A Neuro-Fuzzy Expert System for the Control and Diagnostics of Helicopters Aircraft Engines Technical State

Serhii Vladov[a], Yurii Shmelov[a] and Marina Petchenko[b]

[a] *Kremenchuk Flight College of Kharkiv National University of Internal Affairs, vul. Peremohy, 17/6, Kremenchuk, Poltavska Oblast, Ukraine, 39605*
[b] *Kharkiv National University of Internal Affairs, L. Landau avenue, 27, Kharkiv, Ukraine, 61080*

Abstract

The paper has report the actual scientific and practical problem of constructing a fuzzy expert system for control and diagnostics of helicopter aircraft engines technical state in flight modes. The algorithm for control and diagnostics of air-craft engines technical state has been further developed on the basis of a modified method of diagnostic matrices and fuzzy logic, which differs from the existing ones in that due to the introduction of fuzzy expert rules corresponding to the physics of processes occurring in aircraft engines with a free turbine, it has made it possible to increase the confidence coefficient decision-making on the presence of a defect in a particular node of the flow path of helicopters aircraft engines at the stage of helicopters flight operation. The implementation of a fuzzy expert system with the use of a Wang-Mendel fuzzy neural network is proposed, which made it possible to determine on a test example the presence of a defect in the compressor, the presence of which indicates a 1 % degree of pressure increase in the compressor.

Keywords

Aircraft engine, expert system, neural network, technical state, Wang Mendel's neuro-fuzzy network, diagnostic matrix, fuzzy expert rules.

1. Introduction

The use of expert systems (ES) significantly increases the efficiency of diagnosing an aircraft gas turbine engine (GTE), since it allows you to quickly analyze a variety of information on the specifics of the current situation, develop the necessary recommendations on the possibility of eliminating a particular malfunction, take into account the nonlinearities and uncertain nature of the processes occurring in them make optimal decisions on the operation of this engine.

One of the promising ways to improve the efficiency of modern diagnostic systems is the introduction of new information computer technologies based on "soft" calculations: fuzzy logic (FL), neural networks (NS), genetic algorithms (GA), with adaptation of these technologies in the environment of hybrid dynamic ES, which allows them with equal computing power with conventional ES cover a wider range of solved problems.

ES diagnoses correlate observed system behavioral disorders with their underlying causes, relying on one of the following two methods. The first involves the use of some table of associative relationships between types of system behavior and diagnoses [1–5]. In the second method, the combined use of knowledge about how the system is constructed and knowledge about weaknesses in the design or parts used allows assumptions to be made about faults that are compatible with the observed data [2].

ICTERI-2021, Vol I: Main Conference, PhD Symposium, Posters and Demonstrations, September 28 – October 2, 2021, Kherson, Ukraine
EMAIL: ser26101968@gmail.com (A. 1); nviddil.klk@gmail.com (A. 2); marinapetcenko@gmail.com (B. 1)
ORCID: 0000-0001-8009-5254 (A. 1); 0000-0002-3942-2003 (A. 2); 0000-0003-1104-5717 (B. 1)

CEUR Workshop Proceedings (CEUR-WS.org)

The computing power of the ES is determined, first of all, by the accumulated knowledge base (KB), which stores the reference data describing the area under consideration, and the rules describing the expedient transformations of this area. Modern hybrid diagnostic ES [2, 5] make it possible to operate with fuzzy definitions, allowing more efficient use and storage of acquired knowledge, facilitating the process of their acquisition, and the system as a whole becomes more flexible.

The ES mobility is due to the mobility of the knowledge base and the possibility of its replenishment from various information components (databases (DB), expert knowledge bases (EKB), conceptual knowledge bases (CKB), dynamic files, etc.), as well as various output procedures. Concretization of knowledge in solving diagnostic problems decomposes them into exact and inaccurate, complete and incomplete, static and dynamic, unambiguous and ambiguous, etc. In addition, the expert knowledge itself is inaccurate due to its subjective nature. The approximation and ambiguity of knowledge lead to the fact that ES deals with not one, but with several alternative areas [6]. Therefore, the incompleteness of knowledge makes it possible to use not one, but several sources of knowledge, which is especially important when operating a GTE of the fifth or sixth generations, which require the involvement of intelligent systems capable of effectively localizing a failure, eliminating a malfunction, adjusting parameters and predicting the current state (resource) etc.

When creating the ES for diagnostics and control of GTE parameters, a number of features related to the following were taken into account:

– with the object under study (the number of diagnosed and monitored parameters, model adaptation (accuracy, assumptions), measurement errors);

– with the ES architecture (interaction of information flows, organization of databases (DB) and knowledge (KB) (bases of conceptual and expert knowledge));

– with the adaptation of "soft" computing in the environment of ES and its subsystems;

with the skill level of the user in solving the tasks assigned to him.

2. Fundamentals of methods of application of expert systems in tasks of control and diagnostics of aircraft engines technical state

Control and diagnostics ES of GTE technical state, based on fuzzy logic, known and implemented in the works of Vladimir Vasiliev, Serhii Zhernakov, Serhii Enchev [7–9]. But the shells of these systems are configured only for the GTE bench diagnostics (and only for the class of turbojet engines) and are in no way configured for use in the flight operation of an aircraft, including a helicopter.

The methodology of the developed expert systems of control and diagnostics of the technical condition of aircraft engines, including, in relation to the engine TV3-117, it is proposed to use the method FDI (Fault Detection and Identification), based on a comparison of the results of measurements of gas-dynamic indicators in real time with formulary indicators (fig. 1) [7–10]. In this case, the process of recognizing the technical state and making on the basis of this appropriate decision in the aggregate performs the function of a classifier.

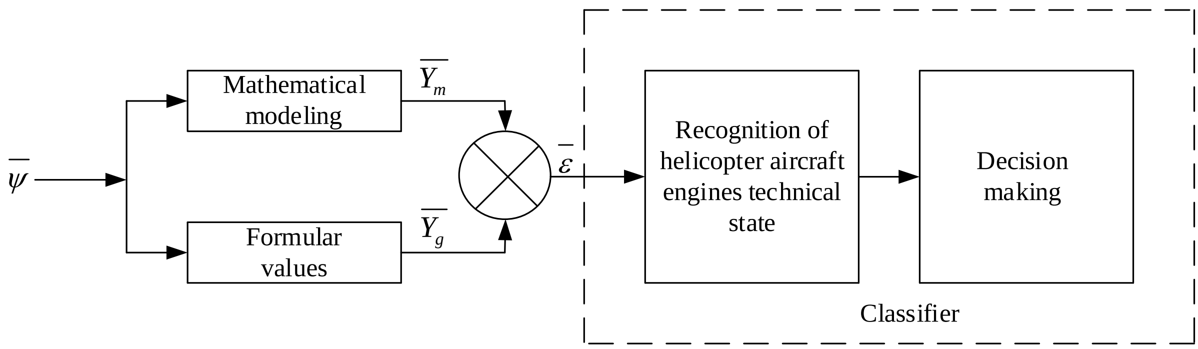


Figure 1: FDI-method implementation [7–10]

Fig. 1 shows are: $\overline{\psi}$ – vector of control actions; $\overline{Y_m}$ – vector of parameters obtained from the results of mathematical modeling of gas-dynamic processes in real time; $\overline{Y_g}$ – vector of form values representing measurement data obtained by sensors; $\overline{\varepsilon} = \overline{Y_g} - \overline{Y_m}$ – residual obtained in the process of componentwise comparison of vectors $\overline{Y_g}$ and $\overline{Y_m}$.

In the process of implementing this method it is necessary to solve the following tasks:
– development and software implementation of aircraft GTE model;
– calculation of mismatch (discrepancy) and recognition of GTE technical state;
– making a decision on aircraft GTE technical state.

The use of fuzzy logic elements in ES [11, 12] allows the latter to separate the classes of aircraft GTE technical state under conditions of incompleteness of the measured information, as well as taking into account the constructive and parametric uncertainty of the characteristics of a real aircraft GTE.

3. Fuzzy expert system for control and diagnostics of helicopter aircraft engines technical state

The developed fuzzy ES contains four components that work sequentially (fig. 2): the translator translates concepts into axioms, and the problems being solved into theorems; synthesizer builds theorem proofs; the generator extracts an algorithm from the proof; the interpreter evaluates the result. All calculations in this ES are performed at the object level.

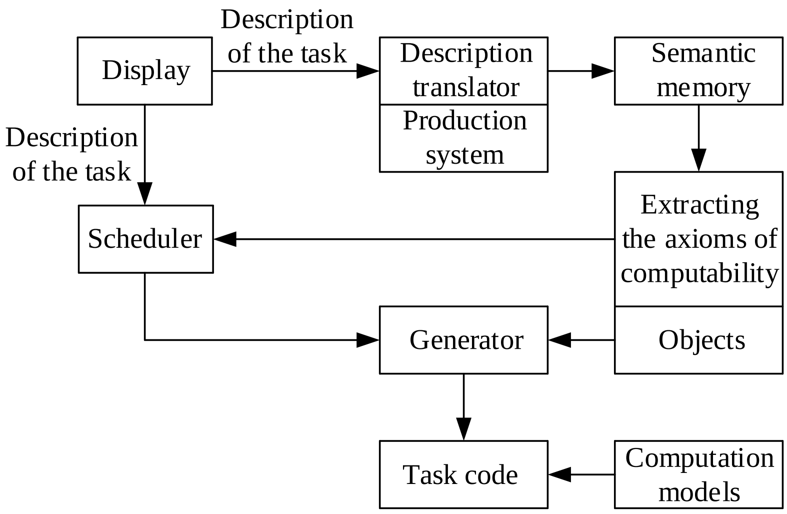


Figure 2: The process of solving problems in fuzzy ES control and diagnostics of helicopter aircraft engines technical state (for example, a turboshaft engine with a free turbine – TV3-117)

The rules in this ES have the form of implications, and express facts and laws, by which new facts and dependencies can be derived (build descriptions, create objects). Descriptions of the task to be solved by the ES are stored in the semantic memory [13]. They can be specified directly in the task conditions or copied from semantic memory implemented on the basis of a hierarchical file system.

In the mathematical aspect, the computational model in the expert system can be represented:

$$W = \langle A, D, B, D_B, F, H \rangle; \tag{1}$$

where A – attribute set; D – set of their corresponding domains; elements B have the form $X \rightarrow Y$; where X and Y – some subsets of the set A. The set B corresponds to the domain D_B, the elements of which are certain programs with input parameters X and output parameters Y. These programs, when substituting values from D_i into X, calculate the D_j values of those attributes that correspond to Y. F – set of descriptions of the types of all functional dependencies used in B, and H defines the set of relations (predicates) over the set of attributes A.

The proposed method of solving the problems of control and diagnosis of GTE on the basis of the FDI-method implies, in contrast to existing classical methods that use tight tolerances on the controlled and diagnosed parameters, as well as hard limits of variation coefficients, linking the experimental and calculated data at the stages of localization of defects in GTE, to apply the rules of fuzzy logic, based on adaptation of the calculated mathematical model to real GTE, taking into account specific external conditions, as well as knowledge and experience of experts for making rights decisions about of aircraft engine technical state.

In this work, as in [7–10], the elements of fuzzy logic are proposed to be used in conjunction with such classical methods as [5, 14–16]:

– method of diagnostic matrices (Urban's matrices);

– variation of the coefficients of engine state parameters, in order to minimize the discrepancies between the measured and calculated parameters of aircraft GTE.

The mathematical model of the aircraft engine being diagnosed is tuned to an individual GTE (for example, TV3-117), taking into account the dispersion of compressor characteristics parameters. The solution to this problem was carried out in two stages:

– direct problem, for the solution of which the statistics of characteristic defects that appeared during the operation of this GTE (for example, TV3-117), as well as similar statistics obtained on an adequate mathematical model (fig. 3) [7–9] were used;

– the inverse problem, the solution of which allows for the resulting vector of deviations (component-wise comparison of the parameters of the mathematical model and measured data from standard sensors) to make a decision on the actual technical state of the GTE (for example, TV3-117) (fig. 4).

–

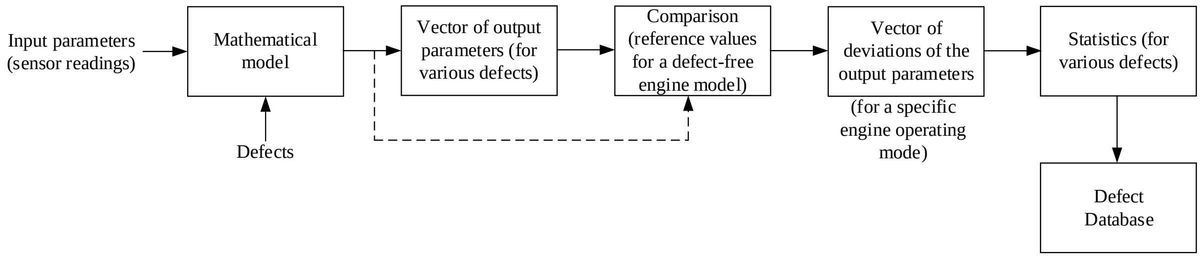


Figure 3: Defect database formation process [7–9]

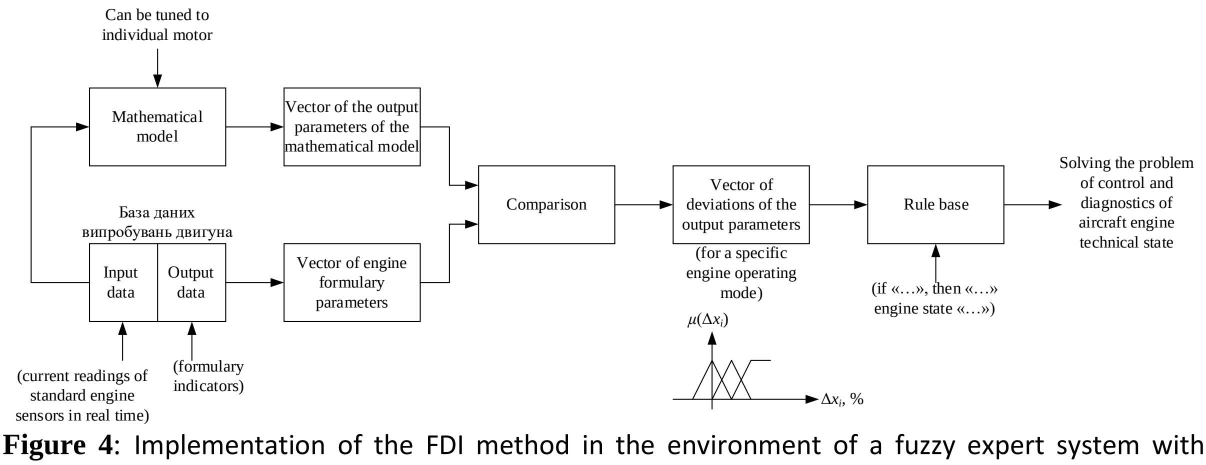


Figure 4: Implementation of the FDI method in the environment of a fuzzy expert system with decision-making based on fuzzy logic [7–9]

The analysis of statistical data on characteristic defects in GTE nodes, as well as their addition by simulation (introduction of a defect) on the mathematical model of the GTE made it possible to construct a diagnostic matrix (table 1) in the form [7–9]:

$$DEF_{\gamma_i} = \overline{M_p}; \tag{2}$$

where γ_i – first column of the matrix containing simulated defects; $i = 1 \ldots N$ – number of defects; $\overline{M_p}$ – vector of parameters obtained in the course of calculations using the component mathematical model (reaction to the manifestation of a defect); $p = 1 \ldots K$ – number of measured parameters.

The first row of this matrix (table 1) is the reference state of the GTE, containing zero values. All subsequent lines are deviations from the reference state due to the manifestation of the defect.

Table 1

Fragment of the diagnostic matrix of TV3-117 aircraft engine parameters

Modified by the instrumental method			Thermogasdynamic parameters								State
			Calculated using a mathematical model of the engine						Flow indicators		
n_C	…	…	…	ΔT_C^*	…	ΔP_G^*	…	ΔP_{TC}^*	ΔG_A	ΔG_F	
…	…	…	…	0		0	…	0	…	…	Etalon
…	…	…	…	–0.18		–0.23	…	0.21	…	…	π_K^* (1 %)
…	…	…	…	…		…	…	…	…	…	…

The inverse diagnostic matrix is obtained by converting the diagnostic matrix to the form:

$$\overline{M_p} = DEF_{\gamma_i}. \quad (3)$$

Adaptation of the diagnostic matrix in the expert knowledge base is carried out in the form of products, and at the logical level the topmost line of the matrix is attributes of the expert knowledge base, and the following lines are attribute values. Analysis of this diagnostic matrix shows that introducing a defect in a particular engine component (simulation on a component mathematical model in the process of decoupling "direct" diagnostic problem, leads to a significant change in several parameters in the row. Conducting an ordinal estimation of change of parameters of the engine on occurrence in it of this or that defect, it is possible to construct the table, on the one hand characterizing change of behavior of each separate parameter, and on the other hand minimizing quantity of standard sensors (the most essential are allocated) (table 2). The sign "minus" in the matrix lines shows the tendency to decrease the value of measured parameter, and the sign "plus" to its increase [7–9].

Table 2

Fragment of the formation of the base of fuzzy rules based on the diagnostic matrix

Modified by the instrumental method			Thermogasdynamic parameters								State
			Calculated using a mathematical model of the engine						Flow indicators		
n_C	…	…	…	ΔT_C^*	…	ΔP_G^*	…	ΔP_{TC}^*	ΔG_A	ΔG_F	
…	…	…	…	0		0	…	0	…	…	Etalon
…	…	…	…	–		–	…	+	…	…	π_K^* (1 %)
…	…	…	…	…		…	…	…	…	…	…

These lines formed the basis for the creation of an expert knowledge base, which is formed on the basis of table. 3 and membership functions of the corresponding linguistic variables T_N, T_C, P_G and P_{CT} (fig. 5).

Thus, the expert knowledge base (rule base) at the logical level will have the form shown in table 3. In this state, the expert system is "trained" only to recognize of GTE actual technical state, provided that the vector of deviations of the output parameters of the GTE contains residuals corresponding to a 5 % change in the parameters of its nodes.

Table 3
Fragment of the base of fuzzy expert rules

No		Rule		Result
1	IF	$(\Delta T_N = MN) \wedge (\Delta T_C = Z) \wedge (\Delta P_G = MP) \wedge (\Delta P_{CT} = Z)$	THEN	$Y_1 = \pi_C^*$
2		… … … … … … … … … …		… … …

Table 3 shows a fragment of the base of fuzzy rules and the corresponding linguistic variables: LN (Large Negative) – very small; MN (Middle Negative) – small; Z (Zero) – about zero; MG (Middle Positive) – average; LP (Large Positive) – very large.

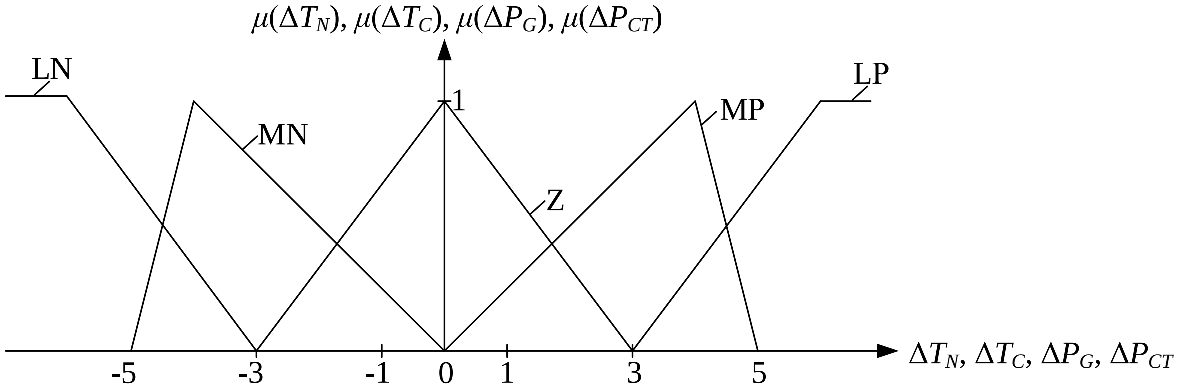


Figure 5: Membership functions of linguistic variables T_N, T_C, P_G and P_{CT}

In the given example for a line which symbolizes decrease in degree of increase of pressure in the compressor by 1 %, having applied fig. 5 can be found: $\mu_Z(\Delta T_N)$ = 0,97, $\mu_{MN}(\Delta T_N)$ = 0,03, $\mu_Z(\Delta T_C)$ = 0,92, $\mu_{MN}(\Delta T_C)$ = 0,08, $\mu_Z(\Delta P_G)$ = 0,86, $\mu_{MN}(\Delta P_G)$ = 0,14, $\mu_Z(\Delta P_{CT})$ = 0,89, $\mu_{MP}(\Delta P_{CT})$ = 0,11.

4. Implementation of a fuzzy expert system for control and diagnostics of helicopter aircraft engines technical state using neural network technologies

In this paper, the practical implementation of a fuzzy expert system using the Vang-Mendel fuzzy neural network, based on the Takagi-Sugeno-Kang fuzzy inference system (TSK) [17] in the conditions of helicopter flight operation is proposed based on the Takagi-Sugeno-Kang (TSK) [18, 19] fuzzy inference system (fig. 6).

The Wang-Mendel fuzzy neural network consists of four layers. The first layer fuzzifies the input variables x_j(j = 1, 2, …, N), determining for each i-th rule of the output the value of the membership coefficient $\mu_A^{(i)}(x_j)$ in accordance with the applied fuzzification function. This is a parametric layer with ($c_j^{(i)}$, $\sigma_j^{(i)}$, $b_j^{(i)}$) parameters to be adapted during training.

The second layer aggregates the activation values of the condition, determining the resulting value of the $w_i = \mu_A^{(i)}(x)$ membership coefficient for the vector x. This layer is nonparametric.

The third (linear) layer aggregates M inference rules (first neuron) and generates a normalizing signal (second neuron). This is a parametric layer in which the linear weights v_i for i = 1, 2, …, M are subject to adaptation, interpreted as the center c_k of the membership function of the corollary of the k-th fuzzy inference rule.

The fourth layer consists of one output neuron and performs normalization, forming the output signal $y(x)$. This is a nonparametric layer.

Thus, the neural network implements the approximation function, which can be written as:

$$y(x)=\frac{1}{\sum_{k=1}^{M}\left[\prod_{j=l}^{N}\mu_A^{(k)}(x_j)\right]}\cdot\sum_{k=1}^{M}\upsilon_k\left[\prod_{j=1}^{N}\mu_A^{(k)}(x_j)\right]. \tag{4}$$

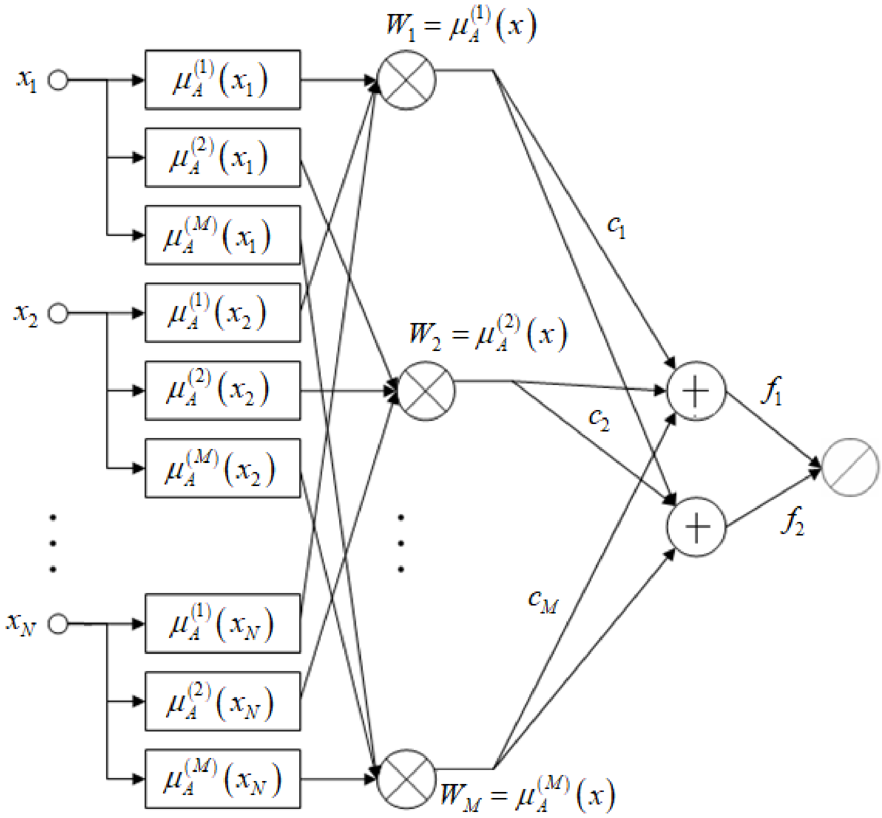


Figure 6: The structure of Wang Mendel's neuro-fuzzy network [16]

5. Wang-Mendel fuzzy neural network training

At the start of training the Wang-Mendel neuro-fuzzy network, the parameters to be adapted are divided into two groups: the linear parameters p_{ij} of the third layer and the parameters of the nonlinear membership function of the first layer. Refinement of parameters is carried out in two stages [20].

At the first stage, when fixing certain values of the parameters of the membership function by solving a system of linear equations, linear parameters are calculated (in the first cycle, these are the values obtained as a result of initialization). With known values of the membership function, dependence (4) can be represented in a linear form.

$$y(x)=\sum_{i=1}^{M}w_i'\left(p_{i0}+\sum_{j=1}^{N}p_{ij}x_j\right); \tag{5}$$

where $w_i'=\frac{\prod_{j=1}^{N}\mu_A^{(i)}(x_j)}{\sum_{i=1}^{M}\left[\prod_{j=1}^{N}\mu_A^{(i)}(x_j)\right]}=\text{const}$ for i = 1, 2, …, M.

With p training samples ($x(t)$, $d(t)$) (t = 1, 2, ..., p) and replacing the output signal of the network with the expected value $d(t)$, we obtain a system of p linear equations of the form:

$$\begin{bmatrix} w'_{11} & w'_{11}x_1^{(1)} & \dots & w'_{11}x_N^{(1)} & \dots & w'_{1M} & w'_{1M}x_1^{(1)} & \dots & w'_{1M}x_N^{(1)} \\ w'_{21} & w'_{21}x_1^{(2)} & \dots & w'_{21}x_N^{(2)} & \dots & w'_{2M} & w'_{2M}x_1^{(2)} & \dots & w'_{2M}x_N^{(2)} \\ & \dots & & \dots & & & \dots & & \\ w'_{p1} & w'_{p1}x_1^{(p)} & \dots & w'_{p1}x_N^{(p)} & \dots & w'_{pM} & w'_{pM}x_1^{(p)} & \dots & w'_{pM}x_N^{(p)} \end{bmatrix} \cdot \begin{bmatrix} p_{10} \\ \dots \\ p_{1N} \\ \dots \\ p_{M0} \\ \dots \\ p_{MN} \end{bmatrix} = \begin{bmatrix} d^{(1)} \\ d^{(2)} \\ \dots \\ d^{(p)} \end{bmatrix}; \quad (6)$$

where w'_{ti} denotes the level of activation (weight) of the condition of the *i*-th rule upon presentation of the *t*-th input vector *x*. This expression can be written in abbreviated matrix form:

$$\mathbf{A} \cdot \mathbf{p} = \mathbf{d}. \quad (7)$$

The dimension of the matrix **A** is equal to $p \times (N + 1) \cdot M$, while the number of rows is much greater than the number of columns $(N + 1) \cdot M$. Using the pseudo-inversion of matrix **A**, the solution can be obtained in one step:

$$\mathbf{p} = \mathbf{A}^{+} \cdot \mathbf{d}. \quad (8)$$

where $\mathbf{A}^{+}$ – pseudo-inversion of the matrix **A**. The pseudo-inversion of the matrix **A** consists in performing the SVD decomposition with subsequent reduction of its dimension [20].

At the second stage, after fixing the values of the linear parameters p_{ij}, the actual output signals $y(t)$ of the network for $t = 1, 2, ..., p$ are calculated, for which the linear dependence is used:

$$\mathbf{y} = \begin{bmatrix} y^{(1)} \\ y^{(2)} \\ \dots \\ y^{(p)} \end{bmatrix} = \mathbf{A} \cdot \mathbf{p} \quad (9)$$

followed by the error vector $\varepsilon = y - d$. The error signals are sent through the connected network towards the network input (backpropagation) up to the first layer, where the components of the objective function gradient with respect to specific parameters ($c_j^{(i)}$, $\sigma_j^{(i)}$, $b_j^{(i)}$) can be calculated. After the formation of the gradient vector, the parameters are refined using one of the gradient learning methods, for example, the steepest descent method. When applying the steepest descent method, the corresponding adaptation expressions take the form:

$$c_j^{(i)}(t+1) = c_j^{(i)}(t) - \eta_c \frac{\partial E(t)}{\partial c_j^{(i)}}; \quad (10)$$

$$\sigma_j^{(i)}(t+1) = \sigma_j^{(i)}(t) - \eta_\sigma \frac{\partial E(t)}{\partial \sigma_j^{(i)}}; \quad (11)$$

$$b_j^{(i)}(t+1) = b_j^{(i)}(t) - \eta_b \frac{\partial E(t)}{\partial b_j^{(i)}}; \quad (12)$$

where *n* – number of the next iteration.

After the refinement of the nonlinear parameters, the process of adapting the linear parameters of the TSK function (first stage) and nonlinear parameters (second stage) is started again. This cycle is repeated until all process parameters are stabilized.

Expressions (10) – (12) require the calculation of the gradient of the objective function relative to the parameters of the membership function. The final form of these expressions depends both on the used definition of the error function at the output of the network, and on the form of the membership function. When using the generalized Gaussian function $\mu_A(x) = \dfrac{1}{1 + \left(\dfrac{x-c}{\sigma}\right)^{2b}}$, the corresponding expressions for the gradient of the objective function $E=\frac{1}{2}\sum_{i=1}^{p}\left(y\left(x^{(l)}\right)-d^{(l)}\right)^2$ for one pair of training data (x, d) take the values:

$$\frac{\partial E}{\partial c_j^{(i)}}=\left(y(x)-d\right)\sum_{i=1}^{M}\left[p_{i0}+\sum_{j=1}^{N}p_{ij}x_j\right]\frac{\partial w_i'}{\partial c_j^{(i)}}; \tag{13}$$

$$\frac{\partial E}{\partial \sigma_j^{(i)}}=\left(y(x)-d\right)\sum_{i=1}^{M}\left[p_{i0}+\sum_{j=1}^{N}p_{ij}x_j\right]\frac{\partial w_i'}{\partial \sigma_j^{(i)}}; \tag{14}$$

$$\frac{\partial E}{\partial b_j^{(i)}}=\left(y(x)-d\right)\sum_{i=1}^{M}\left[p_{i0}+\sum_{j=1}^{N}p_{ij}x_j\right]\frac{\partial w_i'}{\partial b_j^{(i)}}. \tag{15}$$

Derivatives $\frac{\partial w_i'}{\partial c_j^{(i)}}$, $\frac{\partial w_i'}{\partial \sigma_j^{(i)}}$, $\frac{\partial w_i'}{\partial b_j^{(i)}}$, defined based on dependencies w_i' and $\mu_A\left(x\right)$, can be written as

$$\frac{\partial w_k'}{\partial c_j^{(i)}}=\frac{\delta_{ki}m\left(x_j\right)-l\left(x_j\right)}{\left[m\left(x_j\right)\right]^2}\prod_{s=1,s\neq j}^{N}\left[\mu_A^{(i)}\left(x_s\right)\right]\frac{\left[\frac{2b_j^{(i)}}{\sigma_j^{(i)}}\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}-1}\right]}{\left[1+\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}}\right]^2}; \tag{16}$$

$$\frac{\partial w_k'}{\partial \sigma_j^{(i)}}=\frac{\delta_{ki}m\left(x_j\right)-l\left(x_j\right)}{\left[m\left(x_j\right)\right]^2}\prod_{s=1,s\neq j}^{N}\left[\mu_A^{(i)}\left(x_s\right)\right]\frac{\left[\frac{2b_j^{(i)}}{\sigma_j^{(i)}}\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}}\right]}{\left[1+\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}}\right]^2}; \tag{17}$$

$$\frac{\partial w_k'}{\partial b_j^{(i)}}=\frac{\delta_{ki}m\left(x_j\right)-l\left(x_j\right)}{\left[m\left(x_j\right)\right]^2}\prod_{s=1,s\neq j}^{N}\left[\mu_A^{(i)}\left(x_s\right)\right]\frac{\left[-2\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}}ln\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)\right]}{\left[1+\left(\frac{x_j-c_j^{(i)}}{\sigma_j^{(i)}}\right)^{2b_j^{(i)}}\right]^2}; \tag{18}$$

for для k = 1, 2,…, M, where δ_{ki} – Kronecker delta, $l\left(x_j\right)=\prod_{j=1}^{N}\mu_A^{(i)}\left(x_s\right)$, $m\left(x_j\right)=\sum_{i=1}^{M}\left[\prod_{j=1}^{N}\mu_A^{(i)}\left(x_s\right)\right]$.

In the practical implementation of this method of training fuzzy networks, the dominant factor in their adaptation is the first stage, at which the weights p_{ij} are selected using pseudo-inversion in one step. To balance its influence, the second stage (selection of nonlinear parameters by the gradient method) is repeated many times in each cycle.

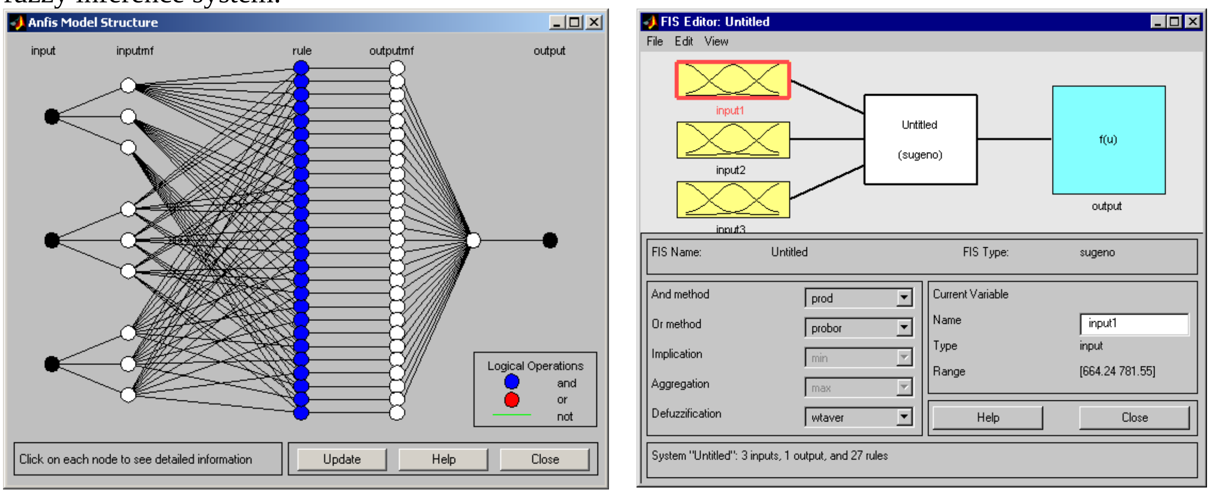
6. Results and discussion

As an example, a test version of the Wang-Mendel neuro-fuzzy network was developed in Matlab, illustrating the change in the degree of pressure increase in the compressor by 1 %, that is, $Y_1=\pi_C^*$ (see table 3) at a constant ambient temperature, that is, T_N = const. The corresponding input variables (in absolute units) are given in table 4.

Table 4
Fragment of the base of fuzzy expert rules

First input variable, T_C	Second input variable, P_G	Third input variable, P_{CT}	Output variable, π_C
1.000	1.000	1.000	9.400
0.973	0.817	0.898	9.306
0.984	0.884	0.933	9.307
0.966	0.767	0.854	9.305
0.975	0.812	0.893	9.306
0.953	0.693	0.808	9.304
0.974	0.821	0.895	9.306
0.975	0.819	0.891	9.306
0.966	0.774	0.849	9.305
0.951	0.769	0.804	9.304
0.951	0.691	0.805	9.304
0.973	0.813	0.892	9.306
0.967	0.761	0.852	9.305
0.962	0.765	0.856	9.305
0.963	0.773	0.851	9.305
0.975	0.815	0.889	9.306
0.974	0.814	0.892	9.306
0.952	0.685	0.809	9.304
0.968	0.762	0.858	9.305
0.952	0.688	0.803	9.304
0.976	0.816	0.887	9.306
0.986	0.879	0.935	9.307
0.985	0.875	0.938	9.307
0.965	0.763	0.849	9.305
0.975	0.819	0.896	9.306

Fig. 7, *a* show the structure of the generated fuzzy inference system, and fig. 7, *b* – generated fuzzy inference system.



a)　　　　　　　　　　*b*)

Figure 7: Wang Mendel's neuro-fuzzy network: *a* – structure of the generated fuzzy inference system; *b* – generated fuzzy inference system editor

Fig. 8, *a* show a graph of the dependence of training errors on the number of training cycles (according to the training results, the average error is only approximately 0.007 at 100 cycles), fig. 8, *b* – results of determining the degree of pressure increase.

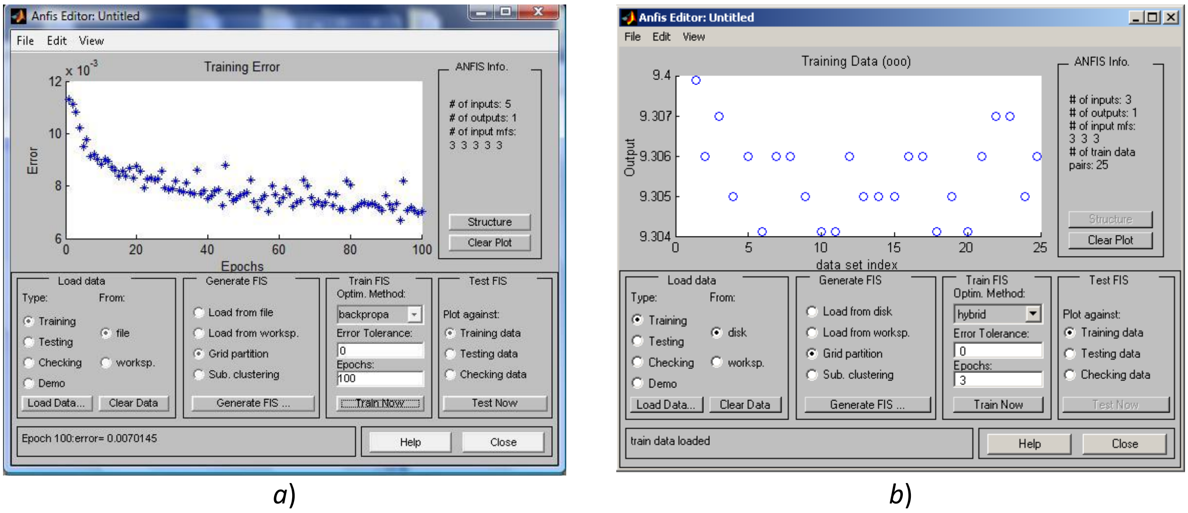


Figure 8: Wang Mendel's neuro-fuzzy network: *a* – graph of dependence of learning errors on the number of training cycles; *b* – results of determining the degree of pressure increase in the compressor in ANFIS graphical editor

Fig. 9 show a test example of the surface of the technical state classes of the aircraft engine TV3-117, implemented in the Matlab software environment (Fuzzy-Logic Toolbox) based on the fuzzy rule "IF $(\Delta T_C = Z)\wedge(\Delta P_G = MP)\wedge(\Delta P_{CT} = Z)$, THEN $Y_1 = \pi_C^*$ " with T_N = const.

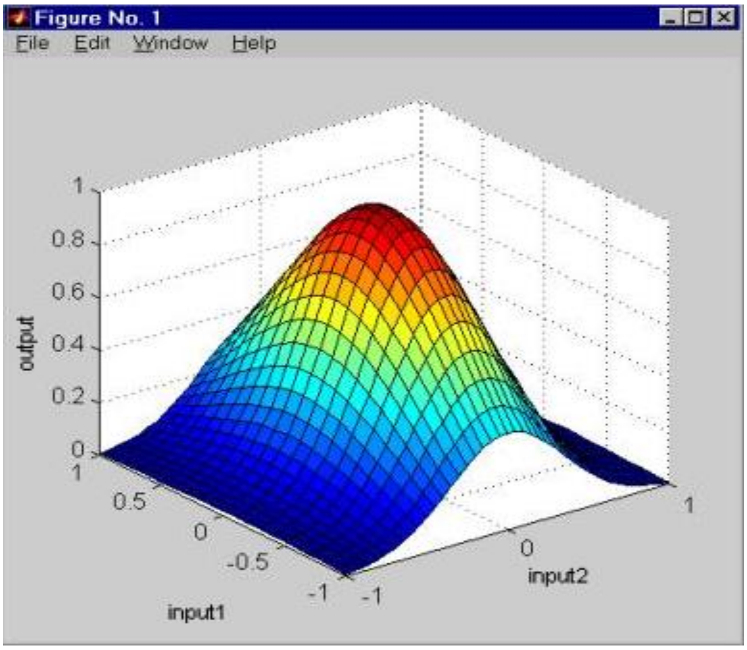


Figure 9: TV3-117 aircraft engine technical states surface classes, implemented in Fuzzy-Logic Toolbox

Thus, the accuracy of control and diagnostics of complex dynamic objects technical state, which include helicopters aircraft engines with a free turbine (for example, TV3-117), depends on the number of rules and the absence of contradictions between them. The use of a control and diagnostics system based on neuro-fuzzy expert systems will make it possible to diagnose of helicopters aircraft engines with a free turbine (for example, TV3-117) technical state in real time with high accuracy, predict and prevent the occurrence of emergency modes, thereby increasing the engine's service life.

A theoretical description of the methodological approach to assessing the effectiveness of the implementation of neuro-fuzzy expert system of control and diagnosis of the technical condition of aircraft helicopter engines in the aviation industry enterprises with the help of rating assessment is proposed:

1. The effect of innovative transformations for each classification feature is assessed by the level of significance (five classification features are used: technical, marketing, economic, environmental, social effect).

2. For each type of economic effects (seven types), the effect is calculated based on the sum of the ratings in the context of classification features.

3. The overall effect is determined by the sum of ratings for all types of economic effects.

The level of the qualitative overall effect of innovative transformations is assessed depending on the value of the overall effect (low, medium, high).

7. Conclusions

The paper posed and solved the problem of creating intelligent systems for control and diagnostics of helicopters aircraft engines technical state in flight modes using its reconfigurable mathematical model and organizing control and diagnostics based on the method of diagnostic matrices and rules of fuzzy logic.

An algorithm for control and diagnostics of aircraft engines technical state was further developed on the basis of a modified method of diagnostic matrices and rules of fuzzy logic as applied to the class of turboshaft engines (aircraft engines with a free turbine), the use of which allows efficient and high-quality control and diagnostics of helicopters aircraft engines technical state.

Engineering techniques have been developed for the implementation of the considered methods and algorithms for creating a research prototype of a fuzzy expert system for control and diagnostics of helicopters aircraft engines technical state using a fuzzy Wang-Mendel neural network, which is based on the Takagi-Sugeno-Kang fuzzy inference system, which allows its practical implementation on board the helicopter.

The study of the problem of detecting a defect in the compressor of TV3-117 aircraft engine, carried out in this work, showed that the developed methods made it possible to increase the confidence in decision-making on the serviceability of the compressor to 0.86 in comparison with [6–8], and fuzzy neural networks are the most suitable for solving its tasks.

The advantage of the fuzzy expert system for control and diagnostics of helicopters aircraft engines technical state in flight modes is the ability of the neural network to learn and the ability to correct the settings of the Wang-Mendel fuzzy neural network to changing influences – the engine thermogasdynamic parameters.

8. References

[1] A. Niederlinski, J. Kasprzyk, J. Figwer, Intelligent Identification: Decision Trees or Knowledge Bases? IFAC Proceedings Volumes, 1994, vol. 27, issue 8, pp. 767–772.

[2] Z. Nagoev, I. Pshenokova, O. Nagoeva, Z. Sundukov, Learning algorithm for an intelligent decision making system based on multi-agent neurocognitive architectures, Cognitive Systems Research, 2021, vol. 66, pp. 82–88.

[3] V. I. Vasiliev, S. V. Zhernakov, Expert systems: Management of the operation of complex technical objects, Ufa State Aviation Technical University, Ufa, 2003.

[4] J. Ye, J. Zhan, Z. Xu, A novel decision-making approach based on three-way decisions in fuzzy information systems, Information Sciences, 2020, vol. 541, pp. 362–390.

[5] A. M. Pashayev, D. D. Askerov, C. Ardil, R. A. Sadiqov, P. S. Abdullayev, Condition monitoring system of aircraft gas turbine engine complex, International Journal of Aerospace and Mechanical Engineering, 2007, vol. 1, no 11, pp. 689–695.

[6] A. L. Zadeh, A. M. Abbasov, R. R. Yager, S. N. Shahbazova, Z. Marek. Reformat: Recent Developments and New Directions in Soft Computing, STUDFUZZ, 2014, vol. 317, 474 p.

[7] S. V. Enchev, S. S. Tovkach, Diagnostic of the Technical Condition Aviation Engines is Based on Fuzzy logic, Scientific Bulletin Kherson State Maritime Academy, 2013, no 1 (8), pp. 216–224.
[8] V. I. Vasiliev, S. V. Zhernakov, Control and diagnostics of aircraft engine technical state based on expert systems, Bulletin of USATU, 2007, vol. 9, no 4 (22), pp. 11–23.
[9] S. V. Zhernakov, R. F. Ravilov, Control and diagnostics of aircraft engine technical state based on the C-Priz expert system, Bulletin of USATU, 2012, vol. 16, no 6 (51), pp. 3–11.
[10] Yu. M. Shmelov, S. I. Vladov, A. S. Khebda, K. G. Kotliarov, Application of the rules of urban logic in the problem of identification of the technical state of the aviation engine TV3-117, Scientific notes of Taurida National V.I. Vernadsky University. Series: Technical Sciences, 2018, vol. 30 (69), no 3, pp. 34–40.
[11] A. P. Rotshtein, H. B. Rakytyanska, Fuzzy Evidence in Identification, Forecasting and Diagnosis, Springer, 2012.
[12] A. Zilouchian, M. Jamshidi, Intelligent control systems using soft computing methodologies, CRC Press, Boca Raton, 2001.
[13] M. Wolski, A. Gomolinska, Data meaning and knowledge discovery: Semantical aspects of information systems, International Journal of Approximate Reasoning, 2020, vol. 119, pp. 40–57.
[14] V. Vlasov, M. Addibpaur, E. Tyugu, NUTS: A distributed object-oriented platform with high-level communication functions, Computers and Artificial Intelligence, 1998, vol. 17, no 4, pp. 305–335.
[15] M. van Steen, A. S. Tanenbaum, A brief introduction to distributed systems, Computing, 2016, vol. 98, pp. 967–1009.
[16] F. Behe, S. Galland, N. Gaud, C. Nicolle, A. Koukam, An ontology-based metamodel for multiagent-based simulations, Simulation Modelling Practice and Theory, 2014, vol. 40, pp. 64–85.
[17] S. I. Vladov, V. M. Moskalyk, N. V. Podhornykh, O. V. Husarova, N. P. Nazarenko, Application of fuzzy neural network in tasks in control and diagnostics of TV3-117 aircraft engine technical state in flight modes, Visnyk of Kherson National Technical University, 2021, no 1 (76), pp. 77–186.
[18] V. S. Mihailenko, R. Y. Harchenko, Using of Takagi-Sugeno Fuzzy Logic in the Adaptive System for Controlling Complex Objects, Artificial Intelligence, 2011, no 2, pp. 53–59.
[19] M. Mrowczynska, Approximation abilities of neuro-fuzzy networks, Geodesy and Cartography, 2010, vol. 59, no 1, pp. 13–27.
[20] Osowski S. Neural networks for information processing, Finance and statistics, Moscow, 2002.