

In order to objectively and completely analyze the state of the monitored object with the required level of efficiency, the method for estimating and forecasting the state of the monitored object in intelligent decision support systems was improved. The essence of the method is to provide an analysis of the current state of the monitored object and short-term forecasting of the state of the monitored object. Objective and complete analysis is achieved using advanced fuzzy temporal models of the object state, taking into account the type of uncertainty and noise of initial data. The novelty of the method is the use of an improved procedure for processing initial data in conditions of uncertainty, an improved procedure for training artificial neural networks and an improved procedure for topological analysis of the structure of fuzzy cognitive models. The essence of the training procedure is the training of synaptic weights of the artificial neural network, the type and parameters of the membership function and the architecture of individual elements and the architecture of the artificial neural network as a whole. The procedure of forecasting the state of the monitored object allows for multidimensional analysis, accounting and indirect influence of all components of the multidimensional time series with their different time shifts relative to each other in conditions of uncertainty. The method allows increasing the efficiency of data processing at the level of 12–18 % using additional advanced procedures. The proposed method can be used in decision support systems of automated control systems (ACS DSS) for artillery units, special-purpose geographic information systems. It can also be used in ACS DSS for aviation and air defense and ACS DSS for logistics of the Armed Forces of Ukraine

Keywords: decision support systems, artificial neural networks, state forecasting, training of artificial neural networks

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1. Introduction

Decision support systems (DSS) are actively used in all spheres of human life.

They are especially common when processing large data sets in databases, process forecasting, providing information support to decision-makers in the decision-making process.

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IMPROVEMENT OF THE METHOD OF ESTIMATION AND FORECASTING OF THE STATE OF THE MONITORING OBJECT IN INTELLIGENT DECISION SUPPORT SYSTEMS

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Existing DSS are based on statistical and artificial intelligence methods, which collect, process, summarize information about the objects (processes) state and forecast their future state.

The creation of intelligent DSS has become a natural continuation of the widespread use of conventional DSS. Intelligent DSS provide information support for all production processes and services of enterprises (organizations, institutions). The main fundamental difference between intelligent DSS and conventional ones is the presence of feedback and adaptability to changes in input processes [1, 2].

Intelligent DSS have been widely used to solve specific military tasks, for example [1, 2]:

- planning of deployment, operation of communication and data transmission systems;
- automation of troops and weapons control;
- planning of combat training of units (subdivisions) and quality control of learning material assimilation;
- reconnaissance of enemy objects and selection of the fire destruction method;
- collection, processing and generalization of intelligence information on the state of intelligence objects, etc.

The structure of intelligent DSS can be conventionally divided into 4 major layers:

- interface layer (interactivity and visualization);
- modeling layer (statistical models and machine learning; numerical models; game theory models, etc.);
- data processing layer (organization of data flow, work with databases and expert assessments);
- data collection layer (web scanning, sensors and programming interface).

Analysis of the experience of creating intelligent DSS shows that the most promising for construction is an information technology based on neural network and statistical modeling [1–4], in particular, on the application of an evolutionary approach to the construction of artificial neural networks (ANN) [5–8]. Approaches to the analysis and evaluation of objects in the interests of civil and special users are considered in [1–4]. New generalized methods of multidimensional data analysis using ANN and algorithms of training them are proposed. In [5–7], complex methods of processing various data are considered, which increase the efficiency of data processing in decision support systems. From these works [1–8], it can be concluded that ANN allow processing different types of data, adapting their structure to the type and volume of initial data, thereby increasing their own productivity.

The application of the evolutionary approach to neural network construction in comparison with traditional approaches gives the following advantages:

- the ability to adapt quickly to the subject area, which, with little or no change, allows forming an ANN structure that corresponds to a specific process;
- the ability to learn quickly; on the basis of models of neurons with corresponding thresholds, weights and transfer functions, at which the trained ANN is constructed already in the first approximation;
- the ability to work in conditions of uncertainty, non-linearity, stochasticity, chaos and various disturbances;
- have both universal approximating properties and fuzzy inference capabilities.

Evolving ANN are widely used to solve various problems of data mining, planning, control, identification, emulation, forecasting, intelligent control, etc. on each of the layers of intelligent DSS.

Despite their successful application to a wide range of data mining problems, these systems have a number of disadvantages.

The most significant shortcomings are as follows:

1. Complexity of system architecture selection. As a rule, the model based on the principles of computational intelligence has a fixed architecture. In the context of ANN, this means that the neural network has a fixed number of neurons and connections. Therefore, adapting the system to new data coming in for processing that is different from previous data may be problematic.

2. Batch training and training for several epochs require significant time resources. Such systems are not adapted to work online with a fairly high rate of new processing data.

3. Many of the existing computational intelligence systems can not determine the evolving rules by which the system develops, and can also present the results of their work in terms of natural language.

4. Problems with many indicators that have a complex structure of relationships and contradict each other.

5. The difficulty of considering the indirect influence of interdependent components in conditions of uncertainty.

6. Nonlinear interaction of objects and processes, non-stochastic uncertainty, nonlinearity of interaction, partial inconsistency and significant interdependence of components.

These shortcomings can be eliminated by fuzzy cognitive maps. Fuzzy cognitive maps have proven themselves well in the tasks of studying the structure of the modeled system and forecasting its behavior under various control influences and evolving ANN.

There is an urgent scientific task to develop a method for estimating and forecasting the monitoring object state in intelligent decision support systems using artificial neural networks and fuzzy cognitive models.

2. Literature review and problem statement

The work [9] presents a cognitive modeling algorithm. The main advantages of cognitive tools are determined. During the construction of the experimental model, target factors of the cognitive map were determined, connectivity analysis was performed, and the process of perturbation propagation on the graph was studied. The proposed model is used to forecast economic activity and determine the expected values of parameters that need to be monitored to diagnose trends in industrial development. The disadvantages of this approach include the lack of consideration of the type of uncertainty about the analysis object state.

The work [10] reveals the essence of cognitive modeling and scenario planning. The system of complementary principles of scenario construction and implementation is proposed, various approaches to scenario construction are allocated, the procedure of scenario modeling on the basis of fuzzy cognitive maps is described. It is proposed to identify the concepts of the cognitive map based on the analysis of internal and external environments of the organization, which will allow taking a systematic look at the business conditions of the enterprise, predicting further development and making right management decisions. The approach proposed by the authors does not take into account the type of uncertainty about the analysis object state and the delay in processing data about the object state.

The work [11] carried out the analysis of the main approaches to cognitive modeling. Cognitive analysis allows you to explore problems with fuzzy factors and relationships, take into account changes in the external environment and take advantage of objective trends in the situation. It is necessary to develop a system of criteria for the formalization and automation of decision-making in problem areas. It is also stated that the objectivity of the information being processed must be taken into account.

The work [12] describes the agent-based approach used in a multi-agent information-analytical system and considers the problems of information support for decision-making. The disadvantages of this approach include the limited representation of complex systems, namely, none of the agents have an idea of the entire system.

The work [13] presents the method of large data sets analysis. This method is focused on finding hidden information in large data sets. The method involves the operations of generating analytical baselines, reducing variables, identifying sparse features and specifying rules. The disadvantages of this method include the inability to take into account different decision evaluation strategies.

The work [14] proposes an approach for estimating the cost of client's life in the field of air transportation. This approach first uses a regression model, followed by an indirect estimation model. At the final stage, the estimation results are compared using both estimation models. The disadvantages of this approach include the inability to determine the adequacy of estimation.

The work [15] shows the approach to quantitative estimation designed to evaluate the optimum selection and testing of analytical methods. Objective criteria related to analytical indicators, sustainability, environmental impact and economic costs are assessed by determining penalty points divided into five different blocks. For each block, the overall qualification is scaled from 0 to 4 and is shown on a regular hexagonal icon that allows you to compare analytical procedures. The disadvantages of this approach include the inability to increase the number of indicators being evaluated.

The work [16] shows the mechanism of transformation of information models of construction objects to their equivalent structural models. This mechanism is designed to automate the necessary transformation, modification and addition operations during such information exchange. The disadvantages of this approach include the inability to assess the adequacy and reliability of the information transformation process.

The work [17] carried out the development of an analytical web platform for studying the geographical and temporal distribution of incidents. The web platform contains several information panels with statistically significant results by territory. The web platform includes certain external sources of data on social and economic issues, which allow studying the relationship between these factors and the distribution of incidents at different geographical levels. The disadvantages of this analytical platform include the inability to assess the adequacy and reliability of the information transformation process and high computational complexity.

The work [18] developed a method of fuzzy hierarchical assessment of the quality of library services. This method allows evaluating the quality of libraries by a set of input parameters. The disadvantages of this method include the inability to assess the adequacy and reliability of assessment.

The work [19] performed an analysis of 30 algorithms for processing large data sets. Their advantages and disadvantages

are shown. It is found that analysis of large data sets should be carried out in layers, in real time and be able to self-study. The disadvantages of these methods include high computational complexity and inability to verify the adequacy of assessment.

The work [20] presents an approach to input data evaluation for decision support systems. The essence of the proposed approach is to cluster the basic set of input data, analyze them, and, based on the analysis, train the system. The disadvantage of this approach is the gradual accumulation of evaluation and learning errors due to the inability to assess the adequacy of decisions.

The work [21] presents the approach to processing data from various sources of information. This approach enables the processing of data from various sources. The disadvantages of this approach include the low accuracy of the assessment and the inability to verify the reliability of the assessment.

The work [22] presents a comparative analysis of existing decision support technologies, for example: the method of hierarchy analysis, neural networks, fuzzy set theory, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The scope of their application is defined. The method of hierarchy analysis has been shown to work well with complete initial information, but due to the need for experts to compare alternatives and select evaluation criteria, it has a high degree of subjectivity. The use of fuzzy set theory and neural networks is justified for forecasting problems in conditions of risk and uncertainty.

The work [23] deals with problematic aspects of information-analytical support of strategic decision-making in modern management. The role and place of management decision-making in strategic planning are specified. The existing approaches to taking into account the regularities of the course and result of strategic processes are analyzed. The analysis found that the approaches and methods of modern model theory in control systems, which allow linguistic approximation of mathematical models of cybernetic systems, are of particular interest. Such an approximation ensures the highest level of abstract system description, which allows identifying the most common concepts and exploring the relationship between them. However, the results obtained here do not fully apply to organizational management systems. To solve the problems of strategic management, it is proposed to use fuzzy set and neural network theories.

The work [24] describes tools and methods for analyzing and processing information on the number and quality of personnel of the Defense Ministry of the Czech Republic. The disadvantages of this approach include high computational complexity, the inability to assess the adequacy and reliability of decisions.

The work [25] describes approaches to processing constantly updated information circulating in social information communications, for example: active use of content monitoring and analysis methods in this process. The disadvantages of these methods include high computational complexity.

The work [26] shows the system of hierarchical fuzzy estimation of factors influencing the rice cultivation process. The disadvantages of this method include the accumulation of evaluation errors due to the inability to assess the adequacy of assessment.

The work [27] carried out the development of a methodology for determining and assessing the strategic economic potential of theoretical and methodological foundations for

forming and assessing the level of strategic economic potential of economic systems. This methodology is based on the hierarchy analysis method. The disadvantages of this methodology include the dependence of the results on experts' competence and high computational complexity.

The work [28] developed an approach for determining the impact of factors influencing the efficiency of economic activity on the economy of integrated structures. This approach is based on the method of expert assessments. The disadvantages of this approach include the dependence of the results on experts' competence and high computational complexity.

The work [29] carried out the development of a systematic approach to assessing the effectiveness of the strategic plan. The system approach is based on the method of expert assessments. The disadvantages of this system approach include the dependence of the results on experts' competence and high computational complexity.

The analysis of [9–29] showed that the vast majority of these works are based on general scientific methods, such as systematic, comparative, structural and functional analysis, the method of expert assessments, the methodology of scenario analysis of socio-economic systems and the theoretical information approach.

Common limitations of the existing methods of multi-criteria fuzzy evaluation of alternatives are:

- complexity of forming a multilevel evaluation structure;
- lack of consideration of compatibility of unevenly significant indicators;
- inability to jointly perform direct and inverse evaluation tasks supported by the selection of the best solutions.

To create decision support software, it is necessary to create fuzzy evaluation methods that meet the following set of requirements:

- the possibility of forming a generalized evaluation indicator and selecting solutions based on sets of partial indicators, which change taking into account the complex multi-level evaluation structure;
- the possibility to aggregate heterogeneous evaluation indicators (both quantitative and qualitative) and select solutions that differ in measuring scales and ranges of values;
- consideration of compatibility and different significance of partial indicators in the generalized assessment of decisions;
- consideration of different decision evaluation strategies;
- flexible adjustment (adaptation) of evaluation models while adding (excluding) indicators and changing their parameters (compatibility and significance of indicators);
- enabling implementation within a single model: the direct task of evaluating the generalized indicator based on partial indicators; inverse evaluation task and joint execution of direct and inverse evaluation tasks;
- consideration of the type of uncertainty of the initial data on the object state;
- consideration of data noise.

To this end, it is proposed to develop an estimation and forecasting method for intelligent decision support systems based on fuzzy temporal models and evolving artificial neural networks.

3. The aim and objectives of the study

The aim of the study is to develop an estimation and forecasting method for intelligent decision support systems,

which would analyze and predict the state of complex and dynamic objects (identification of terrain objects, determining whether objects belong to a grouping of troops (forces) on many grounds).

To achieve the aim, the following objectives were set:

- to conduct a formalized description of the task of analyzing and forecasting the objects state in intelligent decision support systems;
- to formulate the concept of presenting the method for estimating and forecasting the state of monitoring objects in intelligent decision support systems;
- to determine the algorithm of the method;
- to give an example of the application of the proposed method in the analysis and forecasting of the operational situation of the troops (forces) grouping as a monitoring object.

4. Research materials and methods

The research used the general provisions of the artificial intelligence theory to solve the problem of analyzing and forecasting the object state in intelligent decision support systems. Thus, the artificial intelligence theory is the basis of this research.

Fuzzy cognitive models were used to solve the problem of describing the state and forecasting the future state of dynamic objects. This allows describing how complex multi-level objects change over time. The research also uses the method of training artificial neural networks developed in previous works, which allows deep learning of artificial neural networks. The essence of deep learning is to train the architecture, type and parameters of the membership function. The simulation was performed using MathCad 2014 software (USA) and Intel Core i3 PC (USA).

5. Results of research on the development of the estimation and forecasting method

5.1. Formalized description of the problem of analyzing and forecasting the objects state

For analyzing and forecasting the state of the monitored object, it is proposed to apply a systematic approach.

Fig. 1 presents a block diagram of an object state analysis and forecasting control system, which is divided into [11, 30–32]:

- 1) control subsystem (control subject, S);
- 2) controlled subsystem (control object, O);
- 3) object model (in this case, fuzzy cognitive model Y).

The fuzzy cognitive model is used due to the fact that the state of the analysis object is usually characterized by both numerical and qualitative indicators. This requires bringing them to a single unit of measurement.

Here is an explanation of the variables shown in Fig. 1:

- W is the external information;
- Q is the system resources necessary for analysis and forecasting of the object state;
- H is the internal information needed to build fuzzy cognitive models (FCM);
- H^* is the corrected error;
- U is the control effect (management decisions, management teams) (direct communication);

- Y_{CO} is the initial information (actual data, parameters, indicators) characterizing the state of the control object;
- Y_M is the initial model parameters (desired, expected parameters);
- ε is the error (inconsistency);
- ε_{add} is the fixed setpoint;
- $L(Y_{CO}, Y_M)$ is the check of compliance of the data obtained on the basis of the model to the real object for which it is built;
- Y' is the information about the object state (feedback);
- Y'_{adj} is the model adjustment (adding new factors and connections between them);
- Y_a is the adequate model of the monitored object corresponding to its actual state;
- ε_{train} is updating of the knowledge base.

The controlled subsystem (O) refers to control objects to which control effects are directed. The object model is the development and study of a fuzzy cognitive model for estimating the object state using a method of fuzzy cognitive modeling of the object state.

The control subsystem produces a control effect U based on the control aim, as well as information received from the external environment W .

The controlled subsystem receives information (Q, I, U), which generates the task of analyzing and forecasting the object state.

Based on W, Q, I , fuzzy cognitive models are developed and investigated using the method of fuzzy cognitive modeling of the object analysis process, which allows investigating and analyzing possible scenarios of object development. System development scenarios are development scenarios of situations related to the nature of the actions of the monitored object.

If the obtained results (calculated values) Y_M do not correspond to the actual results that characterize the state Y_{CO} (the condition $\varepsilon \leq \varepsilon_{add}$ is not met), the control subsystem makes adjustments to the FCM (Y_{corr}). If the condition $\varepsilon \leq \varepsilon_{add}$ is met, the FCM is adequate Y_a . As a result of obtaining an adequate FCM, the behavior of the object can be predicted.

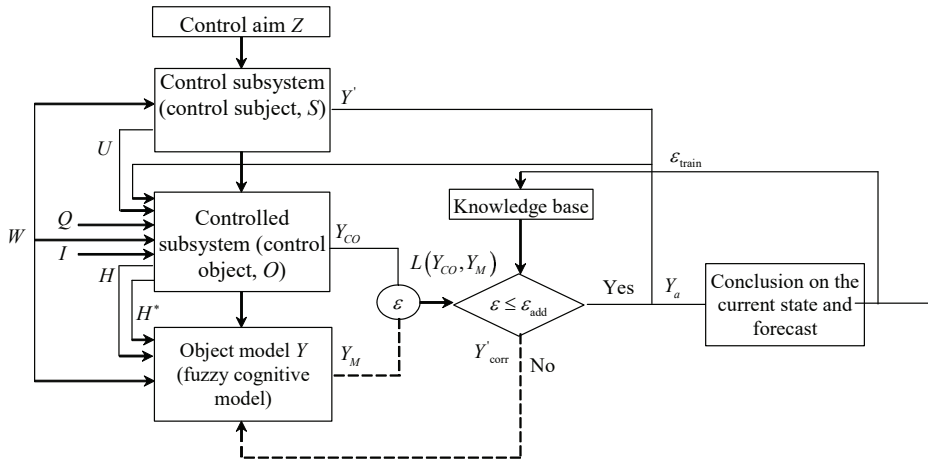


Fig. 1. Block diagram of the object state analysis and forecasting system

To verify the adequacy of the model, a “historical method” is proposed, thus the constructed FCM is applied to similar situations if they occurred in the past and their dynamics are known. In this case, the FCM is operational (the results obtained coincide with the actual course of events), it is considered correct.

5. 2. Concept of presenting the method for estimating and forecasting the monitoring object state in intelligent decision support systems

Control is performed using the feedback Y' . The control subsystem receives information from the controlled subsystem Y' , as well as from the external environment W . The control subsystem processes and compares it with the desired characteristics of the control object, and then makes a new decision, produces the next control effect U based on it. The controlled subsystem also receives information Y' , processes and compares it with the desired characteristics of the control object and corrects the error H^* based on it.

The object state analysis and forecasting control system can be represented as a tuple

$$S_{con} = \langle S, O, Y, Z, W, Q, Y_a, D \rangle, \quad (1)$$

where Z is the control aim; $D = \langle I, H, U, Y_{CO}, Y_M, Y', H^*, Y'_{corr} \rangle$ is the internal environment of the control system S_{con} ; $Y = \langle W, H, H^*, Y_M \rangle$ is the model of the object whose result Y_M is FCM.

Let's write the expression (1) for the dynamic system:

$$\forall t \in \{1, \dots, T, \dots\} S_t = \begin{cases} s_1^{(t)} F_1 \left(\begin{matrix} \left(\Phi_{1,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_1^*)} \right) \right) \\ \left(\Phi_{1,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_1^N)} \right) \right) \end{matrix} \right) \times \iota_1 \times \chi_1, \\ s_2^{(t)} F_2 \left(\begin{matrix} \left(\Phi_{2,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_2^*)} \right) \right) \\ \left(\Phi_{2,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_2^N)} \right) \right) \end{matrix} \right) \times \iota_2 \times \chi_2, \\ \dots \\ s_N^{(t)} F_N \left(\begin{matrix} \left(\Phi_{N,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_N^*)} \right) \right) \\ \left(\Phi_{N,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_N^N)} \right) \right) \end{matrix} \right) \times \iota_N \times \chi_N, \end{cases} \quad (2)$$

where S is the multidimensional time series; $S_t = (s_1^{(t)}, s_2^{(t)}, \dots, s_N^{(t)})$ is the time sample of the state of the analysis object presented as a multidimensional time series at the t -th time point; $s_j^{(t)}$ is the value of the j -th component of the multidimensional time series at the t -th time point; L_j^* is the maximum value of the time delay of the i -th component relative to the j -th one; Φ_{ij} is the operator to account for the interaction between the i -th and j -th component of the multidimensional time series; F_i is the transformation to obtain $s^{(t)}$, $i=1, \dots, N$; N is the number of components of the multidimensional time series; ι is the operator to account for the degree of awareness of the object state; χ is the operator to account for the degree of noise of the object state data.

From the expression (2), we can conclude that it allows describing processes in the analysis object taking into ac-

count time delays. Delays are necessary for the collection, processing and synthesis of information, taking into account the degree of awareness on the object state and data noise. Also, the expression (2) allows describing processes that have both quantitative and qualitative units of measurement and processes occurring in Fig. 1.

5.3. Algorithm for implementing the estimation and forecasting method in intelligent decision support systems

The method of estimation and forecasting in intelligent decision support systems consists of the following sequence of actions (Fig. 2):

1. Entering initial data. At this stage, the initial available data about the object to be analyzed is entered. The basic model of the object state is initialized.

2. Identifying factors and relationships between them.

Analysis of models of multicriteria estimation of alternatives in conditions of uncertainty has shown that the values of model parameters are often presented by intervals as there are differences of opinions when obtaining parameter values. With interval and fuzzy information, it is advisable to use the fuzzy-interval method whose idea is as follows.

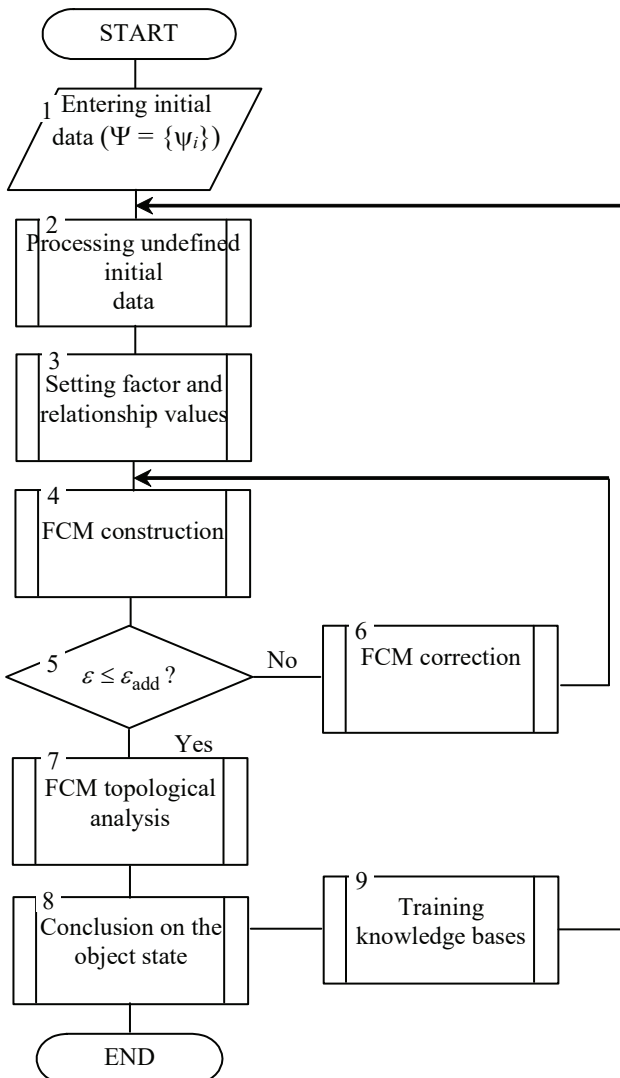


Fig. 2. Algorithm for implementing the method of analyzing and forecasting the monitoring object state

Let there be a set of alternatives for estimating the object state $X = \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$, $x^{(k)} \in X$, $k = \overline{1, m}$, evaluated by a tuple of n partial criteria $C = \langle c_j(x^{(k)}) \rangle$, $j = \overline{1, n}$. The task is to form a scalar interval estimate of the generalized state of the object from the total number of m alternatives using interval arithmetic:

$$P(x^{(1)}) = \sum_{j=1}^n w_j^{\text{norm}} p_j^{\text{norm}}(x^{(k)}), \quad k = \overline{1, m}, \quad j = \overline{1, n}, \quad (3)$$

with the possibility of further selection of an acceptable alternative

$$x^0 = \arg \max_{x^{(k)} \in X} P(x^{(k)}), \quad k = \overline{1, m}, \quad (4)$$

where w_j^{norm} is the normalized interval coefficient of the relative importance of the j -th partial criterion of alternatives $x^{(k)} \in X$; $p_j^{\text{norm}}(x^{(k)})$ are the normalized interval partial criteria of alternatives $x^{(k)} \in X$.

Step 2. 1. Formation of object state alternatives

$$X = \{x^{(1)}, x^{(2)}, \dots, x^{(m)}\},$$

evaluated by partial criteria $C = \langle c_j(x^{(k)}) \rangle$. Note that partial criteria can be given in the form of intervals, as well as fuzzy triangular, trapezoidal numbers.

Step 2. 2. Standardization of partial criteria $p_j^{\text{norm}}(x^{(k)})$ for each k -th project development alternative according to formula (5)–(8) for the intervals

$$c_j(x^{(k)}) = [c_{j1}(x^{(k)}), c_{j2}(x^{(k)})],$$

$$p_j^{\text{norm}}(x^{(k)}) = \left[\frac{c_{j1}(x^{(k)})}{c_j^{\max}}, \frac{c_{j2}(x^{(k)})}{c_j^{\max}} \right], \quad c_j^{\max} = \max_{1 \leq k \leq m} \{c_{j2}^{(k)}\}, \quad (5)$$

where $c_{j1}(x^{(k)})$, $c_{j2}(x^{(k)})$ are the minimum and maximum values of the interval.

Consider possible options of fuzzy numbers that can be used to estimate the object state:

1) for fuzzy triangular numbers

$$c_j(x^{(k)}) = [c_{j1}(x^{(k)}), c_{j2}(x^{(k)}), c_{j3}(x^{(k)})],$$

$$p_j^{\text{norm}}(x^{(k)}) = \left[\frac{c_{j1}(x^{(k)})}{c_j^{\max}}, \frac{c_{j2}(x^{(k)})}{c_j^{\max}}, \frac{c_{j3}(x^{(k)})}{c_j^{\max}} \right],$$

$$c_j^{\max} = \max_{1 \leq k \leq m} \{c_{j3}^{(k)}\}, \quad (6)$$

where $c_{j1}(x^{(k)})$, $c_{j2}(x^{(k)})$, $c_{j3}(x^{(k)})$ are the minimum, most expected and maximum values of the interval;

2) for trapezoidal numbers

$$c_j(x^{(k)}) = [c_{j1}(x^{(k)}), c_{j2}(x^{(k)}), c_{j3}(x^{(k)}), c_{j4}(x^{(k)})],$$

$$p_j^{\text{norm}}(x^{(k)}) = \left[\frac{c_{j1}(x^{(k)})}{c_j^{\max}}, \frac{c_{j2}(x^{(k)})}{c_j^{\max}}, \frac{c_{j3}(x^{(k)})}{c_j^{\max}}, \frac{c_{j4}(x^{(k)})}{c_j^{\max}} \right],$$

$$c_j^{\max} = \max_{1 \leq k \leq m} \{c_{j4}^{(k)}\}, \quad (7)$$

where $c_{j1}(x^{(k)})$, $c_{j4}(x^{(k)})$ are the pessimistic and optimistic estimates of the interval boundaries, $c_{j2}(x^{(k)})$, $c_{j3}(x^{(k)})$ is the interval of the most expected values;

3) for polyhedral numbers

$$c_j(x^{(k)}) = \left[\begin{array}{c} c_{j1}(x^{(k)}), c_{j2}(x^{(k)}), \\ c_{j3}(x^{(k)}), c_{j4}(x^{(k)}), \dots, c_{jN}(x^{(k)}) \end{array} \right],$$

$$p_j^{\text{norm}}(x^{(k)}) = \left[\begin{array}{c} \frac{c_{j1}(x^{(k)})}{c_j^{\max}}, \frac{c_{j2}(x^{(k)})}{c_j^{\max}}, \\ \frac{c_{j3}(x^{(k)})}{c_j^{\max}}, \frac{c_{j4}(x^{(k)})}{c_j^{\max}}, \dots, \frac{c_{jN}(x^{(k)})}{c_j^{\max}} \end{array} \right],$$

$$c_j^{\max} = \max_{1 \leq k \leq m} \{c_{jN}^{(k)}\}. \quad (8)$$

Normalization of partial criteria is necessary because their numerical values differ in units and order of magnitude, which complicates further operations with these criteria. Partial criteria can be represented as interval or fuzzy L - R -type (e.g., triangular, trapezoidal) numbers.

Step 2. 3. Standardization of interval coefficients $j = \overline{1, n}$ of the relative importance of partial criteria

$$w_j^{\text{norm}} = \frac{w_j}{\sum_{j=1}^n w_j}, \quad j = \overline{1, n},$$

where w_j is the interval coefficient of the relative importance of the j -th partial criterion, which can be represented as intervals, fuzzy triangular, trapezoidal numbers and polyhedral numbers.

If the standardized interval coefficient of the relative importance of the j -th partial criterion in the form of the interval $w_j^{\text{norm}} = [\alpha_{j1}, \alpha_{j2}]$, where α_{j1} , α_{j2} are the minimum and maximum values of the interval, then it is assumed that $\sum_{j=1}^n \alpha_{j1} < 1$, $\sum_{j=1}^n \alpha_{j2} < 1$, otherwise, the problem (4) has no solution due to the impossibility to fulfill the constraint $\sum_{j=1}^n \alpha_{j1} = 1$.

If the standardized interval coefficient of the relative importance of the j -th partial criterion in the form of a fuzzy triangular number $w_j^{\text{norm}} = [\alpha_{j1}, \alpha_{j2}, \alpha_{j3}]$, where α_{j1} , α_{j2} , α_{j3} are the minimum, most expected and maximum values of the interval, then it is assumed that $\sum_{j=1}^n \alpha_{j1} < 1$, $\sum_{j=1}^n \alpha_{j3} > 1$.

Otherwise, the problem (4) has no solution. If the standardized interval coefficient of the relative importance of the j -th partial criterion in the form of a fuzzy triangular number $w_j^{\text{norm}} = [\alpha_{j1}, \alpha_{j2}, \alpha_{j3}, \alpha_{j4}]$, where α_{j1} , α_{j4} are the pessimistic and optimistic estimates of the interval boundaries, $[\alpha_{j2}, \alpha_{j3}]$ is the interval of the most expected values, then it is assumed that $\sum_{j=1}^n \alpha_{j1} < 1$, $\sum_{j=1}^n \alpha_{j4} > 1$.

Step 2. 4. Calculation of scalar interval estimates of the generalized utility of each k -th object state estimation alternative for $P(x^{(k)})$.

Step 2. 5. Selection of an acceptable object state estimation alternative on the basis of interval assessment, which is the most important. It should be noted that the problem (4) is correct if the intervals of the partial criteria do not intersect, so it is possible to compare the intervals with each other, and the relationship “more” or “less” is established.

3. Construction of the FCM.

Structure formation (preliminary structural adjustment).

The FCM consists in setting structural relationships (in the form of time lags) between the FCM concepts, weighted by the fuzzy values $w_{ij}^{(t-l_i)}$ of their influence on each other.

Modified ANFIS-type (Adaptive Neuro-Fuzzy Inference System) models are proposed as the FCM FS_i implementing fuzzy temporal transformations F_i . FCM provide generation, storage and output of predicted fuzzy values of the corresponding components of the multidimensional time series with necessary time delays for FCM.

The input temporal fuzzy variables of the FS_i model of the C_i concept are related to the output temporal fuzzy variables of those concepts that have a direct impact on the C_i concept. In this case, the input temporal fuzzy variables C_i are pre-weighted by the corresponding fuzzy degrees of influence $w_{ij}^{(t-l_i)}$, on the basis of which the following transformation is performed:

$$\tilde{s}_j^{(t-l_i)} = \left(w_{ij}^{(t-l_i)} T \tilde{s}_j^{(t-l_i)} \right), \quad l_i = 0, \dots, L_i^j, \quad (9)$$

where T is the T-norm operation.

The output temporal fuzzy variable models FS_i of the C_i concept are designed to generate, store and derive the predicted values of the i -th component of the multidimensional time series corresponding to time lags. Both a priori information about the components of the multidimensional time series available in the knowledge base and the data obtained as a result of estimation or measurement can be used to construct fuzzy component temporal models FS_i .

In the first case, it is assumed that the problem of ensuring the completeness and consistency of the fuzzy rule base of the FS_i model is solved in advance.

If only experimental data are known, then the task is to identify the model. In practice, there is often a mixed case when the initial rule base of the model is built on the basis of heuristic assumptions, and its parametric adjustment (training) is performed on the basis of a training sample.

The input temporal fuzzy variables of the FS_i model are

$$S_1^i = \{ \tilde{s}_3^{(t-1)}, \tilde{s}_3^{(t-3)}, \tilde{s}_4^{(t-3)}, \tilde{s}_5^{(t-3)}, \tilde{s}_1^{(t-3)} \}$$

and its output fuzzy temporal fuzzy variables are

$$S_1^i = \{ \tilde{s}_1^{(t)}, \tilde{s}_1^{(t-1)}, \tilde{s}_1^{(t-2)} \}.$$

While constructing the model, the truth measures are first determined for the current values of the input variables to match these fuzzy statements to the prerequisites of all the model rules. After that, aggregation of the truth degrees of the rule prerequisites based on the T-norm operation is performed

$$\alpha_p = \min(\mu_{\tilde{L}}(\tilde{s}_1^{(t-1)}), \mu_{\tilde{L}}(\tilde{s}_3^{(t-3)}), \mu_{\tilde{M}}(\tilde{s}_4^{(t-3)}), \mu_{\tilde{M}}(\tilde{s}_5^{(t-3)}), \mu_{\tilde{H}}(\tilde{s}_1^{(t-3)})). \tag{10}$$

Then, the conclusion of the corresponding rules is activated in accordance with the truth degrees of their prerequisites based on the implication operation (here, the Mamdani implication of the min-activation operation)

$$\mu_{\tilde{M}}(\tilde{s}_1^{(t)}) = \min(\alpha_p, \tilde{M}). \tag{11}$$

After that, the max-disjunction operation is performed, accumulating the activated conclusions of all the model rules:

$$\tilde{s}_1^{(t)} = \max(\mu_{\tilde{M}}(\tilde{s}_1^{(t)}), \dots, \mu_{\tilde{M}}(\tilde{s}_1^{(t)}), \dots, \mu_{\tilde{H}}(\tilde{s}_1^{(t)})). \tag{12}$$

Next is the normalization, storage and output of fuzzy values of the model output variables with the necessary FCM time delays

$$\tilde{s}_{1(norm)}^{(t)} = Z^0(\tilde{s}_1^{(t-1)}), \tilde{s}_{1(norm)}^{(t-2)} = Z^{-1}(\tilde{s}_1^{(t-1)}). \tag{13}$$

4. Performing a topological analysis of the FCM structure (point 4 is absent).

The procedure of topological analysis of the FCM structure consists of the following sequence of actions:

Step 4. 1. Entering the values of relationships between the FCM vertices.

Step 4. 2. If the values of the relationships between the vertices presented as verbal descriptions are correct, then go to Step 4. 3, otherwise, go to Step 4. 4.

Step 4. 3. Structuring the values of the relationships between the vertices.

Step 4. 4. If the condition that the values of the relationships between the vertices are represented as intervals of fuzzy numbers is met, then go to Step 4. 5; if the condition is not met, that is, the values of the relationships between the vertices are represented by numbers from the interval $w_{ij} \in [1, 1]$, then go to Step 4. 6.

Step 4. 5. Normalizing the values of the relationships between the vertices represented as intervals, fuzzy numbers.

Step 4. 6. Construction of the FCM in the form of a relational matrix.

Step 4. 7. Transition from undefined values to “-1”, “0” and “1”. To apply the topological analysis of the FCM structure, it is recommended to convert the obtained normalized interval values of the relationships between the vertices as follows:

- 1) if the normalized values are in the interval $[-1, 0)$, then minus “one” is assigned;
- 2) if the normalized value is in the interval $(0, 0.5)$ – “zero”;
- 3) if the normalized value is in the interval $[0.5, 1]$ – “one”.

Step 4. 8. Construction of a relational matrix consisting of “- 1”, “0” and “1”.

Step 4. 9. Calculation of the simplex dimension of the complex $K_x(Y; \lambda)$.

First, units in each i -th row are counted, $i=1, 2, \dots, m$ and then the simplex dimension of the complex $K_x(Y; \lambda)$ is calculated:

$$q = q^{(i)} = \sum_{j=1}^m \lambda_{ij} - 1. \tag{14}$$

Step 4. 10. Calculation of the simplex dimension of the complex $K_y(X; \lambda^*)$.

First, units in each j -th column are counted and then the simplex dimension of the complex $K_y(X; \lambda^*)$ is calculated:

$$q = q^{(j)} = \sum_{i=1}^m \lambda_{ij} - 1. \tag{15}$$

Step 4. 11. Matrix transformation.

The transformation of the matrix Λ into ${}^{(1)}\Lambda$ – ordering the rows from top to bottom is carried out by the following rule

$$q_1^{(i)} > q_2^{(i)} > q_3^{(i)} \dots > 0 > -1. \tag{16}$$

The transformation of the matrix ${}^{(1)}\Lambda$ into ${}^{(2)}\Lambda$ – ordering j -columns from left to right is carried out by the rule

$$q_1^{(j)} > q_2^{(j)} > q_3^{(j)} \dots > 0 > -1. \tag{17}$$

Step 4. 12. Construction of simplicial complexes.

The construction of the complex

$$K_x(Y; \lambda) = \{\delta_q^{(v_i)}\}$$

is a sequence of simplexes $\delta_q^{(v_i)}$, ordered by the rule (16) of decreasing their dimension.

The construction of the complex

$$K_x(Y; \lambda) = \{\delta_q^{(v_j)}\}$$

is a sequence of simplexes $\delta_q^{(v_j)}$, ordered by the rule (17) of decreasing their dimension.

Step 4. 13. Determining the first structural vector on the matrix ${}^{(2)}\Lambda$ of the complex $K_x(Y; \lambda)$.

Determination of the first structural vector $Q_x = \{Q_{\dim K}, \dots, Q_g, Q_1, Q_0\}$ on the matrix ${}^{(2)}\Lambda$ of the complex $K_x(Y; \lambda)$ is carried out as follows. For each dimension $q^{(i)}$, the number of simplexes in each equivalence class Q_q is determined by the rule: if at least one unit of the i -row is not included in the previous rows $i-1, i-2, \dots, 1$, then the simplex corresponding to this row forms a separate equivalence class.

Step 4. 14. Determining the first structural vector on the matrix ${}^{(2)}\Lambda K_y(Y; \lambda^*)$. For each dimension $q^{(j)}$, the number of simplexes in each equivalence class Q_q is determined by the rule: if at least one unit of the j -th column is not included in the previous columns $j-1, j-2, \dots, 1$, then the simplex corresponding to this column forms a separate equivalence class.

5. Training artificial neural networks (ANN).

In this procedure, ANN are trained using the method of training evolving ANN developed by the authors in [2]. The difference of this method from the known ones is that it allows training not only synaptic weights, but also the parameters of the membership function together with the ANN architecture. Also, at this stage, all fuzzy component temporal models of the FCM are coordinated. Coordination of all fuzzy component temporal models $FS_i, i=1, \dots, N$ of the FCM is carried out after their “personalized” parametric adjustment. Coordination is such a change in the modal values and fuzzy degrees of influence $\left\{w_{ij}^{(t-t')}\right\}_{L_i^j = 0, \dots, L_i^j}$ between the FCM concepts, which provides a maximum increase in the forecasting accuracy for each of the components of the multidimensional time series without deterioration. The procedure of coordination of fuzzy component temporal models of the FCM is preceded by the formation of an additional “coordinating” training sample, consisting of retrospective

data simultaneously for all components of the multidimensional time series. The procedure for coordinating all fuzzy component temporal FCM models is considered successfully completed if the final error for each of these models does not exceed some threshold. For well-coordinated components of the multidimensional time series, or for these models, the Edgeworth-Pareto principle will be followed.

6. Forecasting the analysis object state.

Multidimensional state forecasting is performed on the basis of the adjusted FCM as follows:

- calculation of the values of the output variables of the models FS_i , $i=1, \dots, N$ for the corresponding sets of values of the input variables of these models set each time;
- self-development and forecast assessment of changes in the system/process state in the absence of external influences on it;
- development and forecast assessment of changes in the system/process state, in which the state dynamics in a certain situation are modeled.

5. 4. Example of application of the proposed method in the analysis and forecasting of the operational situation of the troops (forces) grouping

The method of estimation and forecasting in intelligent decision support systems is proposed. To assess the efficiency of the developed estimation and forecasting method, it was compared with the most popular software:

- ARIS Business Performance Edition (IDS Scheer AG, Germany);
- IBM WebSphere Business Modeler (IBM, USA);
- System21 Aurora (Campbell Lee Computer Services Limited, UK);
- SAP Strategic Enterprise Management (SAP, Germany);
- Hyperion Performance Scorecard (Oracle, USA);
- CA ERWin Process Modeler (CA, USA).

Simulation of the method of processing the search for solutions in accordance with the algorithm in Fig. 2 and expressions (1)–(8) was performed. The simulation of the proposed estimation and forecasting method was carried out in the MathCad 14 software environment (USA). The task of the simulation was to assess the elements of the operational situation of the troops (forces) grouping.

Initial data for assessing the state of the operational situation using the advanced method:

- the number of information sources on the state of the monitoring object is 3 (radio monitoring devices, earth remote sensing devices and unmanned aerial vehicles). To simplify the simulation, the same number of each device was taken – 4 devices;
- the number of information features to determine the monitoring object state is 12. These parameters include: affiliation, type of organizational and staff formation, priority, minimum width on the front, maximum width on the front. The number of personnel, the minimum depth on the flank, the maximum depth on the flank, the number of weapons samples, the number of types of weapons samples and the number of radio communication devices, the type of operational construction are also taken into account;
- options for organizational and staff formations are company, battalion, brigade.

The cognitive map of the operational situation of the grouping is a square table (incidence matrix). Rows and columns mutually uniquely correspond to the basic factors describing the object under research, and the number at the

intersection of the i -th row and the j -th column describes the effect of the i -th factor on the j -th factor. The sign of this number reflects the sign of influence (positive or negative), and the module – the strength of such influence (Table 1).

Table 1

Incidence matrix of the cognitive map of operational situation assessment

No.	w_1	w_2	w_3	w_4	w_5	w_6	w_7	w_8	w_9	w_{10}	w_{11}	w_{12}
w_1	0	1	1	0	0	0	0	1	0	1	1	0
w_2	0	0	1	0	1	1	1	0	0	1	1	0
w_3	0	1	0	0	1	0	0	-1	0	1	0	-1
w_4	0	0	1	0	0	1	-1	0	0	1	1	0
w_5	0	1	1	0	0	0	0	1	1	1	1	0
w_6	0	1	0	0	-1	0	1	1	-1	1	1	0
w_7	1	-1	1	0	0	-1	0	1	0	1	0	0
w_8	0	-1	1	1	1	-1	0	0	0	0	0	0
w_9	1	0	1	1	-1	1	1	0	0	1	1	0
w_{10}	1	-1	0	1	0	1	0	-1	0	0	0	0
w_{11}	1	1	1	-1	0	1	0	0	0	1	1	1
w_{12}	0	0	1	1	0	1	1	1	1	1	0	0

Forecasting of the operational situation of the grouping took place 3 days in advance based on the training sample of 10 days of operation for each modal value of fuzzy degrees of influence of one concept on another. The results of forecasting the operational situation of the grouping obtained taking into account Table 1 are shown in Fig. 3.

Let's determine the error of multidimensional forecasting of the development of the operational situation of the troops (forces) grouping, which is taken as a monitoring and forecasting object. The results of estimating the forecasting error are given in Table 2. The comparison was based on the MAPE criterion.

Table 2

Comparative estimation of forecasting error using different approaches

No.	Time series components	Forecasting error, MAPE %		
		FCM	ANN	Developed method
1	Affiliation	7	6.9	6.6
2	Type of organizational and staff formation	1.5	1.33	1.3
3	Minimum width on the front	8.5	8.3	8.1
4	Maximum width on the front	2.5	2.2	2
5	Number of personnel	2	1.87	1.7
6	Minimum depth on the flank	2.34	2.1	1.8
7	Maximum depth on the flank	2.1	1.95	1.75
8	Number of weapons samples	1.9	1.76	1.6
9	Number of types of weapons samples	1.7	1.52	1.42
10	Number of communication means	2	1.84	1.77
11	Number of structural units	1.6	1.4	1.25
12	Type of operational construction	1.69	1.52	1.3

According to the analysis of the estimation error presented in Table 2, it was found that the evaluation accuracy of this method is higher by an average of 12 % compared to artificial neural networks.

The results of assessing the operational situation of the grouping according to the initial data are given in Table 3, which presents normalized evaluation results.

Table 3

Comparison of the computational complexity of the software and the developed method for assessing the operational situation

No.	Software	Number of calculations	Developed method (by the number of calculations)
1	ARIS Business Performance Edition (IDS Scheer AG)	67,000	58,960
2	IBM WebSphere Business Modeler (IBM)	64,500	58,760
3	System21 Aurora (Campbell Lee Computer Services Limited)	57,000	48,450
4	SAP Strategic Enterprise Management (SAP)	39,830	35,847
5	Hyperion Performance Scorecard (Oracle)	46,200	40,194
6	CA ERWin Process Modeler (CA)	43,050	37,023

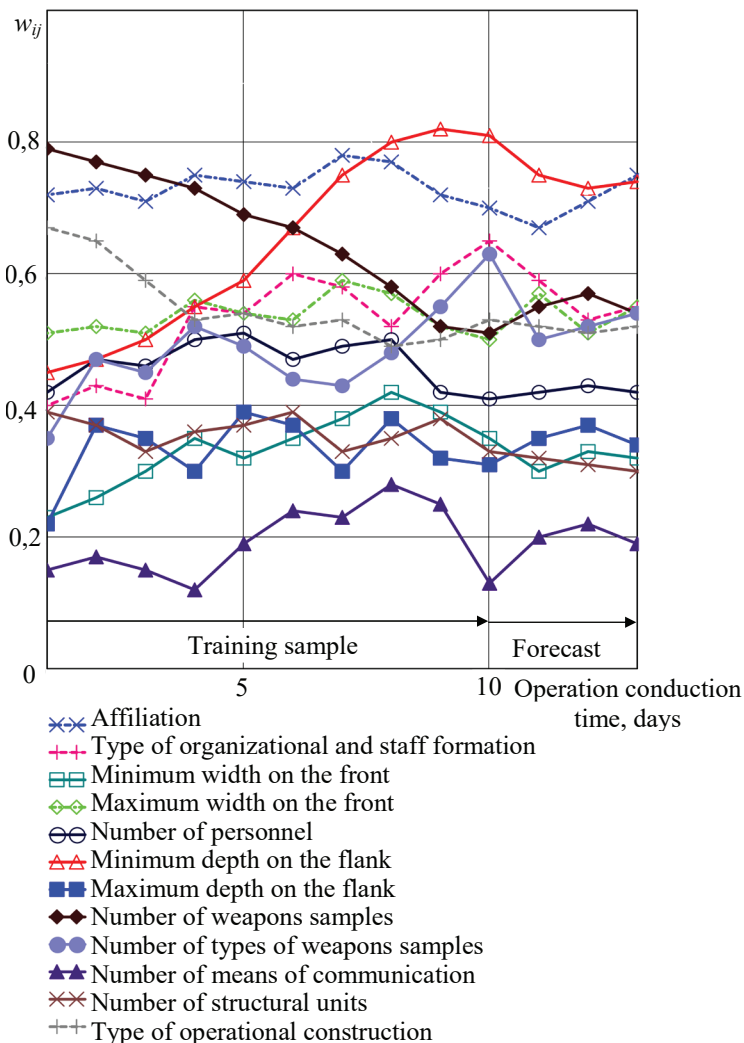


Fig. 3. Results of forecasting changes in the operational situation of the troops grouping for 3 days of operation

From the analysis of the data in Table 3, it is seen that the presented method has fewer calculations compared to the known estimation and forecasting approaches.

The advantage of this method over the known ones is the reduction of computational complexity, which in turn increases the efficiency of decision-making regarding the operational situation of the troops (forces) grouping.

Table 4 shows the comparative results of evaluating the efficiency of training evolving artificial neural networks.

Table 4

Comparative results of evaluating the efficiency of training evolving artificial neural networks

System	Algorithm parameters	XB (Xie-Beni Index)	Time, s
FCM (Fuzzy C-Means)	–	0.2104	3.15
EFCM	Dthr=0.30	0.1218	0.175
EFCM	Dthr=0.23	0.1262	0.21
Proposed system (batch mode)	delta=0.1	0.1	0.32
Proposed system (online mode)	delta=0.1	0.098	0.2

Before training, observational signs were normalized at the interval [0, 1].

The research showed that this training procedure provides an average of 10–18 % higher efficiency of training artificial neural networks and does not accumulate training errors (Table 4).

These results can be seen from the results in the last rows of Table 4, as the difference of the Xie-Beni index. However, as already mentioned, the known methods accumulate errors, that is why the proposed method suggests the use of evolving artificial neural networks.

6. Discussion of the results of developing the estimation and forecasting method

The main advantages of the proposed estimation method are:

- flexible hierarchical structure of indicators, which allows reducing the problem of multi-criteria evaluation of alternatives to one criterion or using a vector of indicators for selection;
- unambiguity of the object state estimation;
- wide scope of use (decision support systems);
- simplicity of mathematical calculations;
- no accumulation of training errors;
- adaptability of the system of indicators during the work;
- learning not only the synaptic weights of the artificial neural network, but also the type and parameters of the membership function;
- learning the architecture of artificial neural networks;
- calculation of data for one epoch without the need to store previous calculations;
- consideration of the type of uncertainty when constructing a fuzzy cognitive temporal model. The types of uncertainties can be as follows: complete uncertainty about the object state,

partial uncertainty about the monitored object state, full awareness of the object state. However, this is based on the expression (2) to correct the results;

- consideration of the noise of the initial data when constructing fuzzy cognitive temporal models. The law of data noise distribution is taken into account: normal law, gamma law and random law. All this is taken into account in the calculations as an additional factor in the expression (2).

The limitations of the study are as follows:

- the need for an initial database of the analysis object;
- availability of a high-quality training sample;
- accounting of time required for training an artificial neural network;
- high requirements to the quality of communication channels;
- the need to know the exact coordinates of intelligence sources to calculate the delay time of message transmission from them to the data center.

The disadvantages of the proposed method include:

- loss of informativeness in estimating the state of the monitoring object due to the construction of the membership function. The loss of informativeness can be reduced by choosing the type of membership function in the practical implementation of the proposed method in decision support systems. The choice of the type of membership function depends on the computing resources of a particular computing device;
- lower accuracy of estimation based on a separate estimation parameter of the object state;
- lower accuracy of estimation compared to other estimation methods.

This method allows:

- estimating the object state;
- identifying effective measures to improve management efficiency;
- increasing the speed of object state estimation;
- reducing the use of computing resources of decision support systems.

The results of the efficiency analysis of the proposed method show that its computational complexity is 12–18 % lower compared to the methods used for assessing the effectiveness of decisions presented in Table 2.

This study is a further development of research aimed at developing methodological principles for improving the efficiency of information and analytical support, published earlier [2, 4–6].

Further research should be aimed at reducing the computational cost in processing various data in special-purpose systems.

The proposed method can be used in decision support systems of automated control systems (artillery units, special-purpose geographic information systems. It can also be used in ACS DSS for aviation and air defense, as well as ACS DSS for the logistics of the Armed Forces of Ukraine.

This study is a further development of research aimed at developing methodological principles for improving the efficiency of data processing in special-purpose information systems [26, 27, 31].

7. Conclusions

1. A formalized description of the problem of analyzing and forecasting the object state in intelligent decision support sys-

tems was carried out. This formalization allows describing the processes that take place in intelligent decision support systems when solving problems of analyzing and forecasting the object state. The efficiency of analyzing and forecasting the object state is chosen as an efficiency criterion of this method.

2. In the course of the study, the concept of presenting the method of estimation and forecasting in intelligent decision support systems is formulated. The concept presents the analysis and forecasting process as a multidimensional time series. This allows creating a hierarchical description of a complex process by generalization levels and conducting an appropriate analysis with subsequent forecasting of its state.

3. The algorithm of the method is determined, which allows:

- conducting multidimensional analysis and forecasting the object state in conditions of uncertainty;

- forecast estimation in the conditions of non-stochastic uncertainty, nonlinearity of mutual influence, partial inconsistency and essential interdependence of the components of a multidimensional time series;

- conducting a topological analysis of the FCM structure;
- considering the noise level of the original data on the efficiency of data processing;

- taking into account the delay time for receiving information from extraction points to processing points;

- taking into account the type of uncertainty of the initial data during FCM construction;

- conducting structural and parametric training of artificial neural networks for intelligent decision support systems;

4. An example of using the proposed method in estimating and forecasting the operational situation of the troops (forces) grouping is given. This example showed an increase in data processing efficiency at the level of 12–18 % using additional advanced procedures.

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References

1. Shyshatskyi, A. V., Bashkyrov, O. M., Kostyna, O. M. (2015). Development of integrated communication systems and data transfer for the needs of the Armed Forces. *Weapons and military equipment*, 1, 35–39.
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskiy, 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. doi: <https://doi.org/10.15587/1729-4061.2020.203301>
3. Bodyanskiy, E., Strukov, V., Uzlov, D. (2017). Generalized metrics in the problem of analysis of multidimensional data with different scales. *Zbirnyk naukovykh prats Kharkivskoho universytetu Povitrianykh Syl*, 3 (52), 98–101.
4. Pievtsov, H., Turinskyi, O., Zhyvotovskiy, 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. doi: <https://doi.org/10.21303/2461-4262.2020.001353>
5. Zuiev, P., Zhyvotovskiy, 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. doi: <https://doi.org/10.15587/1729-4061.2020.208554>
6. Shyshatskyi, A., Zvieriev, O., Salnikova, O., Demchenko, Ye., Trotsko, O., Neroznak, Ye. (2020). Complex Methods of Processing Different Data in Intellectual Systems for Decision Support System. *International Journal of Advanced Trends in Computer Science and Engineering*, 9 (4), 5583–5590. doi: <https://doi.org/10.30534/ijatcse/2020/206942020>
7. Trotsenko, R. V., Bolotov, M. V. (2014). Data extraction process for heterogeneous sources. *Privolzhskiy nauchnyy vestnik*, 12-1 (40), 52–54.
8. Rotshteyn, A. P. (1999). *Intellektual'nye tekhnologii identifikatsii: nechetkie mnozhestva, geneticheskie algoritmy, neyronnye seti*. Vinnitsa: "UNIVERSUM", 320.
9. Alpeeva, E. A., Volkova, I. I. (2019). The use of fuzzy cognitive maps in the development of an experimental model of automation of production accounting of material flows. *Russian Journal of Industrial Economics*, 12 (1), 97–106. doi: <https://doi.org/10.17073/2072-1633-2019-1-97-106>
10. Zagranovskaya, A. V., Eissner, Y. N. (2017). Simulation scenarios of the economic situation based on fuzzy cognitive maps. *Modern economics: problems and solutions*, 10 (94), 33–47. doi: <https://doi.org/10.17308/meps.2017.10/1754>
11. Simankov, V. S., Putyato, M. M. (2013). Issledovanie metodov kognitivnogo analiza. *Perspektivy razvitiya informatsionnykh tekhnologiy*, 13, 31–35.
12. Onykyi, B., Artamonov, A., Ananieva, A., Tretyakov, E., Pronicheva, L., Ionkina, K., Suslina, A. (2016). Agent Technologies for Polythematic Organizations Information-Analytical Support. *Procedia Computer Science*, 88, 336–340. doi: <https://doi.org/10.1016/j.procs.2016.07.445>
13. Ko, Y.-C., Fujita, H. (2019). An evidential analytics for buried information in big data samples: Case study of semiconductor manufacturing. *Information Sciences*, 486, 190–203. doi: <https://doi.org/10.1016/j.ins.2019.01.079>
14. Çavdar, A. B., Ferhatosmanoğlu, N. (2018). Airline customer lifetime value estimation using data analytics supported by social network information. *Journal of Air Transport Management*, 67, 19–33. doi: <https://doi.org/10.1016/j.jairtraman.2017.10.007>
15. Ballester-Caudet, A., Campíns-Falcó, P., Pérez, B., Sancho, R., Lorente, M., Sastre, G., González, C. (2019). A new tool for evaluating and/or selecting analytical methods: Summarizing the information in a hexagon. *TrAC Trends in Analytical Chemistry*, 118, 538–547. doi: <https://doi.org/10.1016/j.trac.2019.06.015>
16. Ramaji, I. J., Memari, A. M. (2018). Interpretation of structural analytical models from the coordination view in building information models. *Automation in Construction*, 90, 117–133. doi: <https://doi.org/10.1016/j.autcon.2018.02.025>
17. Pérez-González, C. J., Colebrook, M., Roda-García, J. L., Rosa-Remedios, C. B. (2019). Developing a data analytics platform to support decision making in emergency and security management. *Expert Systems with Applications*, 120, 167–184. doi: <https://doi.org/10.1016/j.eswa.2018.11.023>
18. Chen, H. (2018). Evaluation of Personalized Service Level for Library Information Management Based on Fuzzy Analytic Hierarchy Process. *Procedia Computer Science*, 131, 952–958. doi: <https://doi.org/10.1016/j.procs.2018.04.233>
19. Chan, H. K., Sun, X., Chung, S.-H. (2019). When should fuzzy analytic hierarchy process be used instead of analytic hierarchy process? *Decision Support Systems*, 125, 113114. doi: <https://doi.org/10.1016/j.dss.2019.113114>
20. Osman, A. M. S. (2019). A novel big data analytics framework for smart cities. *Future Generation Computer Systems*, 91, 620–633. doi: <https://doi.org/10.1016/j.future.2018.06.046>
21. Gödri, I., Kardos, C., Pfeiffer, A., Vánca, J. (2019). Data analytics-based decision support workflow for high-mix low-volume production systems. *CIRP Annals*, 68 (1), 471–474. doi: <https://doi.org/10.1016/j.cirp.2019.04.001>
22. Harding, J. L. (2013). Data quality in the integration and analysis of data from multiple sources: some research challenges. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, XL-2/W1, 59–63. doi: <https://doi.org/10.5194/isprsarchives-xl-2-w1-59-2013>
23. Rybak, V. A., Shokr, A. (2016). Analysis and comparison of existing decision support technology. *System analysis and applied information science*, 3, 12–18.

24. Rodionov, M. A. (2014). Problems of information and analytical support of contemporary strategic management. *Civil Aviation High Technologies*, 202, 65–69.
25. Bednář, Z. (2018). Information Support of Human Resources Management in Sector of Defense. *Vojenské rozhledy*, 27 (1), 45–68. Available at: <https://www.vojenskerozhledy.cz/kategorie-clanku/strategicke-rizeni/informacni-podpora>
26. Palchuk, V. (2017). Methods of Content-Monitoring and Content-Analysis of Information Flows: Modern Features. *Academic Papers of The Vernadsky National Library of Ukraine*, 48, 506–526. doi: <https://doi.org/10.15407/np.48.506>
27. Mir, S. A., Padma, T. (2016). Evaluation and prioritization of rice production practices and constraints under temperate climatic conditions using Fuzzy Analytical Hierarchy Process (FAHP). *Spanish Journal of Agricultural Research*, 14 (4), e0909. doi: <https://doi.org/10.5424/sjar/2016144-8699>
28. Kljushin, V. V. (2014). Theoretical and methodological basis for the formation and evaluation of the level of the economic system's strategic economic potential. *Modern Management Technology*, 12 (48). Available at: <https://sovman.ru/en/article/4805/>
29. Bogomolova, I. P., Omel'chenko, O. M. (2014). Analysis of influence factors of economic efficiency on the economy of the integrated structure. *Proceedings of the Voronezh State University of Engineering Technologies*, 3, 157–162. Available at: <https://www.vestnik-vsuet.ru/vguit/article/view/434/400>
30. Sherafat, A., Yavari, K., Davoodi, S. M. R. (2014). Evaluation of the Strategy Management Implementation in Project-Oriented Service Organizations. *Acta Universitatis Danubius*, 10 (1), 16–25. Available at: <https://ideas.repec.org/a/dug/actaec/y2014i1p16-25.html>
31. Koshlan, A., Salnikova, O., Chekhovska, M., Zhyvotovskiy, R., Prokopenko, Y., Hurskyi, T. et. al. (2019). Development of an algorithm for complex processing of geospatial data in the special-purpose geoinformation system in conditions of diversity and uncertainty of data. *Eastern-European Journal of Enterprise Technologies*, 5 (9 (101)), 35–45. doi: <https://doi.org/10.15587/1729-4061.2019.180197>
32. Mahdi, Q. A., Shyshatskyi, A., Prokopenko, Y., Ivakhnenko, T., Kupriyenko, D., Golian, V. et. al. (2021). Development of estimation and forecasting method in intelligent decision support systems. *Eastern-European Journal of Enterprise Technologies*, 3 (9 (111)), 51–62. doi: <https://doi.org/10.15587/1729-4061.2021.232718>