built SS, we obtain a learning sample for the synthesis of FC mathematical model. Selected as the test inputs are: step-like input $1(t)$ with specified amplitude θ_{set} and harmonic input $\theta_{set}\sin(\omega t)$ with $\omega = 1$, 1/s.

Stages 1 and 2 of the synthesis algorithm for an NFC adjusted by GA are completed.

Stage 3 of the synthesis algorithm operation is associated with selection of FC structure. We shall confine ourselves to the simple “single input – single output” structure. In the SS loop of a vertical pendulum on a trolley, the FC, according to the parameter values of input signal $\Delta\theta$, is to generate a control signal F at the output, the signal further coming to the CO and changing the value of angle θ towards the specified value of θ_{set}.

The structure of the developed FC corresponds to the diagram given in Fig. 1. The “Fuzzification” block contains a fuzzy description of input parameter $\Delta\theta$ and output parameter F in the form of term sets of linguistic variables (see Fig. 2), each one of which corresponds to one of the signal levels: Z – zero, PS – positive small, NS – negative small, PB – positive big, NB – negative big. The parameters of fuzzy variables corresponding to each of the descriptions are determined according to the learning sample (Table 2).

Let us denote the ranges of possible values for the boundaries of linguistic terms of the input and output parameters in accordance with the mathematical simulation results given in Table 2. Thus, for instance, for the small value of input $\Delta\theta$ (PS term), lying within 0 to 30°, output parameter F varies from –7.5 to 235 N. According to this logic, the terms are graphically shown in Fig. 4, and the ranges for term boundaries are described by the following expressions:

$$0 \,''\, a_{10} \,''\, 30; \;\; 30 \,''\, a_{20} \,''\, 60; \;\; 60 \le a_{30} < 90; \qquad (8)$$

Table 2

Learning sample

θ_{set}, deg	$\theta_{set} \cdot 1(t)$		$\theta_{set}\sin(\omega t)$, $\omega = 1$, 1/s
	F_{t_0}, N	F_{est}, N	$\lvert F_{max} \rvert$, N
89.9	707	–23.1	24.5
80	628	–20.5	21.8
70	550	–18	19.1
60	470	–15.4	16.3
50	393	–12.8	13.6
40	314	–10.3	10.9
30	235	–7.7	8.2
20	157	–5.1	5.5
10	78.5	–2.6	2.7
5	39.3	–1.3	1.4
0.5	3.9	–0.1	0.14

Note. For negative values of θ_{set} the result is symmetrical.

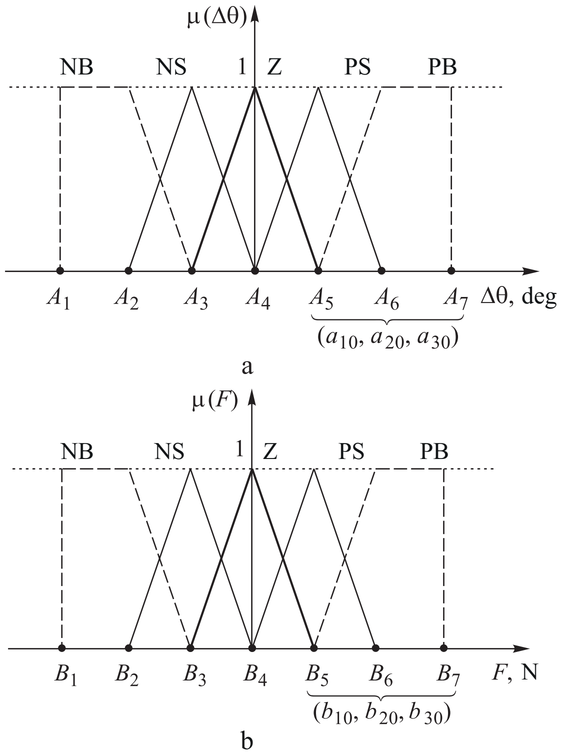

Fig. 4. Term sets of input (a) and output (b) FC parameters

$$[0...3] \le b_{10} \le [-7,5...235];$$

$$[-7,5...235] \le b_{20} \le [-15...470];$$

$$[-15...470] \le b_{30} \le [-23...700]. \qquad (9)$$

To analyse FC operation in the SS of a vertical pendulum on a trolley, without adjustment, we shall set the datum (initial) values of linguistic term boundaries of the input and output parameters as middle values within the accepted ranges:

$$a_{10} = 15°,\ a_{20} = 45°,\ a_{30} = 75°,\ b_{10} = 60 \text{ N},$$

$$b_{20} = 170 \text{ N},\ b_{30} = 285 \text{ N}. \qquad (10)$$

In the rule block, each logical rule must shape an inference in the form of a fuzzy description of variable F, corresponding to each possible input variable $\Delta\theta$.

A rule base in the system of fuzzy logical inference, with account of description of input variable $\Delta\theta$ and output parameter F (see Fig. 4), is given in Table 3.

For making a fuzzy inference in the FC, the Mamdani's mechanism is selected due to its wide use in constructing controllers for technical systems. Defuzzification is performed by the centre-of-gravity method [5]. Stages 3–5 of the synthesis algorithm for an NFC adjusted by GA are completed.

For testing operation of SS with FC (Stage 6), an FC software module was developed, transformed to the view of an SS functional block whose inputs are the arrays of term parameters:

$$A_0[7] = [A_1\ A_2\ A_3\ A_4\ A_5\ A_6\ A_7],$$

$$B_0[7] = [B_1\ B_2\ B_3\ B_4\ B_5\ B_6\ B_7]. \qquad (11)$$

Table 3

FC rule base

Fuzzy controller input and output signals	Rule number				
	1	2	3	4	5
Δθ	NB	NS	Z	PS	PB
F	PB	PS	Z	NS	NB

Testing the operation of SS with FC demonstrated that system with FC, without adjustment, is stable.

For adjustment of the FC parameters, a GA was developed. The genetic algorithm operating procedure is as follows.

1. Generating an initial population. An initial population is generated from the initial data (11), with account of the symmetry of linguistic terms description (see Fig. 4).

For the input and output variables of FC, the initial chromosome populations have the form

$$(a_{10}, a_{20}, a_{30}),\ (b_{10}, b_{20}, b_{30}). \qquad (12)$$

In accordance with the chromosomes (12), the value of fitness function (FF) is calculated by formula (2).

2. Determining values ranges for genes. It is presumed that the value of each gene in the chromosomes (12) is a number within specified intervals:

$$a_1^{min} \le a_1 \le a_1^{max},\ a_2^{min} \le a_2 \le a_2^{max},$$

$$a_3^{min} \le a_3 \le a_3^{max}; \qquad (13)$$

$$b_1^{\min} \le b_1 \le b_1^{\max}, \; b_2^{\min} \le b_2 \le b_2^{\max},$$

$$b_3^{\min} \le b_3 \le b_3^{\max}. \qquad (14)$$

Random choice of the values from intervals (13), (14) forms a new chromosome.

3. Creating a population. Within the value ranges (13), (14), 3 chromosomes, each of type (12), are generated in random manner. An example of chromosome generation is given in Table 4.

Since chromosome a is responsible for generation of FC input variables, and chromosome b – for generation of the output ones, then 9 chromosome combinations (each with each) are generated from the chromosomes given in Table 4.

4. Assessing fitness degree of the current population. Chromosome fitness indicator is defined as follows:

$$\text{if } I_0 < I_{ij}, \text{ then } k_{ij} = 1 \; (i = \overline{1,3}, \; j = \overline{1,3}). \qquad (15)$$

Table 4

Initial data for generating current population

Chromosome number	Chromosome designation	
	(a_1, a_2, a_3)	(b_1, b_2, b_3)
1	$a_1 = (a_{11}, a_{21}, a_{31})$	$b_1 = (b_{11}, b_{21}, b_{31})$
2	$a_2 = (a_{12}, a_{22}, a_{32})$	$b_2 = (b_{12}, b_{22}, b_{32})$
3	$a_3 = (a_{13}, a_{23}, a_{33})$	$b_3 = (b_{13}, b_{23}, b_{33})$

Otherwise, $k_{ij} = 0$.

The survival index is determined as follows:

$$\text{if } k_{ij} = 1, \text{ then } \Delta_n = I_0 - I_{ij}, \text{ where } n = \overline{1,9}. \qquad (16)$$

Otherwise, $\Delta_n = 0$.

5. Calculating survival percentage. Since the task is to select, according to fitness indicator, those population chromosomes that have the highest survival index, then the survival percentage is calculated by the following expression:

$$B_n = \left(\Delta_n / \sum_{n=1}^{9} \Delta_n \right) \cdot 100\%. \qquad (17)$$

Imagining a roulette wheel divided into percentages for each chromosome, we have to ‘spin’ it twice for each pair (father – mother). The three pairs of chromosome combinations thus selected are still just candidate chromosomes for the next population. Before actually copying them into a new population, these chromosomes have to be subjected to crossing-over and mutation [1]. In the algorithm being considered, the mutation process is not applied.

6. Building a new chromosome population. Suppose that at the previous step the pairs of chromosome combinations given in Table 5 are selected.

7. Performing crossing-over operation. The operation applies to the chromosomes having undergone selection for a new population (see Table 5). For crossing-over, we divide chromosome combinations into the input and output ones. The first part of an offspring chromosome is always formed by paternal chromosome, and the second part, by maternal chromosome.

Table 5

Example of generating a new population

Chromosome combination	Combination number	Combination
Paternal	7	$a_3 b_1$
	5	$a_2 b_2$
	7	$a_3 b_1$
Maternal	5	$a_2 b_2$
	1	$a_1 b_1$
	7	$a_3 b_1$

The offsprings of chromosome b, i. e. b_s^{Π} ($s = \overline{1.4}$), are generated similarly to the data of Table 6. Further, based on the obtained data, combinations $\left(a_m^{\Pi}, b_s^{\Pi}\right)$ are built, where $m = \overline{1.4}$, $s = \overline{1.4}$, and fitness of the found solutions is calculated again. The algorithm steps are repeated until the minimum value of integral criterion (2) is found, i. e. for all chromosome combinations, when fitness indicator k becomes equal to 0 for all the offsprings.

Performance capability of the developed GA was verified on the SS of a vertical pendulum on a trolley. An example of the process of FC parameters optimisation by means of GA is given in Table 7.

Table 6

Example of crossing-over operation

Chromosome *a* paternal	Chromosome *a* maternal	Chromosome *a* offspring
$a_{13} \mid a_{23}, a_{33}$	$a_{12} \mid a_{22}, a_{32}$	$a_1^{\Pi} = (a_{13}, a_{22}, a_{32})$
$a_{13}, a_{23} \mid a_{33}$	$a_{12}, a_{22} \mid a_{32}$	$a_2^{\Pi} = (a_{13}, a_{23}, a_{32})$
$a_{12} \mid a_{22}, a_{32}$	$a_{11} \mid a_{21}, a_{31}$	$a_3^{\Pi} = (a_{12}, a_{21}, a_{31})$
$a_{12}, a_{22} \mid a_{32}$	$a_{11}, a_{21} \mid a_{31}$	$a_3^{\Pi} = (a_{12}, a_{22}, a_{31})$
$a_{13} \mid a_{23}, a_{33}$	$a_{13} \mid a_{23}, a_{33}$	$a_4^{\Pi} = (a_{13}, a_{23}, a_{33})$

At step $i = 0$ (before GA operation start) the boundaries of terms correspond to the initial values (10), (11). At $i = 1$ (the first step of GA operation), the boundaries of terms changed within the limits of ranges (13), (14) towards improvement of the performance quality of SS with FC. The value of criterion (2) decreased from 1.26 to 0.032. The GA stopped its operation at the third step, when SS performance quality increased to IPC = 0.0071, and the result could not be improved any further. At $i = 3$, repeating of the result and termination of GA operation occurred.

Stage 10 of the synthesis algorithm for an NFC adjusted by GA is implemented in accordance with the diagram given in Fig. 3. A formal neuron is implanted in the fuzzy inference algorithm, by means of which the FC is further configured (Stage 11) regarding the weights of each inference rule in the base (see Table 2).

The development of an NFC adjusted by GA for the SS of a vertical pendulum on a trolley is complete.

Testing of the operation of an NFC adjusted by GA in the SS of a vertical pendulum on a trolley was performed with the CO subjected to random influence both of the 'white noise' type and of random pulse nature (Fig. 5, a). Given in Fig. 5, b, is an SS with NFC in direct circuit and random disturbance on the CO.

Fig. 6 features graphs of temporal changes of SS output parameter θ in the presence of random disturbance of pulse nature (see Fig. 5, a) on the CO (pendulum) at $t = 0.2$, 1.5, and 2.5 s. The graphs in Fig. 6 allow to infer that under proper adjustment an NFC ensures high quality of SS performance even if there are random disturbances on the CO.

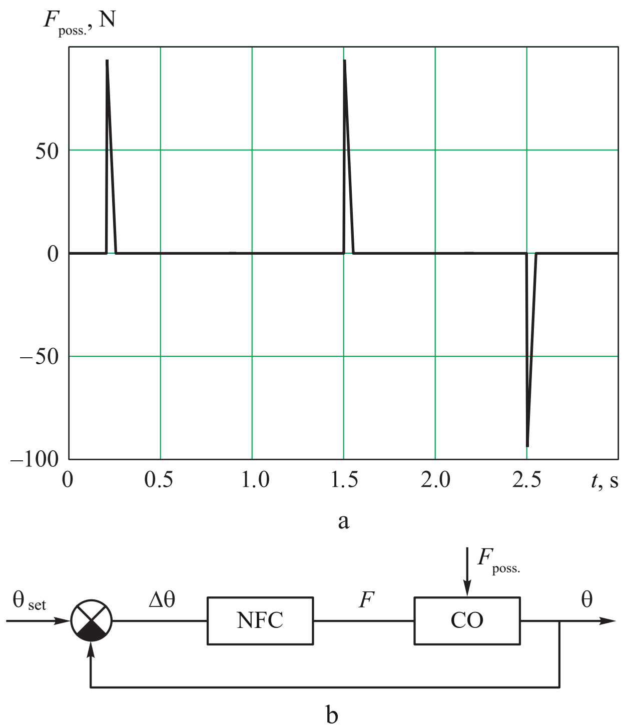

Fig. 5. Example of random disturbance on CO in the SS of vertical pendulum on a trolley (a) and SS structure (b)

Table 7

Data from the output file of software module implementing GA for FC adjustment

i	IPC	Term boundaries of FC input parameters							Term boundaries of FC output parameters						
		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	1.2614	–75.0	–45.0	–15.0	0	15.0	45.0	75.0	–285.0	–170.0	–60.0	0	60.0	170.0	285.0
1	0.322	–79.7	–58.8	–23.8	0	23.8	58.8	79.7	–204.7	–165.9	–21.7	0	21.7	165.9	204.7
2	0.0071	–71.4	–43.2	–1.0	0	1.0	43.2	71.4	–457.7	–213.3	–115.1	0	115.1	213.3	457.7
3	0.0071	–71.4	–43.2	–1.0	0	1.0	43.2	71.4	–457.7	–213.3	–115.1	0	115.1	213.3	457.7

Notes: i – GA operation step; IPC – integral performance criterion (2).

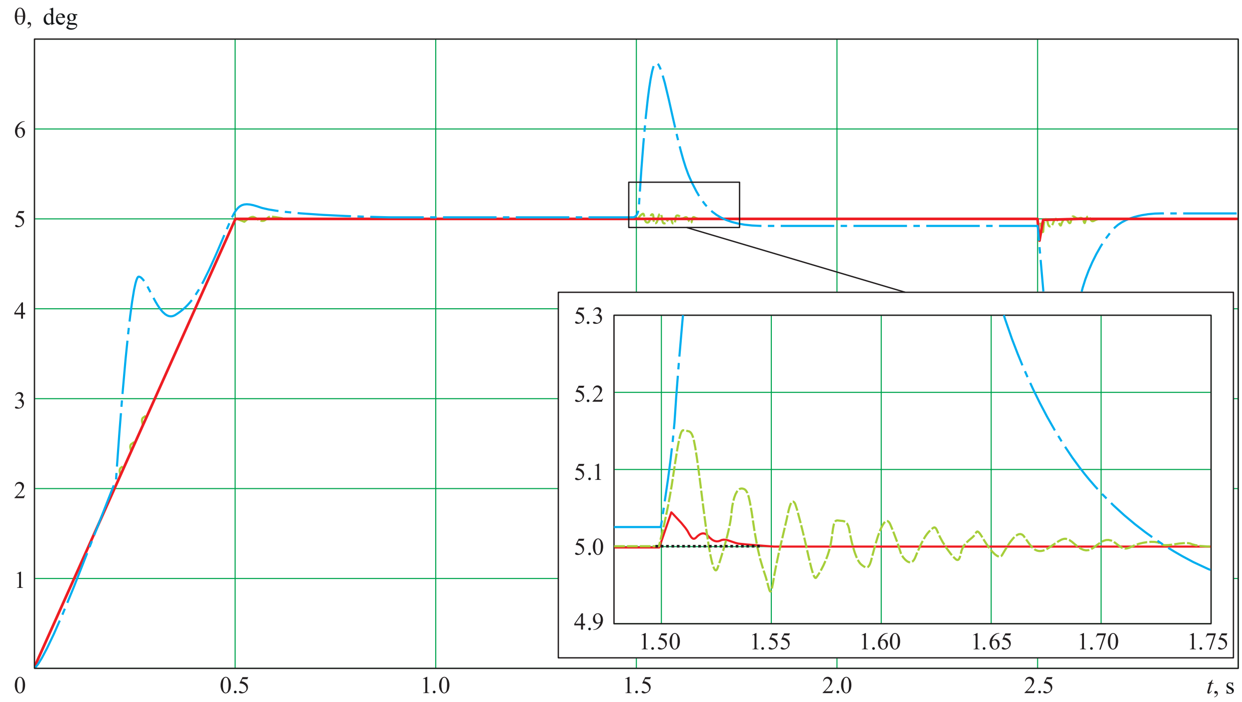

Fig. 6. Result of SS operation testing with different controller types in the presence of random disturbances: – FC; – test input signal; – NFC; – PID controller

Conclusion

The methodology of NFC synthesis proposed in the paper has been tested under conditions of limited initial data volume (learning sample volume), which does not affect the quality of algorithm performance. Just two or three values of the sample parameters are sufficient to generate ranges for the term boundaries of fuzzy variables, whereupon the optimal values are picked by the GA. In the absence of the initial data (no learning sample), the developed GA will still be able to accomplish its task, but the ranges for the values of term boundaries will have to be set wider, without referencing to the learning sample values, and the number of steps in GA reckoning will increase by a factor of hundreds.

The developed synthetic methodology of NFC adjusted by GA can be recommended for application in development of stabilisation systems for controllable unmanned aerial vehicles.

Bibliography

1. *Rutkowska D., Piliński M., Rutkowski L.* Sieci neuronowe, algorytmy genetyczne i systemy rozmyte. M.: Goriachaya liniya. Telekom, 2004. 452 p. (Russian)

2. *Vasilyev V. I., Ilyasov B. G.* Intellektualnye sistemy upravleniya. Teoriya i praktika. M.: Radiotekhnika, 2009. 392 s. (Russian)

3. *Dorf R. C., Bishop R. H.* Modern Control Systems. M.: Laboratoriya Bazovykh Znaniy, 2004. 832 p. (Russian)

4. *Piegat A.* Fuzzy Modeling and Control. M.: BINOM. Laboratoriya znaniy, 2013. 798 p. (Russian)

5. *Zolotov A. V.* Razrabotka intellektualnogo algoritma upravleniya obyektami tipa perevernutyi mayatnik. URL: http://giab-online.ru/files/Data/2014/08/59_Zolotov.pdf (request date 23.05.2017).

6. *Belyanina A. S., Rudnitsky V. A.* Metody PID i MRS regulirovaniya sistemy perevernutogo mayatnika // Resursoeffektivnym tekhnologiyam – energiyu i entuziazm molodykh: sbornik dokladov IV Universitetskoy konferentsii studentov Elitnogo tekhnicheskogo obrazovaniya. Tomsk: Izd-vo TPU, 2013. S. 107–110. (Russian)

Submitted on 21.03.2018

Pervushina Natalia Aleksandrovna – Candidate of Physical and Mathematical Sciences, Senior Research Fellow, Federal State Unitary Enterprise "Russian Federal Nuclear Center – Zababakhin All-Russian Research Institute of Technical Physics", Snezhinsk.
Science research interests: intellectual data processing systems, fuzzy and neuro-fuzzy control, algorithms of aircraft control systems.

Donovskiy Dmitriy Evgenievich – Candidate of Engineering Sciences, Head of Department, Federal State Unitary Enterprise "Russian Federal Nuclear Center – Zababakhin All-Russian Research Institute of Technical Physics", Snezhinsk.
Science research interests: aerodynamics, ballistics, flight dynamics, algorithms of aircraft control systems.

Khakimova Alisa Nailevna – Research Engineer, Federal State Unitary Enterprise "Russian Federal Nuclear Center – Zababakhin All-Russian Research Institute of Technical Physics", Snezhinsk.
Science research interests: intellectual data processing systems, fuzzy and neuro-fuzzy control.

Разработка методики синтеза нейро-нечеткого регулятора с настройкой генетическим алгоритмом

Приведена методика синтеза нейро-нечеткого регулятора с настройкой генетическим алгоритмом для динамического объекта управления. Разработаны алгоритм синтеза регулятора и генетический алгоритм настройки его параметров. Апробация методики проведена на классической задаче стабилизации вертикального маятника на подвижной тележке. Полученные результаты подтверждают работоспособность методики и позволяют сделать вывод о том, что нейро-нечеткий регулятор при соответствующей настройке обеспечивает высокое качество работы системы стабилизации, в том числе и при наличии случайных возмущений на динамический объект.

Ключевые слова: нечеткий регулятор, нейро-нечеткий регулятор, генетический алгоритм, формальный нейрон, система стабилизации.

Первушина Наталья Александровна – кандидат физико-математических наук, старший научный сотрудник Федерального государственного унитарного предприятия «Российский федеральный ядерный центр – Всероссийский научно-исследовательский институт технической физики имени академика Е. И. Забабахина», г. Снежинск.
Область научных интересов: интеллектуальные системы обработки данных, нечеткое и нейро-нечеткое управление, алгоритмы систем управления летательными аппаратами.

Доновский Дмитрий Евгеньевич – кандидат технических наук, начальник отдела Федерального государственного унитарного предприятия «Российский федеральный ядерный центр – Всероссийский научно-исследовательский институт технической физики имени академика Е. И. Забабахина», г. Снежинск.
Область научных интересов: аэродинамика, баллистика, динамика полета, алгоритмы систем управления летательными аппаратами.

Хакимова Алиса Наилевна – инженер-исследователь Федерального государственного унитарного предприятия «Российский федеральный ядерный центр – Всероссийский научно-исследовательский институт технической физики имени академика Е. И. Забабахина», г. Снежинск.
Область научных интересов: интеллектуальные системы обработки данных, нечеткое и нейро-нечеткое управление.