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5 DEVELOPMENT OF METHODS FOR EVALUATING COMPLEX ORGANIZATIONAL AND TECHNICAL SYSTEMS USING THE THEORY OF ARTIFICIAL INTELLIGENCE

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ABSTRACT

Complex organizational and technical systems are the object of the study. The problem that is solved in the study is an increase in the efficiency of the assessment of the operation process yof complex organizational and technical systems (OTS) while maintaining a given level of reliability.

Methods of evaluating complex organizational and technical systems using the theory of artificial intelligence were developed. The originality of the study is:

– in full coverage of critical events occurring during the OTS operation. This is achieved due to the use of the Dempster-Schafer theory, which achieves the completeness of the assessment of the entire spectrum of critical events in the OTS;

– in a comprehensive description of the process of OTS operation. This makes it possible to increase the accuracy of OTS modeling for subsequent management decisions;

– adapt to the type and duration of abnormalities due to multi-level adaptation of the artificial immune system;

– in the ability to carry out initial adjustment of OTS knowledge bases using an improved genetic algorithm. This allows to reduce the computational complexity during the further formation of the OTS knowledge base by reducing the metric of rule formation in the OTS knowledge base;

– in the ability to model the nature of the development of atypical events in the OTS due to the use of time series, which achieves the possibility of developing preventive measures to minimize the impact of the specified events on the process of OTS operation;

– in the gradual reduction of the metric of the formation of the knowledge base about the states of OTS, due to the training of agents of the improved genetic algorithm. This allows to reduce the number of computing resources of the subsystem for assessing the OTS state operation.

The proposed methods provide an average increase in efficiency from 16% to 23%, while ensuring high convergence of the obtained results at the level of 93.17%.

KEYWORDS

Reliability of technical systems, complex technical systems, efficiency of assessment, comprehensive assessment.

Organizational and technical systems (OTS), as a separate class of systems, are becoming more and more widespread regardless of the field of use and the tasks solved by them [1, 2].

However, for the correct and full application of OTS, it is necessary to use in their evaluation subsystem the appropriate mathematical and software that evaluates their condition and the very process of performing the tasks set by OTS [2].

The following tasks are distinguished among the tasks solved by the subsystems for assessing the OTS state [2, 3]:

– forecasting the trend of changes in the operation process of the OTS state;

– detection of deviations of OTS operation parameters at the initial stages;

– formation of trends of further deviation of the parameters of the OTS operation;

– detection of faulty OTS elements in real time;

– determination of control influences to bring the OTS state to nominal, etc.

Depending on the depth of available knowledge about the physical essence of the processes of changing the state of operation of OTS, different types of models are used: deterministic, probabilistic, fuzzy, etc.

A feature of the models of the first type is a single trajectory that determines the relationship between the OTS state and the nature of the deviation of its parameters from the nominal ones.

In the second case, the probabilistic properties of causation must be taken into account due to the hypothetical nature of the transformation operator. In the third case, it is necessary to operate with the concept of uncertainty when building a diagnostic model.

As the number of OTS elements (their constituent parts) increases, the difficulty of identifying the reasons for the deviation of their parameters from the nominal ones increases. This creates serious prerequisites for the use of neuro-fuzzy expert systems (NFES) in subsystems for assessing the OTS state.

The use of NFES in subsystems for assessing the OTS state provides support for decision-making by the persons who make them for decision-making, regardless of their level of training [4, 5].

In practice, two modes of NFES operation may be defined, when used in the subsystem for assessing their condition [6]:

1. The OTS is managed by the decision maker in such a way as to focus on specific anomalous deviations in their condition.

2. The system continuously monitors the OTS state and gives recommendations to the decision-maker when there are grounds for this. Special methods and techniques are used in the NFES to address these issues [4, 5].

The NFES structure is usually considered as consisting of a database (DB), a knowledge base (KB) and some management system [3]. DB is a set of current states of OTS and observed signs. KB contains decision-making rules that combine basic fundamental knowledge in this subject area and heuristics obtained as a result of the activities of specialists. In addition, KB includes the concepts of classes and relationships in the specified subject area.

Taking into account the above, one of the options for increasing the effectiveness of the assessment of the OTS state is the improvement of existing (development of new) methods of assessing their state using neuro-fuzzy expert systems.

The analysis of works [9–74] showed that the common shortcomings of the above-mentioned studies are:

– assessment of the OTS state is carried out only at a separate level of their operation, or only at a separate element of OTS;

– with a comprehensive approach to the OTS assessment, as a rule, one or two components of the process of their operation are considered. This does not allow to fully assess the impact of management decisions on the further OTS operation;

– the approaches listed above (methods, techniques), provide weak integration into each other (or make it impossible at all), which does not allow them to be combined with each other for a joint assessment of the operation of the OTS state;

– the above approaches to assessing the OTS state operation use a different mathematical apparatus, which requires appropriate mathematical transformations, which in turn increase computational complexity and reduce the accuracy of assessing the OTS state operation, etc.

The purpose of the study is to develop methods for evaluating complex organizational and technical systems using the theory of artificial intelligence.

This will make it possible to obtain an assessment of the state of operation of complex OTS at different levels of their operation (separate elements of OTS) for the development of subsequent management decisions. This will make it possible to develop (improve) the software of modern and promising OTS by integrating this method into the corresponding software.

Complex organizational and technical systems are the object of the study. The problem that is solved in the study is an increase in the efficiency of the assessment of the operation process of complex organizational and technical systems while maintaining a given level of reliability.

The subject of the study is the process of evaluating complex organizational and technical systems using the theory of artificial intelligence.

The hypothesis of the study is the possibility of increasing the efficiency of the operation of complex organizational and technical systems while maintaining the given level of reliability of their assessment due to the development of a method for assessing the state of their operation.

5.1 DEVELOPMENT OF A METHOD FOR EVALUATING COMPLEX ORGANIZATIONAL AND TECHNICAL SYSTEMS USING THE THEORY OF ARTIFICIAL INTELLIGENCE

OTS should be considered as a complex dynamic system. A dynamic system can be in two states: stationary and non-stationary.

The stationarity of a dynamic system lies in the immutability of its parameters and structure, but under the influence of disturbances that change its state, the OTS can turn into a non-stationary state.

The transition process determines the new steady state of the established OTS, which does not depend on the initial one. Bifurcation is a variant of the development of a situation where OTS moves from resilience to chaos [3, 4].

Thus, it is the task of finding anomalies during the OTS operation [5–8].

To solve the task of detecting the bifurcation point in the continuous process of OTS operation, it is necessary to evaluate the continuous flow of their state variables from sensors, as well as other sources of information extraction.

The evaluation is carried out at regular intervals Δt. The evaluation is carried out at regular intervals T values form multidimensional (D – measurable) a time series that reflects the dynamics of the OTS state operation.

OTS consists of a set of D sensors (sources of information). Thus, for any sensor $d = 1, 2, \ldots, D$ time series $y_1^d, y_2^d, \ldots, y_t^d$ it is a set of values of the OTS state y_t^d, what are measured at the moment of time t. Limitations in the form of upper ones are imposed on the values of these parameters y_u^d and lower ones y_l^d border.

As an OTS for simulation, the communication and informatization system of the operational grouping of troops (forces) has been adopted in this study. The operational group of troops (forces) was formed according to the state of martial law (typical state). Mode of operation of the communication and information systems system – defence operation.

A computational experiment of the proposed method was conducted in the Microsoft Visual Studio 2022 software environment (USA). The hardware of the research process is AMD Ryzen 5.

The method of evaluating complex organizational and technical systems using the theory of artificial intelligence structurally and logically consists of three main procedures that are performed sequentially:

– procedure for processing streaming data on the OTS state;

– the procedure for forming hypotheses about the reasons for deviations of OTS indicators from nominal ones;

– the procedure for forming the knowledge base of a neuro-fuzzy expert system.

Action 1. Entering initial data about the OTS and the conditions of its operation.

At this stage, the following initial data on OTS are entered:

– the number of component parts (communication nodes and dedicated means of communication) that are part of the OTS;

– the bandwidth of each element of the OTS (component communication and informatization system);

– the type of traffic transmitted by each element of the OTS;

– topology of placement of OTS elements on the terrain;

– the number of means of destructive influence on the OTS (in this case, the number of means of radio-electronic countermeasures and cyber warfare);

– frequency-energy characteristics of means of destructive influence on OTS (means of radio-electronic countermeasures);

– the type of means of fire damage that operate in the OTS lane;

– the number of means of fire damage that operate in the OTS lane;

– intensity of fire damage (applications (hit)/per hour) by each means of fire damage, etc.

To search for bifurcations of the OTS state, a flow data analysis procedure using a double sliding window is used, the essence of which is to check the stationarity conditions based on sample data for short time series [1, 2].

The procedure for processing streaming data on the OTS state consists of the following interrelated actions.

Action 2. Formation of the output time series for each sensor (sensor).

Forming the output time series of the size for a given sensor d

$$HY^{d}=\left[y_{1}^{d},y_{2}^{d},\ldots,y_{H}^{d}\right], \tag{5.1}$$

where H multiple N.

Action 3. Division of the obtained time series and their subsequent transformation.

Division of the obtained time series by N tuples size h. Receiving $k=\overline{1;N}$ time series of the species

$$Y^{d,k}=\left[y_{1}^{d,k},y_{2}^{d,k},\ldots,y_{h}^{d,k}\right]. \tag{5.2}$$

Action 4. Processing of received data tuples.

Processing of each received tuple $Y^{d,k}$ using the size sliding window algorithm l. At the output, it is possible to obtain a set of tuples of the form

$$Y^{d,k}=\left[y_{1}^{d,k},y_{2}^{d,k},\ldots,y_{h-l+1}^{d,k}\right]. \tag{5.3}$$

Action 5. Obtaining average values of data results and their squares.

Obtaining average values and squares of average values for each tuple $Y^{d,k}$. Formation of two tuples of the species

$$\left[\overline{y_{d,1}},\overline{y_{d,2}},\ldots,\overline{y_{d,k}},\ldots,\overline{y_{d,N}}\right] \text{ and } \left[\overline{y_{d,1}^{2}},\overline{y_{d,2}^{2}},\ldots,\overline{y_{d,k}^{2}},\ldots,\overline{y_{d,N}^{2}}\right]. \tag{5.4}$$

Action 6. Checking the obtained sequences for the presence of a trend.

To check the obtained sequences for the presence of a trend, this study uses a modification of the Foster-Steward criterion. For this, sets are calculated u_k, v_k, u_k^2 and v_k^2 according to formulas:

$$u_{k}=\begin{cases}1\leftarrow if\,\overline{y_{k}}>\overline{y_{k-1}},\overline{y_{k-2}},\ldots,\overline{y_{1}}\\ 0\leftarrow \text{else}\end{cases}, \tag{5.5}$$

$$v_{k}=\begin{cases}1\leftarrow if\,\overline{y_{k}}<\overline{y_{k-1}},\overline{y_{k-2}},\ldots,\overline{y_{1}}\\ 0\leftarrow \text{else}\end{cases}, \tag{5.6}$$

$$u_{k}^{2}=\begin{cases}1\leftarrow if\,\overline{y_{k}^{2}}>\overline{y_{k-1}^{2}},\overline{y_{k-2}^{2}},\ldots,\overline{y_{1}^{2}}\\ 0\leftarrow \text{else}\end{cases}, \tag{5.7}$$

$$v_{k}^{2}=\begin{cases}1\leftarrow if\,\overline{y_{k}^{2}}<\overline{y_{k-1}^{2}},\overline{y_{k-2}^{2}},\ldots,\overline{y_{1}^{2}}\\ 0\leftarrow \text{else}\end{cases}. \tag{5.8}$$

Action 7. Non-stationarity hypothesis testing.

The next stage for testing the hypothesis of the absence of stationarity in time series is two statistics:

$$W=\sum_{k=2}^{N}\left(u_k-v_k\right), \tag{5.9}$$

$$F=\sum_{k=2}^{N}\left(u_k+v_k\right), \tag{5.10}$$

and similarly, for squares:

$$W^2=\sum_{k=2}^{N}\left(u_k^2-v_k^2\right), \tag{5.11}$$

$$F^2=\sum_{k=2}^{N}\left(u_k^2+v_k^2\right). \tag{5.12}$$

Action 8. Definition of values t_W, t_F, t_{W^2} and t_{F^2} by formulae

$$t_W=\frac{W}{\sigma_W},\ \ t_{W^2}=\frac{W^2}{\sigma_W},\ \ t_F=\frac{F-\mu}{\sigma_F},\ \ t_{F^2}=\frac{F^2-\mu}{\sigma_F}, \tag{5.13}$$

where

$$\sigma_W=\left(2\times\sum_{k=2}^{N}\frac{1}{k}\right)^{0,5},\ \sigma_F=\left(\mu-4\times\sum_{k=2}^{N}\frac{1}{k^2}\right)^{0,5},\ \mu=2\times\sum_{k=2}^{N}\frac{1}{k}. \tag{5.14}$$

Action 9. Description of normalized values and their comparison with nominal ones.

In the absence of a trend, the normalized values of statistics are roughly described by the Student distribution with the number of degrees of freedom *df=N*. The obtained values are compared with the calculated values module t_W, t_F, t_{W^2} and t_{F^2} and if the obtained values are exceeded, the transition of the process to a non-stationary state is recorded.

The second main procedure of this method is the procedure for forming hypotheses about the reasons for deviations of OTS indicators from nominal ones. The Dempster-Schafer theory [2] is a general framework for decision-making with uncertainty and allows evidence from different sources to be combined and to arrive at a certain degree of confidence in the presence of one event or another.

Action 10. Analysis of diagnostic variables about the state of operation of OTS. The analysis of the specified data consists in the formation of hypotheses about the causes of the pre-emergency OTS state using the theory of evidence.

This uses data obtained using the double sliding window algorithm and a matrix of fuzzy expert evaluations

$$\Lambda = \begin{array}{ccccc} & A_1 & A_2 & \cdots & A_r \\ d_1 & m_{11} & m_{12} & \cdots & m_{1r} \\ d_2 & m_{21} & m_{22} & \cdots & m_{2r} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_n & m_{n1} & m_{n2} & \cdots & m_{nr} \end{array}, \qquad (5.15)$$

where r – the number of possible hypotheses; n – the number of diagnostic indicators to be analyzed; d – diagnostic indicator; A – hypothesis; m – expert assessment.

Action 11. Formation of a hypothesis about the OTS state.

To form hypotheses, it is necessary to perform the following steps.

Action 11.1. Selection from the matrix Λ only those lines d_n, in the streaming data of which bifurcations were found.

Action 11.2. Calculation of indicator functions P_n.

The measured diagnostic variable about the state is presented in the form of an interval number $D_n = \left[\underline{d_n}, \overline{d_n}\right]$, where $\underline{d_n}$ – lower limit, $\overline{d_n}$ – upper limit. Range of normative values of diagnostic variables $S_n = \left[\underline{\delta_n}, \overline{\delta_n}\right]$, where $\underline{\delta_n}$ – lower limit, $\overline{\delta_n}$ – upper limit.

For the case when the crisis OTS state occurs when the interval of the measured diagnostic variable is released $D_n = \left[\underline{d_n}, \overline{d_n}\right]$ beyond the upper limit of the range of its normative values $\overline{\delta_n}$ the following indicator function is used:

$$P_n = \begin{cases} 0, \text{ if } \overline{d_n} \le \overline{\ddot{a}_n}, \\ 1, \text{ if } \underline{d_n} \le \overline{\ddot{a}_n}, \\ \dfrac{\overline{d_n} - \overline{\ddot{a}_n}}{\overline{d_n} - \underline{d_n}}, \text{ if } \underline{d_n} < \overline{\ddot{a}_n} < \overline{d_n}. \end{cases} \qquad (5.16)$$

For the case when the crisis OTS state occurs at the output of the interval D_n at the lower end of the range of its normative values $\underline{\delta_n}$ the following indicator function is used:

$$P_n = \begin{cases} 0, \text{ if } \underline{d_n} \le \underline{\ddot{a}_n}, \\ 1, \text{ if } \overline{d_n} \le \underline{\ddot{a}_n}, \\ \dfrac{\underline{\ddot{a}_n} - \underline{d_n}}{\overline{d_n} - \underline{d_n}}, \text{ if } \underline{d_n} < \underline{\ddot{a}_n} < \overline{d_n}. \end{cases} \qquad (5.17)$$

Action 11.3. Calculation of normalized values of basic probabilities using the formula

$$\tilde{m}_{nr} = \frac{m_{nr}}{\sum_{i=1}^{r} m_{ni}}. \tag{5.18}$$

Action 11.4. Redistribution of probability values.

Then, using the value of the indicator function, the probability values are redistributed using the formulas

$$m_{nr} = m_{nr} \times P_n \text{ and } m_{n*} = 1 - P_n. \tag{5.19}$$

Action 11.5. Combining hypotheses.

Evidence theory is used to combine several hypotheses. To combine different evidence with probability distributions m_1 and m_2 in favor of one hypothesis, the Dempster-Schafer rule is used

$$m_1 \oplus m_2(A) = \frac{1}{1 - M(\varnothing)} \times \sum_{Y \cap Z = A} m_1(Y) \times m_2(Z), \tag{5.20}$$

where

$$M(\varnothing) = \sum_{Y \cap Z = \varnothing} m_1(Y) \times m_2(Z). \tag{5.21}$$

Action 11.6. Determination of the degree of confidence and the degree of plausibility.

According to the theory of evidence, estimates of the degree of confidence are determined $Bel(A_r)$ and the degree of plausibility $Pl(A_r)$ acceptance of hypotheses using formulas:

$$Bel(A_r) = \sum \left\{ m_n(C) \mid C \subseteq A_r \right\}, \tag{5.22}$$

$$Pl(A_r) = 1 - Bel(\overline{A_r}) = 1 - \sum \left\{ m_n(C) \mid C \cap A_r \neq \varnothing \right\}, \tag{5.23}$$

where C – a set of events.

Trust functions are calculated based on the obtained basic probabilities $Bel(A_r)$ and plausibility $Pl(A_r)$ for all analyzed hypotheses, and the most likely one is determined.

The final procedure in this method is the procedure for forming the knowledge base of a neuro-fuzzy expert system.

Action 12. Primary customization of the knowledge base using an improved genetic algorithm.

With the improved genetic algorithm proposed in study [19], the primary formation of the knowledge base takes place.

Action 13. Formation of a knowledge base about the OTS state.

At the specified stage, knowledge bases about the OTS state are formed on the basis of expressions (5.1)–(5.23). Formally, the model of the neuro-fuzzy knowledge (NFK) base of the OTS state can be written as follows (5.24)

$$\{P_n\} = \{\text{Rule}\}, \tag{5.24}$$

where Rule – rule of NFK.

Each NFK rule is defined as follows (5.25)

$$\text{Rule} = < C \to S >, \tag{5.25}$$

where C – condition of the rule on the OTS state; S – consequence of the rule on the OTS state.

A recursive mechanism for describing nodes and finite vertices of the OTS state decision tree was used. The condition parameter of the rule on the OTS state C defined as follows (5.26)

$$\tilde{N} = < C_l, R, C_r >, \tag{5.26}$$

where C_l – the left node of the condition of the OTS state rule; R – the relationship between the nodes of the OTS state rules; C_r – the right node of the condition of the OTS state rule.

Next, let's consider in detail the given parameters according to which the formation of the knowledge base about the OTS state is carried out:

$$C_l = FC_l \,\|\text{Null}\|\, C, \tag{5.27}$$

$$C_r = FC_r \,\|\text{Null}\|\, C, \tag{5.28}$$

where FC_l – the left final three of the condition of the rule about the OTS state; FC_r – the right final three conditions of the rule on the OTS state.

Expressions (5.27) and (5.28) make it possible to describe the conditions of OTS operation with different degrees of nesting:

$$FC_l = < L, Z, W >, \tag{5.29}$$

$$FC_r = < L, Z, W >, \tag{5.30}$$

where L – linguistic variable of the OTS state; Z – condition sign $Z = \{<, >, <=, >=, =, != \}$; W – the value of the condition of the OTS state, which is determined as follows (5.31)

$$W = L \| V, \tag{5.31}$$

where L – linguistic variable of the OTS state; V – fixed value (5.32)

$$V = T_i \| \text{const}, \tag{5.32}$$

where T_i – the value of a fuzzy variable from the term sets of a linguistic variable; const – constant.

This procedure allows the use of not only linguistic variables, but also classical variables. In this case, their value can also be compared with constants [3]. R – a set of possible relations between nodal vertices $R \subset (C_l \times C_r)$ or $R : C_l \to C_r$.

Similar to the parameter C the parameter is determined S – consequence of the OTS state rule

$$S = < S_l, R, S_r > , \tag{5.33}$$

where Sl – the left node of the consequence of the OTS state rule; R – the relationship between the nodes of the consequence of the OTS state rule; Sr – the right node of the consequence of the rule:

$$S_l = FS_l \| \text{Null} \| S, \tag{5.34}$$

$$S_r = FS_r \| \text{Null} \| S, \tag{5.35}$$

where FSl – the left final three consequence of the OTS state rule; FSr – the right final three consequence of the state rule of the OTS. Formulas (5.34) and (5.35) describe consequences with varying degrees of nesting:

$$FS_l = < L, \text{Op}, W >, \tag{5.36}$$

$$FS_r = < L, \text{Op}, W >, \tag{5.37}$$

where L – linguistic variable of the OTS state; Op – operation to assess the OTS state $\text{Op} = \{:=\}$; W – the meaning of the consequence of the rule on the OTS state.

Action 14. Determination of the amount of necessary computing resources for the assessment of the OTS state.

In order to prevent looping of calculations during calculations on actions 1–13 of this method, and to increase the efficiency of calculations, the load of computing resources is additionally determined. If the specified computational complexity threshold is exceeded, the number of software and hardware resources that must be additionally attracted is determined using the method proposed in work [19].

Action 15. Training of knowledge bases of agents of the improved genetic algorithm.

At this stage, knowledge bases of agents of the improved genetic algorithm are trained to increase its convergence. As a teaching method, the deep learning method proposed in the work [19] is used.

End.

To determine the effectiveness of the proposed method, a computational experiment of its work was conducted to solve the task of assessing the OTS state (state of the communication and informatization system) of the operational group of troops (forces).

Let n-number of rules in a neuro-fuzzy expert system, m_i – the number of conditions in i-th rules $\left(i=1,..,n\right)$, k – the number of different linguistic variables involved in the terms of the rules, t_i – the power of the term set i-th a linguistic variable involved in the conditions of the rules, s – the number of relationships between variables in conditions.

Separate parts of the computational experiment using the proposed method are given in **Tables 5.1** and **5.2**. The general computational experiment is laid out on more than 196 sheets, in this section only its final part is presented.

Table 5.1 The value of complexity estimates

	n	m_{ave}	k	t_{ave}	S	Classic NFS [19]	NFS with Rete [19]	NFS with Treat [19]	NFS with Rete II [19]	NFS with the proposed method
RB1	20	9	8	4	10	150	140	145	124	**98**
RB 2	400	9	8	4	10	1500	1420	1590	1280	**1020**
RB 3	800	9	8	4	10	2905	2737	2820	2350	**1916**
RB 4	1600	9	8	4	10	5726	5549	5666	4990	**4050**
RB 5	3200	9	8	4	10	11000	9568	9850	8540	**6354**
RB 6	6400	9	8	4	10	19738	17597	17966	15800	**12430**
RB 7	12800	9	8	4	10	37918	34679	35291	31560	**25660**
RB 8	25600	9	8	4	10	74008	70264	71292	61690	**49505**
RB 9	51200	9	8	4	10	140561	129170	133421	115000	**86594**
RB 10	102400	9	8	4	10	251007	217590	225666	180429	**134140**

Table 5.2 Comparative results of the process of assessing the OTS state

	With use method	**Without use method**
Efficiency of the process of assessing the state of the group		
Better case, sec.	39 – 203	56 – 507.1
Worse case, sec.	155.1 – 2501.5	482.8 – 5977
Reliability of the decisions received		
Better case, sec.	0.89 – 1.0	0.64 – 0.85
Worse case, sec.	0.8 – 1.0	0.617 – 0.75

From the analysis of **Table 5.1** and **5.2**, it can be concluded that the proposed method provides an increase in efficiency by an average of 23%, while ensuring a high convergence of the obtained results at the level of 93.17%.

The advantages of the proposed method of evaluating complex organizational and technical systems are as follows:

– full coverage of critical events occurring during the OTS operation (actions 9–11.6, expressions (5.15)–(5.23)). This is achieved due to the use of the Dempster-Schafer theory, which achieves the completeness of the assessment of the entire spectrum of critical events in the OTS, in comparison with works [2, 8];

– the ability to take into account the uncertainty about the received information from various sources of information about the OTS state (actions 9–11.6, expressions (5.15)–(5.23)). This is achieved due to the use of the Dempster-Schafer theory, which achieves the completeness of the assessment of the entire spectrum of critical events in the OTS, in comparison with works [1, 3];

– comprehensively describe the operation process of OTS (expressions (5.1)–(5.37)), compared to works [4, 6]. This makes it possible to increase the accuracy of OTS modeling for subsequent management decisions;

– allows to describe OTS in a dynamic form (expressions (5.1)–(5.37)), compared to works [7, 9];

– carry out initial adjustment of OTS knowledge bases using an improved genetic algorithm (action 12). This allows to reduce the computational complexity in the further formation of the OTS knowledge base by reducing the metric of rule formation in the OTS knowledge base in comparison with works [4, 7];

– conduct modeling of the nature of the development of atypical events in the OTS due to the use of time series (actions (2)–(11.6)), which achieves the possibility of developing preventive measures to minimize the impact of these events on the process of OTS operation, in comparison with works [5, 10];

– by gradually reducing the metric of the formation of a knowledge base about the states of OTS, due to the training of agents of the improved genetic algorithm (action 12). This makes it possible to reduce the number of computing resources of the subsystem for assessing the OTS state operation, in comparison with works [8, 11];

– the ability to work with opinions of experts of different physical origins and units of measurement, which achieves the elimination of the problem of dimensionality during the operation of the subsystem for assessing the OTS state (actions 11.5–11.6), in comparison with works [7, 13];

– increase the efficiency of obtaining an assessment of the OTS state (actions 1–15), due to the reduction of the decision space, compared to works [5, 14].

The disadvantages of the proposed method include:

– greater computational complexity of performing computational operations in OTS compared to known research;

– the need for additional calculations when working with data of various sizes.

The proposed method will allow to:

– simulate the process of OTS operation;

– determine effective measures to increase the efficiency of the assessment of the OTS state;

– reduce the use of computing resources of the OTS state assessment subsystem.

The limitations of the study are the need to take into account the delay time for collecting and proving information from OTS sensors (sensors).

The proposed method should be used as software for automated troop control systems such as "Dzvin-AS", "Oreanda-PS", as well as integrated information systems such as "Delta".

5.2 DEVELOPMENT OF A METHOD FOR DETECTING ANOMALIES IN ORGANIZATIONAL AND TECHNICAL SYSTEMS

The method of detecting anomalies in the OTS consists of the following sequence of actions:

Action 1. Entering output data.

At this stage, the initial data available about the OTS are entered, namely: the number and type of means that are part of it, the type of data circulating in the OTS, available computing resources, the number and type of connections between each element of the OTS, information on technical characteristics of control channels and data transmission, information on the application environment, etc.

Action 2. Verification of OTS parameters.

At this stage, the parameters of the OTS are verified with the help of a bio-inspired algorithm. In case of detection of deviations from the input data, the output data is adjusted using the results of the bio-inspired algorithm.

Action 3. Determination of destabilizing factors affecting OTS. In the specified action, the initial identification of attacks inherent in the OTS takes place:

$$CBT_{\mu}=\begin{cases}\left\langle F^{(i)}_{jL_{\mu}R_{\mu}},CBT_{L_{\mu}},CBT_{R_{\mu}}\right\rangle, & \text{if } \#\mu\geq 2,\\ \mu, & \text{if } \#\mu=1,\end{cases} \tag{5.38}$$

where $\mu=\{0,\ldots,m\}$ – the original set of anomaly class labels; $L_{\mu}\subsetneq\mu$ – an arbitrarily generated or defined subset; $\mu\left(\#L_{\mu}<\#\mu\right)$, $R\mu=\mu\backslash L\mu$ – left classification subtree; $CBT_{R_{\mu}}$ – right classification subtree; $F^{(i)}_{jL_{\mu}R_{\mu}}$ – a nodal detector trained on plural elements $\left\{\left(x_l,0\right)\middle|\overline{c_l}\in L_{\mu}\right\}_{l=1}^{M}\cup\left\{x_l,1\middle|\overline{c_l}\in R_{\mu}\right\}_{l=1}^{M}$.

Action 4. Initiation of an artificial immune system.

In the initialization step, a population of N candidate antibodies is randomly generated $Ab(t)=\{Ab_1(t), Ab_2(t),\ldots, Ab_N(t)\}$, where Ab_i — it's i-th agent (antibody) on t-th iterations. The affinity of these antibodies is assessed by the function Aff(). At each iteration, any antibody is cloned to form offspring, after which all clones except the parent undergo mutation. Only the clone with the highest affinity remains.

To improve the accuracy of solving calculation tasks and the speed of convergence, this study proposes an artificial immune system with deep learning mechanisms to solve the task of detecting anomalies in the OTS.

Action 5. Antibody pre-selection.

At this stage, an initial selection of antibodies to each of the swarms is carried out using an improved genetic algorithm proposed in work [20].

Action 6. Distribution of agents of the artificial immune system between swarms.

At the swarm renewal stage, antibodies that are candidates for the solution are redistributed between the elite swarm and the general swarm. Elite swarm antibodies undergo an affinity-dependent cloning operator and a self-learning mutation operator, where the search radius is updated adaptively using a specially designed mechanism.

Action 7. Antibody cloning. In this study, the number of clones created from one parent antibody is determined by its affinity.

The higher the affinity of the parent antibody, the more offspring it produces.

At the same time, the number of clones is a nonlinear function of the affinity of the parent antibody. The procedure for calculating the antibody cloning procedure is given below:

$$Aff_{\max} = \max\{Aff(Ab_i(t)),\ i = 1, 2,\dots, N), \tag{5.39}$$

$$Aff_{\min} = \min\{Aff(Ab_i(t)),\ i = 1, 2,\dots, N), \tag{5.40}$$

$$Aff^*(i) = (Aff(Ab_i(t)) - Aff_{\min})/(Aff_{\max} - Aff_{\min}), \tag{5.41}$$

$$Nc_i(t) = \text{round}((N_{c\max} - N_{c\min})\ Aff(A_{bi}(t))\ n + N_{c\min}), \tag{5.42}$$

where $N_{c\max}$ and $N_{c\min}$ — maximum and minimum number of antibody descendants; n — power factor of control function. All antibodies, including generic and elite swarms, perform this cloning operator once on each iteration.

Action 8. Antibody mutation.

Elite swarm antibodies have higher affinity and play the role of memory cells responding much more aggressively and faster in the secondary immune response.

Consequently, these elite swarm antibodies play an important role in local search and undergo a self-learning mutation. On the other hand, general swarm antibodies play the role of global search led by elite swarm antibodies, so all general swarm antibodies undergo deep training to accelerate convergence.

If $Aff(Ab_i(t)) < Aff(Ab_i(t))$, then the affinity of one antibody of the general swarm is less than the affinity of an antibody selected from an elite swarm. In this case, the general swarm antibody is trained on the basis of the selected elite swarm antibody. Said case is described by the following mathematical expression

$$\Delta A_{bi}(t) = \text{rand} * (A_{bj}(t) - A_{bi}(t)). \tag{5.43}$$

If $Aff(Ab_i(t)) < Aff(Ab_e(t))$ the affinity of one total swarm antibody is greater than that of the selected elite swarm antibody, but less than that of the best elite swarm antibody. Training in this case is described as follows

$$\Delta Ab_i(t) = \text{rand} * (Ab_e(t) - Ab_i(t)). \tag{5.44}$$

Otherwise, the general swarm antibody performs a deep mutation

$$\Delta Ab_i(t) = \text{rand}n * \lambda_i(t), \tag{5.45}$$

where rand – a uniformly distributed random variable; rand$n$ – a normally distributed random variable with a mean of 0 and a standard deviation of 1; $Ab_e(t)$ – the best elite swarm antibody by affinity; $\lambda_i(t)$ – antibody search radius $Ab_i(t)$ for t-th iterations.

In this artificial immune system, the search radius is fixed, which impairs the speed of convergence and accuracy of the solution. This is because any elite antibody can easily go beyond the optimum if it is located close to it, but has too large a search radius.

On the other hand, if the search radius is too small, the rate of convergence of artificial immune systems is significantly reduced.

Thus, the search radius $\lambda_i(t)$ can be updated dynamically according to the following rule:

$$\lambda_i(t) = \begin{cases} \lambda_i(t-1), \text{if Aff}\left(Ab_i(t) > Ab_i(t-1)\right), \\ \dfrac{\lambda_i(t-1)}{2}, \text{ otherwise } \dfrac{\lambda_i(t-1)}{2} \geq \lambda_{\min}, \\ \lambda_0(k), \text{ otherwise,} \end{cases} \tag{5.46}$$

where $\lambda_{\min}$ – the lower limit of the search radius and is defined as:

$$\lambda_0(k) = \begin{cases} \dfrac{\lambda_0(k-1)}{2}, \text{if } \dfrac{\lambda_0(k-1)}{2} \geq \lambda_{\min}, \\ \lambda_0(0), \text{otherwise.} \end{cases} \tag{5.47}$$

For each antibody $Ab_i(t)$, according to (5.46) and (5.47), the initial search radius is given by λ_0, the value of which is equal to half of the threshold value $\text{Th}_s(t)$

$$\lambda_0(k) = \text{Th}_s/2. \tag{5.48}$$

Because after performing the suppression operator, the distance between any two antibodies exceeds $\text{Th}_s(t)$, value $\lambda_0 = \text{Th}_s(t)/2$ allows to cover the search space as much as possible without overlap.

If the affinity of the antibody $Ab_i(t)$ improves after mutation, its search radius $\lambda_i(t)$ stored. Otherwise $\lambda_i(t)$ halved:

$$\text{Aff}(Ab_i(t)) > \text{Aff}(Ab_i(t-1)), \tag{5.49}$$

$$\lambda_i(t) = \lambda_i(t-1). \tag{5.50}$$

However, the search radius cannot be less than $\lambda_{min}(t)$, because a search radius that is too small can significantly reduce the rate of convergence. Therefore, if $\lambda_i(t)$ becomes smaller than $\lambda_{min}(t)$, its value is set equal $\lambda_0(k)$, which decreases to half the previous value $\lambda_0(k\text{-}1)$. At the same time $\lambda_0(k)$ also cannot be less than $\lambda_{min}(t)$, and if it does, its value is reset $\lambda_0(k)$.

Action 9. Deep learning of the artificial immune system.

The learning mechanism of the artificial immune system is described as follows

$$p\left(Ab_j\left(t\right)\right)=\frac{Aff^*\left(Ab_j\left(t\right)\right)}{\sum\limits_{\text{³}=1}^{N_{\text{äë³ò}}} Aff^*\left(Ab_i\left(t\right)\right)}. \tag{5.51}$$

Obviously, the probability of selection is uneven: the higher the affinity of the antibody, the greater the probability of its selection, so the roulette method is used to select an elite swarm antibody for training.

Let's suppose that the optimal values of the multimodal function differ significantly in affinity. In this case, antibodies with higher affinity are more likely to evolve into the global optimum, so this learning algorithm will demonstrate faster convergence.

Action 10. Antibody suppression.

The proposed artificial immune system uses a dynamic mechanism of suppression, which is described by the following mathematical expressions:

$$D_{max} = \max\{ D_{i,j}(t)|i,j = 1,2,\ldots, N,i \neq j), \tag{5.52}$$

$$D_{min} = \min\{D_{i,j}(t)|i,j = 1,2,\ldots, N,i \neq j), \tag{5.53}$$

$$\mathrm{Th}_s(t) = D_{min} + \xi(D_{max} - D_{min}), \tag{5.54}$$

where $\mathrm{Th}_s(t)$ – a threshold that is proportional to the similarity of the antibody population; *Di,j* – euclidean distance between *i*-м and *j*-th antibodies on *t*-th iterations; $\xi \in (0, 1)$ – control parameter. After the application of the suppression operator, a certain amount of randomly generated antibodies is added to the population to maintain its size at *N*.

Action 11. Swarm update.

As is known, some general swarm antibodies can achieve higher affinity than elite swarm antibodies due to the elitist learning mechanism.

Accordingly, the composition of swarms must be reviewed, allowing the preferred antibodies of the total swarm to transition to the elite swarm. During swarm renewal, all antibodies are sorted by affinity in descending order. Then the first *N*elite antibodies move to the elite swarm, while the rest remain in the general swarm. It is important to note that after initial initialization, all antibodies undergo a deep learning mechanism until the suppression operator is triggered. This enables all antibodies to evolve in a fairly small area around them, which helps in the search for local extrema.

Action 12. Determination of the amount of necessary computing resources, intelligent decision support system.

In order to prevent looping of calculations on actions 1–11 of this method, and to increase the efficiency of calculations, the system load is additionally determined. If the specified computational complexity threshold is exceeded, the number of software and hardware resources that must be additionally attracted is determined using the method proposed in work [20].

The end of the algorithm.

The effectiveness of the proposed method of detecting anomalies in OTS based on artificial intelligence technologies is given in the **Table 5.3.**

Table 5.3 Evaluation of the effectiveness of the proposed method of detecting anomalies in OTS

Algorithm name	Accuracy	Convergence	Efficiency, sec	Percentage of system resources deployed
[6]	77.92%	80.23%	5.23E + 04	100
[7]	75.71%	77.4%	3.72E + 04	100
[8]	77.01%	76.66%	6.40E + 02	100
[9]	76.17%	81.15%	5.06E + 01	100
[10]	80.31%	80.67%	7.07E + 02	100
[11]	70.05%	81.03%	6.16E + 03	100
[12]	70.28%	75.18%	5.19E + 03	100
[13]	75.24%	73.12%	7.04E + 02	100
[14]	77.41%	74.2%	7.55E + 07	100
[15]	75.16%	74.28%	5.42E + 05	100
[16]	81.44%	85.9%	5.56E + 04	100
Proposed method	**97.3%**	**95.23%**	**5.23E + 04**	**80**

From the analysis of **Table 5.3**, it can be concluded that the proposed method provides an increase in accuracy by an average of 16%, an increase in efficiency by an average of 12%, while ensuring a high convergence of the obtained results at the level of 95.23%.

The advantages of the proposed method are due to the following:

– verifies OTS parameters (action 2) using an improved bat flock algorithm, compared to works [6–10]. This allows to minimize the error of entering incorrect data for the operation of data on the OTS state;

– there is a primary identification of the anomalies that are inherent in the specified OTS using the classification tree (action 3), compared to works [7, 9];

– the possibility of adaptation to the type and duration of anomalies due to multi-level adaptation of the artificial immune system (actions 1–12), compared to works [8, 12];

– primary selection of antibodies to each of the swarms of the artificial immune system is carried out using an improved genetic algorithm (action 5), compared to works [11, 13];

– the ability to train general swarm antibodies with elite swarm antibodies, which ensures the possibility of deep learning (action 9), compared to works [9, 12];

– to perform replacement of unsearchable individuals by updating the antibody population (actions 11), compared to works [9, 16];

– the ability to simultaneously find a solution in different directions (actions 1–12, **Table 5.3**);

– by the possibility of calculating the required number of computing resources to be attracted in case of impossibility of making calculations with available computing resources (action 12), compared to works [9, 13].

The disadvantages of the proposed method include:

– less accuracy of evaluation by a single anomaly evaluation parameter;

– loss of validity of received solutions when finding a solution in several directions at the same time;

– lower evaluation accuracy compared to other anomaly detection methods.

The specified method will allow to:

– determine the optimal indicator of anomaly detection depending on the OTS in which it is used;

– identify effective measures to improve the effectiveness of anti-anomalies in OTS;

– increase the speed of processing heterogeneous data while ensuring the given reliability of decision-making during their processing;

– reduce the use of computing resources of decision support systems.

The limitations of the study are the need to take into account the delay time for collecting and proving information from the constituent parts of organizational and technical systems.

The proposed approach should be used to solve the task of managing complex technical systems characterized by a high degree of complexity.

CONCLUSIONS

The study proposes a method of evaluating complex organizational and technical systems using the theory of artificial intelligence. The novelty of the proposed method is:

– in full coverage of critical events occurring during the OTS operation. This is achieved due to the use of the Dempster-Schafer theory, which achieves the completeness of the assessment of the entire spectrum of critical events in the OTS;

– in a comprehensive description of the process of OTS operation. This makes it possible to increase the accuracy of OTS modeling for subsequent management decisions;

– in the description of OTS in a dynamic form;

– in the ability to carry out initial adjustment of OTS knowledge bases using an improved genetic algorithm. This allows to reduce the computational complexity during the further formation of the OTS knowledge base by reducing the metric of rule formation in the OTS knowledge base;

– in the ability to model the nature of the development of atypical events in the OTS due to the use of time series, which achieves the possibility of developing preventive measures to minimize the impact of the specified events on the process of OTS operation;

– in the gradual reduction of the metric of the formation of the knowledge base about the states of OTS, due to the training of agents of the improved genetic algorithm. This allows to reduce the number of computing resources of the subsystem for assessing the OTS state operation;

– in the ability to work with opinions of experts of different physical origins and units of measurement, which achieves the elimination of the problem of dimensionality during the operation of the subsystem for assessing the OTS state.

The proposed method provides an increase in efficiency by an average of 23%, while ensuring high convergence of the obtained results at the level of 93.17%, which is confirmed by the results of a numerical experiment.

The method implementation algorithm is defined, thanks to additional and improved procedures, which allows to:

– verify OTS parameters using an improved bat flock algorithm. This allows to minimize the error of entering incorrect data for the operation of data on the OTS state;

– perform the initial identification of anomalies that are inherent in the specified OTS using the classification tree;

– adapt to the type and duration of abnormalities due to multi-level adaptation of the artificial immune system;

– conduct initial selection of antibodies to each of the swarms of the artificial immune system using an improved genetic algorithm;

– train antibodies of the general swarm with antibodies of the elite swarm, which ensures the possibility of deep learning;

– replace unsearchable individuals by updating the antibody population;

– simultaneously search for a solution in different directions;

– calculate the required number of computing resources that must be attracted in case of impossibility of making calculations with available computing resources.

An example of the use of the proposed method was carried out using the example of detecting anomalies in the OTS, which showed an increase in accuracy by an average of 16%, an increase in efficiency by an average of 12%, while ensuring high convergence of the obtained results at the level of 95.23%.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest in relation to this research, whether financial, personal, authorship or otherwise, that could affect the research and its results presented in this paper.

USE OF ARTIFICIAL INTELLIGENCE

The authors confirm that they did not use artificial intelligence technologies in creating the submitted work.

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