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DEVELOPMENT OF A METHOD FOR EVALUATING COMPLEX ORGANIZATIONAL AND TECHNICAL SYSTEMS USING NEURO-FUZZY EXPERT SYSTEMS

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Complex organizational and technical systems are the object of research. The problem that is solved in the study is an increase in the efficiency of the assessment of the process of operation of complex organizational and technical systems (OTS) while maintaining a given level of reliability. A method of evaluating complex organizational and technical systems using neuro-fuzzy expert systems was developed. The originality of the research 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 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 state of OTS operation;

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

Keywords: reliability of technical systems, complex technical systems, efficiency, comprehensive assessment, computing resources

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1. Introduction

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 OTS application, 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].

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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 process of OTS operation 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 OTS operation, 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 (NNES) in subsystems for assessing the OTS state.

The use of NNES 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 operation of NNES 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 NNES to address these issues [4, 5].

The NNES structure is usually considered as consisting of a database (DB), a knowledge base (KB) and some management system [3]. KB 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 OTS assessment state is the improvement of existing (development of new) methods of assessing their state using neuro-fuzzy expert systems.

Therefore, research devoted to the development of new methods of evaluating OTS using NFES is relevant.

2. Literature review and problem statement

Article [6] proposes to use Bayesian hierarchical networks to determine the quantitative assessment of the level of cyber security risks in special purpose OTS. However, said approach is limited by the statistical distribution that can be used and by the extensibility of the model structure. This imposes restrictions on the architecture of the information system and does not take into account qualitative factors that affect the cyber security of the information system.

Article [7] proposed a security certification methodology developed for OTS to enable various stakeholders to evaluate security solutions for large-scale OTS deployments automatically. The methodology supports transparency regarding the level of OTS safety for consumers, as the methodology provides labeling as one of the main results of the certification process. The disadvantages of the proposed approach should include the inability to train knowledge bases for new threats, the problematic nature of generalization and analysis of various types of data circulating in the network.

Article [8] proposes a model that integrates fault tree analysis, decision theory, and fuzzy theory to establish the current causes of refusals to prevent cyber attacks. The model has been applied to assess cybersecurity risks associated with a website attack, e-commerce and corporate resource planning, and to assess the possible consequences of such attacks. The specified model has a flexible architecture, at the same time, the disadvantages of the proposed model include the accumulation of evaluation error during the fuzzification and defuzzification procedure.

Article [9] proposes a model for the distribution of special purpose OTS resources in conditions of insufficient information on the development of the operational situation. In the specified model, mechanisms for the distribution of OTS resources are proposed, taking into account the impact of cyber attacks. This allows the representation of the solution of the vector optimization problem in binary relations of conflict, facilitation and indifference. And it also takes into account the operational situation and allows to predict the OTS state taking into account external influences, build utility and guaranteed gain functions, as well as a numerical optimization scheme on this set. At the same time, the specified model does not allow working with various indicators of the OTS assessment operation state.

Article [10] proposes a hierarchical concept for the introduction of a governance model based on e-government. The article examines the main threats to critical cyber-physical systems as the basis of mechanisms for performing e-government functions. The specified hierarchical system is based on the use of symmetric and asymmetric cryptosystems, which does not allow them to be used for the task of identifying cyber influences on the system.

Article [11] proposes a model for selecting the optimal set of cybersecurity insurance policies by a firm, given the limited number of policies offered by one or more insurance companies. The model allows for the systematic evaluation of various insurance policies as a function of the likelihood that a cyber security breach will occur during the term of policy-related policies and premiums. The proposed model provides a risk-sharing approach that helps the root-mean-square choices of cybersecurity insurance policies in a way that contributes to an efficient cybersecurity insurance market. At the same time, the disadvantages of this approach include the impossibility of introducing new risks to the knowledge base during work and a limited number of assumptions. This makes it impossible for it to work in real time.

Article [12] discusses the importance of including vulnerability analysis in cybersecurity not only as part of process hazard analysis, but also in terms of protecting the process management network and implementing adequate safeguards in general against cyber threats. Protection level analysis is tailored to assess potential weaknesses and ensure critical applications are protected from cyber attack resistance. The integration of cyber security into hazard and risk analysis, as well as other elements of technological process security management, is demonstrated by examples, making the plant more resistant to traditional and cyber threats. However, the proposed approach is adapted only for a clear architecture and is not intended for adjustment during operation.

Article [13] proposes a risk management process to identify, analyze, assess, respond to cyber threats and monitor risks at each stage of the cyber protection chain. This approach can be used in organizations that are going to implement security mechanisms to align them to current requirements or reduce cyber risks to accepted levels. Risk assessment method based on continuous Markov chain. At the same time, the disadvantages of the proposed method include the impossibility of simultaneous consideration of both quantitative and qualitative indicators, and the impossibility of adaptation to new threats in the system.

Article [14] proposes a theoretical-analytical approach to the analysis of the impact of information transmission delay in traffic regulation caused by cyber influence. The estimation is by means of the method of successive means. However, this approach is limited only to use in motion control systems and is not adapted for use in other systems.

Article [15] proposed that cyber security of an object be treated as a transient graph. Said approach allows to describe the threats that affect the object, to determine their degree of impact on cyber security. Disadvantages of the proposed approach include the possibility of working only with single-dimensional values and the impossibility of adding new threats during the operation of the proposed approach.

Article [16] presents a method for creating and solving a game theory model to address cybersecurity issues specifically for advanced manufacturing systems with high-level integrated computer integration. This method introduces a unique approach to determining the content of the game's payoff matrix, including support for defense strategies, production losses, and recovery from attacks as part of the cost function. Disadvantages of the proposed method include great computational complexity and the possibility of working only with one-dimensional values.

So, summarizing the above, the general disadvantage of all these approaches is the impossibility of working with various-dimensional data in real time. Below is an analysis of known works that allow solving the specified shortcoming. Several different solutions have been proposed to eliminate this shortcoming.

Work [17] presents an approach to evaluating input data for OTS. The essence of the proposed approach is the clustering of the basic set of input data, their analysis, after which the system is trained based on the analysis. The disadvantages of the mentioned approach are the gradual accumulation of evaluation and learning error due to the lack of possibility to evaluate the adequacy of the decisions made.

Work [18] presents an approach regarding the processing of data from different sources of information. This approach allows processing data from various sources. The disadvantages of the specified approach include the low accuracy of the received assessment and the impossibility of checking the reliability of the received assessment.

In the work [19], a comparative analysis of existing decision support technologies was carried out, namely: the method of analyzing hierarchies, neural networks, the theory of fuzzy sets, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The areas of their application are defined. For the tasks of assessing the state of OTS operation state in conditions of risk and uncertainty, the use of neuro-fuzzy expert systems is justified.

Work [20] states that the use of a combination of using different strategies for applying metaheuristic algorithms. The disadvantages of this approach are the insufficient efficiency of heterogeneous data processing when several metaheuristic algorithms are used together to evaluate the OTS operation.

Carrying out an analysis of the works [9–20] showed that the common shortcomings of the above studies are:

– OTS assessment 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 OTS assessment operation state;

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

3. The aim and objectives of the study

The aim of the study is to develop a method 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.

To achieve the aim, the following objectives were set:

– define the basic procedures of the method of evaluating complex organizational and technical systems using neuro-fuzzy expert systems;

– calculate the effectiveness of the proposed evaluation method.

4. Materials and methods

Complex organizational and technical systems are the object of the study. The problem that is solved in the research is an increase in the efficiency of the assessment of the process of operation 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.

In the course of the study, the following research methods were used:

– is a general scientific method of analysis – for decomposing problematic issues of assessing the OTS state when they perform tasks as intended. Also, the general scientific method of analysis is used to determine the advantages and disadvantages of known approaches to assessing the OTS state when they perform tasks as intended;

– general scientific method of synthesis – to substantiate the most appropriate approaches to the OTS assessment when they perform tasks as intended;

– improved genetic algorithm [20] – for determining the primary most optimal metric (according to the criterion of the minimum involved computing resources to perform the optimization task) for the formation of knowledge bases of neuro-fuzzy expert systems. The use of the specified approach is due to the possibility of conducting a directed and circular search on the entire available plane of possible solutions. Also, the use of the proposed improved genetic algorithm is due to the presence of improved mutation and selection procedures, which increases the efficiency of the obtained solutions while maintaining the given reliability;

– neuro-fuzzy expert systems – to obtain a comprehensive assessment of the state of OTS operation when they perform tasks as intended. The use of this mathematical apparatus is due to its ability to work with indicators of different units of measurement and origin, according to which the state of OTS operation is assessed when performing tasks as intended.

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 state of OTS 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 – defense 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.

5. Development of a method for evaluating complex organizational and technical systems using neuro-fuzzy expert systems

5. 1. Basic procedures for the method of evaluating complex organizational and technical systems

The method of evaluating complex organizational and technical systems using neuro-fuzzy expert systems structurally and logically consists of three main procedures that are performed sequentially:

– procedure for processing streaming data about the OTS state;

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

– 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 OTS element (component communication and informatization system);

– the type of traffic transmitted by each OTS element;

– 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*

$$HY^d=\left[y_1^d, y_2^d,\ldots,y_H^d\right], \tag{1}$$

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

$$Y^{d,k}=\left[y_1^{d,k}, y_2^{d,k},\ldots,y_h^{d,k}\right]. \tag{2}$$

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

$$Y^{d,k}=\left[y_1^{d,k}, y_2^{d,k},\ldots,y_{h-l+1}^{d,k}\right]. \tag{3}$$

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

$$\left[\overline{y_{d,1}},\overline{y_{d,2}},\ldots,\overline{y_{d,k}},\ldots,\overline{y_{d,N}}\right]$$

and

$$\left[\overline{y_{d,1}^2},\overline{y_{d,2}^2},\ldots,\overline{y_{d,k}^2},\ldots,\overline{y_{d,N}^2}\right]. \tag{4}$$

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:

$$u_k=\begin{cases}1\leftarrow \text{if } \overline{y_k}>\overline{y_{k-1}},\overline{y_{k-2}},\ldots,\overline{y_1},\\ 0\leftarrow \text{else,}\end{cases} \tag{5}$$

$$v_k=\begin{cases}1\leftarrow \text{if } \overline{y_k}<\overline{y_{k-1}},\overline{y_{k-2}},\ldots,\overline{y_1},\\ 0\leftarrow \text{else,}\end{cases} \tag{6}$$

$$u_k^2=\begin{cases}1\leftarrow \text{if } \overline{y_k^2}>\overline{y_{k-1}^2},\overline{y_{k-2}^2},\ldots,\overline{y_1^2},\\ 0\leftarrow \text{else,}\end{cases} \tag{7}$$

$$v_k^2=\begin{cases}1\leftarrow \text{if } \overline{y_k^2}<\overline{y_{k-1}^2},\overline{y_{k-2}^2},\ldots,\overline{y_1^2},\\ 0\leftarrow \text{else.}\end{cases} \tag{8}$$

Action 7. Non-stationarity hypothesis testing. The next stage for testing the hypothesis of the absence of stationarity in time series is two statistics:

$$W=\sum_{k=2}^{N}\left(u_k-v_k\right), \tag{9}$$

$$F=\sum_{k=2}^{N}\left(u_k+v_k\right), \tag{10}$$

and similarly for squares:

$$W^2=\sum_{k=2}^{N}\left(u_k^2-v_k^2\right), \tag{11}$$

$$F^2=\sum_{k=2}^{N}\left(u_k^2+v_k^2\right). \tag{12}$$

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

$$t_W=\frac{W}{\sigma_W},\ t_{W^2}=\frac{W^2}{\sigma_W},\ t_F=\frac{F-\mu}{\sigma_F},\ t_{F^2}=\frac{F^2-\mu}{\sigma_F}, \tag{13}$$

where:

$$\sigma_W=\left(2\times\sum_{k=2}^{N}\frac{1}{k}\right)^{0.5},\ \sigma_F=\left(\mu-4\times\sum_{k=2}^{N}\frac{1}{k^2}\right)^{0.5},$$

$$\mu=2\times\sum_{k=2}^{N}\frac{1}{k}. \tag{14}$$

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}, 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 OTS operation. 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:

$$\Lambda=\begin{array}{cccccc} & A_1 & A_2 & \cdots & A_r \\ d_1 & m_{11} & m_{12} & \cdots & m_{1r} \\ d_2 & m_{21} & m_{22} & \cdots & m_{2r} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ d_n & m_{n1} & m_{n2} & \cdots & m_{nr}\end{array}, \tag{15}$$

where r – 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 $D_n=[\underline{d_n},\overline{d_n}]$, where $\underline{d_n}$ – lower limit, $\overline{d_n}$ – upper limit. Range of normative values of diagnostic variables $S_n=[\underline{\delta_n},\overline{\delta_n}]$, 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 $D_n=[\underline{d_n},\overline{d_n}]$ beyond the upper limit of the range of its normative values $\overline{\delta_n}$ the following indicator function is used:

$$P_n=\begin{cases}0, \text{ if } \overline{d_n}\le\overline{\delta_n},\\ 1, \text{ if } \underline{d_n}\le\overline{\delta_n},\\ \dfrac{\overline{d_n}-\overline{\delta_n}}{\overline{d_n}-\underline{d_n}}, \text{ if } \underline{d_n}<\overline{\delta_n}<\overline{d_n}.\end{cases} \tag{16}$$

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:

$$P_n=\begin{cases}0, \text{ if } \underline{d_n}\le\underline{\delta_n},\\ 1, \text{ if } \overline{d_n}\le\underline{\delta_n},\\ \dfrac{\underline{\delta_n}-\underline{d_n}}{\overline{d_n}-\underline{d_n}}, \text{ if } \underline{d_n}<\underline{\delta_n}<\overline{d_n}.\end{cases} \tag{17}$$

Action 11. 3. Calculation of normalized values of basic probabilities using the formula

$$\tilde{m}_{nr}=\frac{m_{nr}}{\sum_{i=1}^{r}m_{ni}}. \tag{18}$$

Action 11. 4. Redistribution of probability values.

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

$$m_{nr} = m_{nr} \times P_n \text{ and } m_{n*} = 1 - P_n. \tag{19}$$

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

$$m_1 \oplus m_2(A) = \frac{1}{1 - M(\varnothing)} \times \sum_{Y \cap Z = A} m_1(Y) \times m_2(Z), \tag{20}$$

where

$$M(\varnothing) = \sum_{Y \cap Z = \varnothing} m_1(Y) \times m_2(Z). \tag{21}$$

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:

$$Bel(A_r) = \sum \{ m_n(C) \mid C \subseteq A_r \}, \tag{22}$$

$$Pl(A_r) = 1 - Bel(\overline{A_r}) = 1 - \sum \{ m_n(C) \mid C \cap A_r \neq \varnothing \}, \tag{23}$$

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 (1)–(23). Formally, the model of the neuro-fuzzy knowledge (NFK) base of the OTS state can be written as follows (24)

$$\{P_n\} = \{\text{Rule}\}, \tag{24}$$

where Rule – rule of NFK. Each NFK rule is defined as follows (25)

$$\text{Rule} =< C \to S >, \tag{25}$$

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 (26)

$$C =< C_l, R, C_r >, \tag{26}$$

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:

$$C_l = FC_l \| \text{Null} \| C, \tag{27}$$

$$C_r = FC_r \| \text{Null} \| C, \tag{28}$$

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 (27) and (28) make it possible to describe the conditions of OTS operation with different degrees of nesting:

$$FC_l =< L, Z, W >, \tag{29}$$

$$FC_r =< L, Z, W >, \tag{30}$$

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 (31)

$$W = L \| V, \tag{31}$$

where L – linguistic variable of the OTS state, V – fixed value (32)

$$V = T_i \| \text{const}, \tag{32}$$

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

$$S =< S_l, R, S_r >, \tag{33}$$

where S_l – 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, S_r – the right node of the consequence of the rule:

$$S_l = FS_l \| \text{Null} \| S, \tag{34}$$

$$S_r = FS_r \| \text{Null} \| S, \tag{35}$$

where FS_l – the left final three consequence of the OTS state rule, FS_r – the right final three consequence of the state rule of the OTS. Formulas (34) and (35) describe consequences with varying degrees of nesting:

$$FS_l =< L, \text{Op}, W >, \tag{36}$$

$$FS_r =< L, \text{Op}, W >, \tag{37}$$

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 OTS assessment 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.

5. 2. Evaluation of the effectiveness of the proposed evaluation method

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 grouping of troops (forces) under the initial conditions specified in section 4.

Let n-number of rules in a neuro-fuzzy expert system, m_i – number of conditions in i-th rules ($i = 1, ..., n$), 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 – number of relationships between variables in conditions.

Separate parts of the computational experiment using the proposed method are given in Tables 1, 2. The general computational experiment is laid out on more than 196 sheets, in this section only its final part is presented.

From the analysis of Tables 1, 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%.

Table 1

The value of complexity estimates

No. of RB	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 2

Comparative results of the process of assessing the OTS state

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

Areas of further research will be aimed at increasing the efficiency of the evaluation method proposed in the study.

6. Discussion of the results of the development of a method for evaluating complex organizational and technical systems

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 (15)–(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 (15)–(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 process of OTS operation (expressions (1)–(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 (1)–(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];

– to 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 state of OTS 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];

– to increase the efficiency of obtaining an OTS assessment 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 OTS assessment 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".

7. Conclusions

1. The main procedures of the method of evaluating complex organizational and technical systems using neuro-fuzzy expert systems are proposed, the originality of which 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 OTS description 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 state of OTS 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.

2. 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.

Conflict of interest

The authors declare that they have no conflict of interest in this study, including financial, personal, authorship or other nature that could affect the study and its results presented in this article.

Financing

The study was conducted without financial support.

Data availability

The manuscript has related data in the data warehouse.

Use of artificial intelligence tools

The authors confirm that they did not use artificial intelligence technologies when creating the presented work.

Authors' contributions

Andrii Shyshatskyi: Conceptualization; Methodology; Project administration; Writing – original draft; Writing – review & editing; **Ganna Plekhova**: Methodology; Writing; Writing – review & editing; **Olena Feoktystova**: Writing – original draft; **Igor Shostak**: Writing – review & editing; **Andrii Veretnov**: Resources; Data Curation; **Sergii Pronin**: Validation; Data Curation; **Vadym Kaidalov**: Software; Validation; Data Curation; **Olena Shaposhnikova**: Methodology; Formal analysis; Visualization; **Nataliia Hnatiuk**: Software: Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code components; Validation; Data Curation; **Hryhorii Stepanov**: Software; Validation; Data Curation.

References

1. Sova, O., Radzivilov, H., Shyshatskyi, A., Shvets, P., Tkachenko, V., Nevhad, S. et al. (2022). Development of a method to improve the reliability of assessing the condition of the monitoring object in special-purpose information systems. Eastern-European Journal of Enterprise Technologies, 2 (3 (116)), 6–14. https://doi.org/10.15587/1729-4061.2022.254122
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskyi, R., Repilo, I. et al. (2020). Development of a method for training artificial neural networks for intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (2 (105)), 37–47. https://doi.org/10.15587/1729-4061.2020.203301
3. Sova, O., Shyshatskyi, A., Salnikova, O., Zhuk, O., Trotsko, O., Hrokholskyi, Y. (2021). Development of a method for assessment and forecasting of the radio electronic environment. EUREKA: Physics and Engineering, 4, 30–40. https://doi.org/10.21303/2461-4262.2021.001940

4. Pievtsov, H., Turinskyi, O., Zhyvotovskyi, R., Sova, O., Zvieriev, O., Lanetskii, B., Shyshatskyi, A. (2020). Development of an advanced method of finding solutions for neuro-fuzzy expert systems of analysis of the radioelectronic situation. EUREKA: Physics and Engineering, 4, 78–89. https://doi.org/10.21303/2461-4262.2020.001353
5. Zuiev, P., Zhyvotovskyi, R., Zvieriev, O., Hatsenko, S., Kuprii, V., Nakonechnyi, O. et al. (2020). Development of complex methodology of processing heterogeneous data in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (9 (106)), 14–23. https://doi.org/10.15587/1729-4061.2020.208554
6. Wang, J., Neil, M., Fenton, N. (2020). A Bayesian network approach for cybersecurity risk assessment implementing and extending the FAIR model. Computers & Security, 89, 101659. https://doi.org/10.1016/j.cose.2019.101659
7. Matheu-García, S. N., Hernández-Ramos, J. L., Skarmeta, A. F., Baldini, G. (2019). Risk-based automated assessment and testing for the cybersecurity certification and labelling of IoT devices. Computer Standards & Interfaces, 62, 64–83. https://doi.org/10.1016/j.csi.2018.08.003
8. Henriques de Gusmão, A. P., Mendonça Silva, M., Poleto, T., Camara e Silva, L., Cabral Seixas Costa, A. P. (2018). Cybersecurity risk analysis model using fault tree analysis and fuzzy decision theory. International Journal of Information Management, 43, 248–260. https://doi.org/10.1016/j.ijinfomgt.2018.08.008
9. Folorunso, O., Mustapha, O. A. (2015). A fuzzy expert system to Trust-Based Access Control in crowdsourcing environments. Applied Computing and Informatics, 11 (2), 116–129. https://doi.org/10.1016/j.aci.2014.07.001
10. Mohammad, A. (2020). Development of the concept of electronic government construction in the conditions of synergetic threats. Technology Audit and Production Reserves, 3 (2 (53)), 42–46. https://doi.org/10.15587/2706-5448.2020.207066
11. Bodin, L. D., Gordon, L. A., Loeb, M. P., Wang, A. (2018). Cybersecurity insurance and risk-sharing. Journal of Accounting and Public Policy, 37 (6), 527–544. https://doi.org/10.1016/j.jaccpubpol.2018.10.004
12. Cormier, A., Ng, C. (2020). Integrating cybersecurity in hazard and risk analyses. Journal of Loss Prevention in the Process Industries, 64, 104044. https://doi.org/10.1016/j.jlp.2020.104044
13. Hoffmann, R., Napiórkowski, J., Protasowicki, T., Stanik, J. (2020). Risk based approach in scope of cybersecurity threats and requirements. Procedia Manufacturing, 44, 655–662. https://doi.org/10.1016/j.promfg.2020.02.243
14. Perrine, K. A., Levin, M. W., Yahia, C. N., Duell, M., Boyles, S. D. (2019). Implications of traffic signal cybersecurity on potential deliberate traffic disruptions. Transportation Research Part A: Policy and Practice, 120, 58–70. https://doi.org/10.1016/j.tra.2018.12.009
15. Promyslov, V. G., Semenkov, K. V., Shumov, A. S. (2019). A Clustering Method of Asset Cybersecurity Classification. IFAC-PapersOnLine, 52 (13), 928–933. https://doi.org/10.1016/j.ifacol.2019.11.313
16. Zarreh, A., Saygin, C., Wan, H., Lee, Y., Bracho, A. (2018). A game theory based cybersecurity assessment model for advanced manufacturing systems. Procedia Manufacturing, 26, 1255–1264. https://doi.org/10.1016/j.promfg.2018.07.162
17. Kosko, B. (1986). Fuzzy cognitive maps. International Journal of Man-Machine Studies, 24 (1), 65–75. https://doi.org/10.1016/s0020-7373(86)80040-2
18. Koval, M., Sova, O., Shyshatskyi, A., Artabaiev, Y., Garashchuk, N., Yivzhenko, Y. et al. (2022). Improving the method for increasing the efficiency of decision-making based on bio-inspired algorithms. Eastern-European Journal of Enterprise Technologies, 6 (4 (120)), 6–13. https://doi.org/10.15587/1729-4061.2022.268621
19. Shyshatskyi, A. (Ed.) (2024). Information and control systems: modelling and optimizations. Kharkiv: TECHNOLOGY CENTER PC. https://doi.org/10.15587/978-617-8360-04-7
20. Voznytsia, A., Sharonova, N., Babenko, V., Ostapchuk, V., Neronov, S., Feoktystov, S. et al. (2025). Development of methods for intelligent assessment of parameters in decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (4 (136)), 73–82. https://doi.org/10.15587/1729-4061.2025.337528