

DEVELOPMENT OF ESTIMATION AND FORECASTING METHOD IN INTELLIGENT DECISION SUPPORT SYSTEMS

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The method of estimation and forecasting in intelligent decision support systems was developed. The essence of the method is the analysis of the current state of the object and short-term forecasting of the object state. Objective and complete analysis is achieved by using improved fuzzy temporal models of the object state and an improved procedure for processing the original data under uncertainty. Also, the possibility of objective and complete analysis is achieved through an improved procedure for forecasting the object state and an improved procedure for learning evolving artificial neural networks. The concepts of fuzzy cognitive model are related by subsets of influence fuzzy degrees, arranged in chronological order, taking into account the time lags of the corresponding components of the multidimensional time series. The method is based on fuzzy temporal models and evolving artificial neural networks. The peculiarity of the method is the possibility of taking into account the type of a priori uncertainty about the object state (full awareness of the object state, partial awareness of the object state and complete uncertainty about the object state). The possibility to clarify information about the object state is achieved using an advanced training procedure. It consists in training the synaptic weights of the artificial neural network, the type and parameters of the membership function, as well as the architecture of individual elements and the architecture of the artificial neural network as a whole. The object state forecasting procedure allows conducting multidimensional analysis, consideration, and indirect influence of all components of a multidimensional time series with their different time shifts relative to each other under uncertainty. The method provides an increase in data processing efficiency at the level of 15–25 % using additional advanced procedures

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

Received date: 29.03.2021

Accepted date: 17.05.2021

Published date: 30.06.2021

How to Cite: Mahdi, Q. A., Shyshatskyi, A., Prokopenko, Y., Ivakhnenko, T., Kupriyenko, D., Golian, V., Lazuta, R., Kravchenko, S.,

Protas, N., Momit, A. (2021). Development of estimation and forecasting methodology 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>

1. Introduction

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

processing of large data sets, process forecasting, providing information support for decision-makers.

The basis of existing DSS are methods of artificial intelligence, which provide collection, processing, generalization of

information about the state of objects (processes) and forecasting of their future state.

The creation of intelligent DSS has become a natural continuation of the widespread use of the classical type DSS. Intelligent DSS provide information support for all production processes and services of enterprises (organizations, institutions). The main fundamental difference between intelligent DSS and classical type DSS is the presence of feedback and the ability to adapt to changing input processes [8, 23]. With the help of intelligent DSS, we can conduct the design, manufacture and sale of products, financial and economic analysis, planning, personnel management, marketing, support for the creation (operation, repair) of products and long-term planning. Also, intelligent DSS have been widely used to solve specific military tasks, namely [1, 2]:

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

Conventionally, the structure of intelligent DSS can be divided into 4 major layers:

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

Analysis of the experience of creating intelligent DSS shows that the most promising is an information technology based on neural network modeling [1–8], in particular on the application of an evolutionary approach to the construction of artificial neural networks (ANN) [2–7]. ANN allow processing various types of data, adapting their structure to the type and amount of input data, thereby increasing their own productivity.

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

- the ability to quickly adapt to the subject area, which almost without any changes makes it possible to form an ANN structure, which corresponds to this process;
- the ability to learn quickly; based on models of neurons with the corresponding thresholds, weights and transfer functions to construct the trained ANN already in the first approximation;
- the ability to work under uncertainty, nonlinearity, stochasticity and chaos, various disturbances and interference;
- it has both universal approximating properties and the possibility of fuzzy inference.

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

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

The most significant shortcomings are as follows:

1. The complexity of choosing the system architecture. 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

processing data that are different from the 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 data for processing.

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 taking into account the indirect influence of interdependent components under uncertainty.

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

Fuzzy cognitive maps can eliminate these shortcomings. Fuzzy cognitive maps have proven themselves well in the problems of studying the structure of the modeled system and forecasting its behavior under various control influences and evolving ANN.

There is an urgent scientific problem of developing methods of assessment and forecasting in intelligent decision support systems using artificial neural networks and fuzzy cognitive models.

2. Literature review and problem statement

The work [9] presents the algorithm of cognitive modeling. The main advantages of cognitive tools are determined. While constructing the experimental model, the target factors of the cognitive map were determined, the analysis of the connection 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 to be monitored to diagnose trends in industrial development. The disadvantages of this approach include the lack of uncertainty type consideration about the state of the analyzed object.

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 the internal and external environment 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 state of the analyzed object and the delay in processing data about the object state.

In [11], the analysis of the main approaches to cognitive modeling is carried out. Cognitive analysis allows you to explore problems with fuzzy factors and relationships, take into account changes in the external environment and use objectively formed trends in the situation to your advantage. The need to develop a system of criteria for the formalization and automation of decision-making in problem areas is noted. It is also stated that the objectivity of processed information 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 of decision-making. The disadvantages of this approach include the limited representation of complex systems, so none of the agents has the whole image of the 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 includes operations of generating analytical baselines, reducing variables, detecting sparse features and specifying rules. The disadvantages of this method include the inability to take into account various decision making evaluation strategies.

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

The work [15] shows the approach to quantitative estimation for evaluating the optimum selection and/or testing of analytical methods. Objective criteria related to analytical performance, 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 depicted on a regular hexagonal icon, which allows comparing 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 construction objects information models transformation to their equivalent structural models. This mechanism is designed to automate the necessary operations of conversion, modification and addition 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] carries out the development of an analytical web platform for studying the geographical and temporal incidents distribution. 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, as well as high computational complexity.

The work [18] develops 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 the assessment.

The work [19] performs an analysis of 30 algorithms for processing large data sets. Their advantages and disadvantages are shown. It is found that the 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 the inability to verify the estimates adequacy.

The work [20] presents an approach for evaluating input data for decision support systems. The essence of the proposed approach is to cluster the basic set of input data, analyze them, and then then train the system based on the analysis. The disadvantages of this approach are the gradual accumulation of

evaluation and learning errors due to the inability to assess the decisions adequacy.

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

The work [22] carries out a comparative analysis of existing decision support systems: 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 spheres of their application are defined. It is shown that the method of hierarchy analysis works well with complete initial information, but due to the need for experts to compare alternatives and choose evaluation criteria, it has a high share of subjectivity. The use of fuzzy set theory and neural networks is justified for forecasting problems under risk and uncertainty.

The work [23] considers the problematic aspects of information-analytical support of strategic decision-making in modern management. The role and place of the process of developing and making management decisions in strategic planning are specified. The existing approaches to the account of course regularities and result of strategic processes are analyzed. In the course of the analysis, it was found that the approaches and methods of modern model theory in control systems, which allow for linguistic approximation of mathematical models of cybernetic systems, are of special interest. This approximation ensures the achievement of the highest level of abstract description of systems, which allows identifying the most general concepts and exploring relationship between them. However, the results do not fully apply to organizational management systems. To solve the problems of strategic management, it is proposed to use the fuzzy set and neural network theories.

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

The work [25] describes the approaches to the processing of constantly updated information circulating in social information communications: active use of content monitoring, content 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 the factors influencing the process of rice cultivation. The disadvantages of this method include the accumulation of evaluation errors due to the inability to assess the evaluation adequacy.

The work [27] performs the methodology development for determining and assessing the strategic economic potential of the theoretical and methodological foundations of the formation and assessment of the level of strategic economic potential of economic systems. This method is based on the hierarchy analysis method. The disadvantages of this method include the dependence of the results on experts' competence and high computational complexity.

The work [28] performs the development of an approach to determine the impact of factors influencing the economic efficiency on the economy of integrated structures. This approach is based on the use of the expert evaluation method. The disadvantages of this approach include the dependence of the results on experts' competence and high computational complexity.

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

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

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

- the complexity of forming a multilevel evaluation structure;
- lack of consideration of the compatibility of unevenly significant indicators;
- lack of possibility to jointly perform direct and inverse evaluation tasks with the support of choosing the best solutions.

To create software tools to support decision-making, it is necessary to create fuzzy evaluation methods, which must meet the following set of requirements:

- the possibility to form a generalized evaluation indicator and choose 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 choose solutions that differ in measuring scales and ranges of values;
- taking into account the compatibility and different significance of partial indicators in the generalized decision evaluation;
- 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);
- ensuring the implementation of the direct task of evaluating the generalized indicator on the basis of partial indicators, inverse evaluation task and joint execution of direct and inverse evaluation tasks within a single model;
- taking into account the type of uncertainty of the initial data about the object state.

To achieve the goal, it is proposed to develop a method for estimation and forecasting in 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 a method for estimation and forecasting in intelligent decision support systems, which would allow analyzing and forecasting the objects state.

To achieve the aim, the following objectives were set:

- to conduct a formalized description of the problem of analyzing and forecasting the object state in intelligent decision support systems;
- to formulate the presentation concept of the estimation and forecasting method in intelligent decision support systems;
- to determine the algorithm of the method;
- to give an example of applying the proposed method in analyzing and forecasting the operational situation of troops (forces).

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 and forecasting the state of dynamic objects. This allows describing how complex multi-level objects change over time. This study also uses the method of training artificial neural networks developed in previous works which allows for deep learning of artificial neural networks. The essence of deep learning is to learn the architecture, type and parameters of the membership function. The simulation was performed using MathCad 2014 software and an Intel Core i3 PC.

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

5. 1. Formalized description of the problem of analyzing and forecasting the object 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 the control system for analyzing and forecasting, which is divided into [11, 30]:

1) control subsystem (control subject, S);

2) controlled subsystem (control object, O);

3) object model (fuzzy cognitive model Y). The fuzzy cognitive model is used because the state of the analyzed object is usually characterized by both numerical and qualitative indicators. This requires bringing them to a single unit of measurement.

Here are the explanations of the variables shown in Fig. 1:

W – external information;

Q – system resources for analyzing and forecasting the object state;

H – internal information to build fuzzy cognitive models (FCM);

H^* – corrected error;

U – control effect (management decisions making, management teams) (direct communication);

Y_{CO} – source information (actual data, parameters, indicators) that characterizes the control object state;

Y_M – initial parameters of the model (desired, expected parameters);

ϵ – error (inconsistency);

ϵ_{add} – fixed setpoint;

$L(Y_{CO}, Y_M)$ – checking the correspondence of the data obtained on the basis of the model to the real object for the description of which it is built;

Y' – object state information (feedback);

Y'_{adj} – model adjustment (adding new factors and relationships between them);

Y_a – adequate model of the monitored object that corresponds to its actual state;

E_{train} – 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.

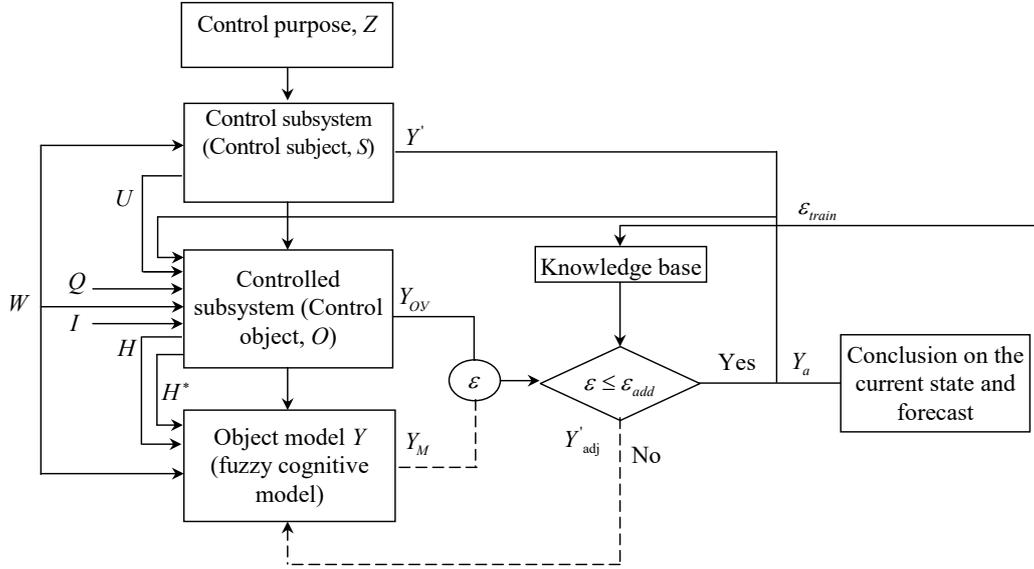


Fig. 1. Block diagram of the object state analysis and forecasting system

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

The controlled subsystem receives information (Q, I, U) , which forms the task of analyzing and predicting 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 the situation scenarios related to the nature of the monitored object actions.

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

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

5. 2. Concept of presenting the method of estimation and forecasting in intelligent decision support systems

The 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 the information Y' , processes and compares it with the desired characteristics of the control object and on its basis corrects the error H^* .

The control system for the process of analyzing and forecasting the object state 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 purpose of control; $D = \langle I, H, U, Y_{CO}, Y_M, Y', H^*, Y_{adj} \rangle$ is the internal environment of the control system S_{con} ; $Y = \langle W, H, H^*, Y_M \rangle$ is the object model, the result Y_M of which is FCM.

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

$$\forall t \in \{1, \dots, T, \dots\} S_t = \begin{cases} s_1^{(t)} F_1 \begin{pmatrix} \Phi_{1,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_1^1)} \right) \\ \Phi_{1,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_N^1)} \right) \end{pmatrix} \times \mathbf{t}_1, \\ s_2^{(t)} F_2 \begin{pmatrix} \Phi_{2,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_2^1)} \right) \\ \Phi_{2,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_N^2)} \right) \end{pmatrix} \times \mathbf{t}_2, \\ \dots \\ s_N^{(t)} F_N \begin{pmatrix} \Phi_{N,1} \left(s_1^{(t-1)}, \dots, s_1^{(t-L_N^N)} \right) \\ \Phi_{N,N} \left(s_N^{(t-1)}, \dots, s_N^{(t-L_N^N)} \right) \end{pmatrix} \times \mathbf{t}_N, \end{cases} \quad (2)$$

where S is the multidimensional timeseries; $S_t = (s_1^{(t)}, s_2^{(t)}, \dots, s_N^{(t)})$ is the time sample of the analyzed object state 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^i is the maximum value of the time delay of the i -th component relative to the j -th one; Φ_j is the operator that takes into account 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; \mathbf{t} is the operator that takes into account the degree of awareness of the object state.

From the expression (2) we can conclude that it allows describing the processes in the analyzed object, taking into account time delays. Delays are required to collect, process and summarize information and take into account the degree of awareness of the object state. Also, this expression (2) allows describing the 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 the source data. At this stage, available initial data about the analyzed object are entered. The basic model of the object state is initialized.

2. Identifying the factors and relationships between them.

In the known works, for example [3, 8, 13], the stage of processing initial data and the initial uncertainty of the information type to be modeled are not considered. To simplify the modeling process, the authors limit themselves to the fact that the values of the factors are represented by dimensionless quantities, the values in the interval [0, 1] and the values of the relationships between them in the interval [- 1, 1]. To solve this problem, we propose a procedure for processing uncertain source data while identifying factors and relationships between them.

Step 2. 1. Entering the source data (values of the FCM vertices parameters, the values of the relationships between them and a priori type of uncertainty of the source data). The a priori types of uncertainty of the source data can be as follows – complete uncertainty, partial uncertainty and full awareness. The parameters of the vertices x_{v_i} , $i=1, \overline{h}$ (h is the number of factors) can be represented as:

1) numbers that differ in verbal descriptions, units and order of quantities;

2) intervals, fuzzy triangular numbers, fuzzy trapezoidal numbers and polyhedral numbers).

The initial values of the vertex parameters are represented simultaneously in each of the listed forms, and the initial values of the relationships between them are presented simultaneously in only one of the given forms.

Step 2. 2. Considering the condition.

If the values of the vertex parameters are represented by intervals, fuzzy numbers, i.e. in the form of intervals, fuzzy triangular numbers; fuzzy trapezoidal (polyhedral) numbers, the condition is met, then proceed to step 2. 3. If the condition is not met, then proceed to step 2. 4.

Step 2. 3. Normalization of the vertex parameters values presented as intervals and fuzzy numbers.

As a result of normalization, the vertex parameters values represent intervals with the normalized values of the vertex parameters. In order to obtain one normalized fuzzy value from the interval, the following is recommended:

– for normalized intervals, fuzzy trapezoidal, fuzzy polyhedral numbers, it is recommended to choose the arithmetic mean;

– for normalized fuzzy triangular numbers, it is recommended to choose the expected normalization value.

Step 2. 4. Considering the condition:

– if the condition that the vertex parameters values are presented as verbal descriptions is met, then proceed to step 2. 5;

– if the condition is not met, then proceed to step 2. 6.

Step 2. 5. Structuring the vertex parameters values. After performing the specified step, proceed to step 2. 8.

For the vertex parameters, the values of which are presented as verbal descriptions, it is proposed to carry out structuring, where each verbal description of the vertex parameter is assigned one number from the interval [0, 1]. To assess the value of the vertex parameters, the verbal description “Factor level” was introduced (Table 1).

Table 1

Estimation of the value of the vertex parameter for the verbal variable “Factor level”

| Verbal description | Numerical value |
|--------------------|-----------------|
| Low | [0.1; 0.3] |
| Below average | [0.31; 0.5] |
| Average | [0.51; 0.7] |
| Above average | [0.71; 0.9] |
| High | [0.91; 1] |

The normalization and structuring of the values of the vertex parameters are necessary so that the numerical values of the vertex parameters do not differ in units, order of magnitude and belong to the interval [0, 1].

Step 2. 6. Considering the condition:

– provided that the values of the vertex parameters are presented as numbers (do not differ in units and order of magnitude), the condition is met, then proceed to step 2. 8;

– if the condition is not met, that is, the values of the vertex parameters differ in units and order of magnitude, then proceed to step 2. 7.

Step 2. 7. Normalization of the vertex parameters values presented as numbers.

$$x_{v_i}^{norm} = \frac{x_{v_i}^{cur} - x_{v_i}^{min}}{x_{v_i}^{max} - x_{v_i}^{min}}, \quad x_{v_i}^{norm} \in [0,1], \tag{3}$$

where $x_{v_i}^{cur}$ is the current value of the vertex parameter; $x_{v_i}^{min}$, $x_{v_i}^{max}$ is the minimum and maximum value of the vertex parameter $v_i \in V$, $i = 1, \overline{h}$.

Formula (3) is not suitable for normalizing the values of the vertex parameters, which are presented as intervals, fuzzy triangular and fuzzy trapezoidal (polyhedral) numbers. Because the interval values of the vertex parameters x_{v_i} should not intersect, since only in this case the “more” (maximum) or “less” (minimum) ratios are set. In order for the intervals $a=[a_1, a_2]$ and $b=[b_1, b_2]$ to be comparable with respect to $a \geq b$, it is necessary and sufficient to meet the condition $a_1 \geq b_1, a_2 > b_2$.

Step 2. 8. Normalization of the values of the relationships between the vertices represented as intervals and fuzzy numbers.

Estimation of the nature and strength of the connections between the vertices presented as intervals, fuzzy triangular and trapezoidal (polyhedral) numbers on a five-point scale, is given in Table 2.

As a result of normalization, the values of the relationships between the vertices are the intervals with the normalized values of the relationships. In order to obtain one normalized fuzzy value from the interval, the following is recommended:

1) for the normalized intervals $w_{ij}^{norm} = [w_{ij1}^{norm}, w_{ij2}^{norm}]$, fuzzy trapezoidal $w_{ij}^{norm} = [w_{ij1}^{norm}, w_{ij2}^{norm}, w_{ij3}^{norm}, w_{ij4}^{norm}]$ and fuzzy polyhedral $w_{ij}^{norm} = [w_{ij1}^{norm}, \dots, w_{ijN}^{norm}]$ numbers, choose the arithmetic mean $w_{ij}^{*norm} = \frac{w_{ijN}^{norm}}{N}$.

2) for the normalized fuzzy triangular numbers $w_{ij}^{norm} = [w_{ij1}^{norm}, w_{ij2}^{norm}, w_{ij3}^{norm}]$, choose the expected normalized value $w_{ij1}^{*norm} = w_{ij2}^{norm}$, where w_{ij}^{norm} is the normalized interval value of the relationships between the vertices v_i and v_j ; $w_{ij}^{norm} \in [-1,1]$; w_{ij}^{*max} .

Table 2

Estimation of the nature and strength of the relationships between the vertices presented as intervals

| Numerical value | Verbal description |
|-------------------------------|-------------------------|
| For intervals | |
| 0 | Absent |
| [0.1, 1] | Very weakly amplifies |
| [-0.1, -1] | Very weakly weakens |
| [1.1, 2] | Weakly amplifies |
| [-1.1, -2] | Weakly weakens |
| [2.1, 3] | Moderately amplifies |
| [-2.1, -3] | Moderately weakens |
| [3.1, 4] | Strongly amplifies |
| [-3.1, -4] | Strongly weakens |
| [4.1, 5] | Very strongly amplifies |
| [-4.1, -5] | Very strongly weakens |
| For fuzzy triangular numbers | |
| 0 | Absent |
| [0.1, 0.5, 1] | Very weakly amplifies |
| [-0.1, -0.5, -1] | Very weakly weakens |
| [1.1, 1.5, 2] | Weakly amplifies |
| [-1.1, -1.5, -2] | Weakly weakens |
| [2.1, 2.5, 3] | Moderately amplifies |
| [-2.1, -2.5, -3] | Moderately weakens |
| [3.1, 3.5, 4] | Strongly amplifies |
| [-3.1, -3.5, -4] | Strongly weakens |
| [4.1, 4.5, 5] | Very strongly amplifies |
| [-4.1, -4.5, -5] | Very strongly weakens |
| For fuzzy trapezoidal numbers | |
| 0 | Absent |
| [0.1, 0.3, 0.6, 1] | Very weakly amplifies |
| [-0.1, -0.3, -0.6, -1] | Very weakly weakens |
| [1.1, 1.3, 1.6, 2] | Weakly amplifies |
| [-1.1, -1.3, -1.6, -2] | Weakly weakens |
| [2.1, 2.3, 2.6, 3] | Moderately amplifies |
| [-2.1, -2.3, -2.6, -3] | Moderately weakens |
| [3.1, 3.3, 3.6, 4] | Strongly amplifies |
| [-3.1, -3.3, -3.6, -4] | Strongly weakens |
| [4.1, 4.3, 4.6, 5] | Very strongly amplifies |
| [-4.1, -4.3, -4.6, -5] | Very strongly weakens |
| For fuzzy polyhedral numbers | |
| 0 | Absent |
| [0.1, w_{jn}/N , 1] | Very weakly amplifies |
| [-0.1, w_{jn}/N , -1] | Very weakly weakens |
| [1.1, w_{jn}/N , 2] | Weakly amplifies |
| [-1.1, $-w_{jn}/N$, -2] | Weakly weakens |
| [2.1, w_{jn}/N , 3] | Moderately amplifies |
| [-2.1, w_{jn}/N , -3] | Moderately weakens |
| [3.1, w_{jn}/N , 4] | Strongly amplifies |
| [-3.1, w_{jn}/N , -4] | Strongly weakens |
| [4.1, w_{jn}/N , 5] | Very strongly amplifies |
| [-4.1, w_{jn}/N , -5] | Very strongly weakens |

Step 2. 9. Structuring the values of the relationships between the vertices.

To determine causal relationships, a scale is defined to assess the nature and strength of the relationships between the vertices (Table 3).

The structuring consists in the following: each value of the relationships presented as a verbal description is assigned one number from the interval [-1, 1].

Table 3

Estimation of the nature and strength of the relationships between the vertices presented as verbal descriptions

| Verbal description | Numerical value |
|-----------------------|-----------------|
| Absent | 0 |
| Very weakly amplifies | [0.1, 0.3] |
| Very weakly weakens | [-0.1, -0.3] |
| Weakly amplifies | [0.31, 0.5] |
| Weakly weakens | [-0.31, -0.5] |
| Moderately amplifies | [0.51, 0.7] |
| Moderately weakens | [-0.51, -0.7] |
| Strongly amplifies | [0.91, 1] |
| Strongly weakens | [-0.91, -1] |

The normalization and structuring of the relationships values between the vertices are necessary so that all the relationships values belong to the interval [-1, 1].

4. FCM construction.

Formation of structure (preliminary structural adjustment).

FCM consists in setting structural relationships (in the form of displayed time lags) between the FCM concepts, weighted by the fuzzy values $w_{ij}^{(t-l)}$ of their influence on each other. In this work, modified ANFIS-type models (Adaptive Neuro-Fuzzy Inference System) are proposed as the FCM FS_i that implement fuzzy temporal transformations F_i . FCM provide the formation, storage and output of the predicted fuzzy values of the respective components of the multidimensional time series with the 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 $w_{ij}^{(t-l)}$ on the basis of which the following transformation is performed:

$$\tilde{s}_j^{(t-l)} = \left(w_{ij}^{(t-l)} T \tilde{s}_j^{(t-l)} \right), \quad l_i^j = 0, \dots, L_i^j, \quad (4)$$

where T is the operation of the T -norm.

The original temporal fuzzy variables of the FS_i model of the C_i concept are intended for the formation, storage and derivation of 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 estimation or measurement data can be used to construct fuzzy component temporal FS_i models.

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

If only experimental data is known, then the problem of model identification is set. In practice, there is often a mixed

case where the initial base of the model rules is built on the basis of heuristic assumptions, and its parametric tuning (learning) is performed on the basis of a training sample.

The input temporal fuzzy variables of the FS_i model are $S_i = \{\tilde{s}_3^{(t-1)}, \tilde{s}_3^{(t-3)}, \tilde{s}_4^{(t-3)}, \tilde{s}_5^{(t-3)}, \tilde{s}_1^{(t-3)}\}$ and its output fuzzy temporal fuzzy variables are $S_i' = \{\tilde{s}_1^{(t)}, \tilde{s}_1^{(t-1)}, \tilde{s}_1^{(t-2)}\}$.

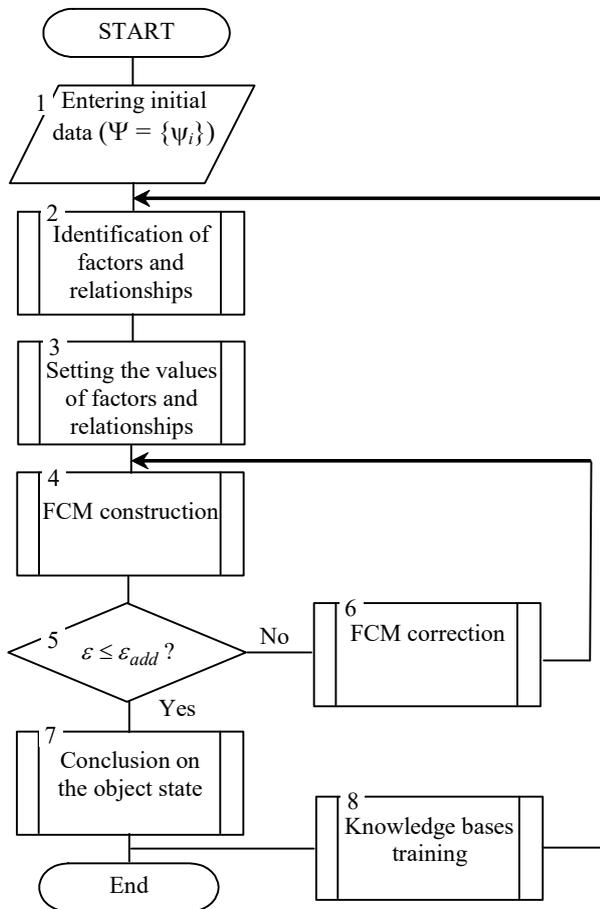


Fig. 2. Algorithm for implementing the method of analyzing and forecasting the object state

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

$$\alpha_p = \min \mu_L(\tilde{s}_1^{(t-1)}), \mu_L(\tilde{s}_3^{(t-3)}), \mu_M(\tilde{s}_4^{(t-3)}), \mu_M(\tilde{s}_5^{(t-3)}), \mu_H(\tilde{s}_1^{(t-3)}) \tag{5}$$

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

$$\mu_{\tilde{M}}(\tilde{s}_1^{(t)}) = \min(\alpha_p, \tilde{M}) \tag{6}$$

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

$$\tilde{s}_1^{(t)} = \max(\mu_{\tilde{M}}(\tilde{s}_1^{(t)}), \dots, \mu_{\tilde{M}}(\tilde{s}_1^{(t)}), \dots, \mu_{\tilde{H}}(\tilde{s}_1^{(t)})) \tag{7}$$

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

$$\tilde{s}_{i(norm)}^{(t)} = Z^0(\tilde{s}_1^{(t-1)}), \tilde{s}_{i(norm)}^{(t-2)} = Z^{-1}(\tilde{s}_1^{(t-1)}) \tag{8}$$

5. Training of artificial neural networks (ANN).

In this procedure, the ANN is trained using the evolving ANN learning method developed by the authors in [2]. This method differs from the known ones because 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 FCM are coordinated. The coordination of all fuzzy component temporal models $FS_i, i=1, \dots, N$ of FCM is carried out after their “personalized” parameter adjustment. Coordination is such a change in the modal values and fuzzy degrees of influence $\{\omega_{ij}^{(t-l)} | l^j = 0, \dots, L_i^j\}$ between the FCM concepts, which provides the maximum increase in the accuracy of forecasting each of the components of the multidimensional time series without deterioration. The procedure of coordinating fuzzy component temporal models of 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 models of FCM is considered to be 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 used.

6. Forecasting the state of the analyzed object.

Multidimensional analysis and forecasting of the state of a complex system/process is performed on the basis of structurally and parametrically configured FCM and can be performed as follows:

- firstly, direct multidimensional forecasting of the state of a complex system/process for the t -th moment of time, i. e. the calculation of the values of the output variable models $FS_i, i=1, \dots, N$ for each given the corresponding sets of values of the input variables of these models;
- secondly, self-development and forecast assessment of changes in the state of a complex system/process, in which the modeling of the state change dynamics is carried out from a situation given by the initial values of all FCM concepts, in the absence of external influences;
- thirdly, the development and forecast assessment of state changes of a complex system/process in which modeling the state dynamics is carried out in a given situation. The situation is given by the initial knowledge of all the FCM concepts with external influence on the values of the concepts and/or the relationship of influence between the FCM concepts.

5.4. Example of applying the proposed method in analyzing and forecasting the operational situation of troops (forces)

The method of estimation and forecasting in intelligent decision support systems is proposed. To assess the effective-

ness of the developed estimation and forecasting method, it was compared with the most popular software products:

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

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

The initial data for assessing the state of the operational situation using the proposed method:

- the number of information sources on the state of the monitored object – 3 (radio monitoring devices, earth remote sensing devices and unmanned aerial vehicles) To simplify the simulation, the same amount of each devices was taken (4 devices);
- the number of information features used to determine the state of the monitored object– 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 total number of personnel, the number of weapons samples, the number of weapons samples types and the number of communication devices are also taken into account;
- the options of organizational and staff formation – company, battalion and brigade.

The cognitive map of the operational group situation is a square table (incidence matrix). Rows and columns mutually unambiguously 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 4).

The results of the assessment of the operational group situation according to the initial data are given in Table 5, which presents the normalized evaluation results.

Table 5
Comparison of the computational complexity of the software and the developed method for assessing the operational situation

| No. | Software | Amount of computations | Developed method (by the amount of computations) |
|-----|--|------------------------|--|
| 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 |

From the analysis of the data presented in Table 5, it is seen that the presented method has a smaller amount of computations compared to the known estimation and forecasting approaches. The advantage of this method in comparison with the known ones is the reduction of computational complexity, which in turn increases the efficiency of decision-making regarding the operational situation of troops (forces).

Tables 6, 7 present the comparative results of evaluating the learning efficiency of artificial evolving neural networks.

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

It should be noted that the proposed training procedure showed the best PC (partition coefficient) result compared to EFCM and the best operating time result compared to FCM. The research showed that this training procedure provides on average 10–18% higher learning efficiency of artificial neural networks and does not accumulate training errors (Tables 6, 7).

Table 4

Incidence matrix of the cognitive map of 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 |

Table 6
Comparative results of evaluating the learning efficiency of artificial evolving neural networks

| System | Algorithm parameters | XB (Xie-Beni Index) | Time, s |
|-------------------------------|----------------------|---------------------|---------|
| FCM (Fuzzy C-Means) | – | 0.1903 | 2.69 |
| EFCM | Dthr=0.24 | 0.1136 | 0.14 |
| EFCM | Dthr=0.19 | 0.1548 | 0.19 |
| Proposed system (batch mode) | delta=0.1 | 0.0978 | 0.37 |
| Proposed system (online mode) | delta=0.1 | 0.1127 | 0.25 |

Table 7
Comparative results of clustering

| System | Algorithm parameters | XB (Xie-Beni Index) | Time, s |
|-------------------------------|----------------------|---------------------|---------|
| FCM (Fuzzy C-Means) | Dthr=0.6 | 0.2963 | 0.81 |
| EFCM | Dthr=0.6 | 0.2330 | 0.54 |
| Proposed system (batch mode) | delta=0.4 | 0.2078 | 0.45 |
| Proposed system (online mode) | delta=0.4 | 0.2200 | 0.30 |

These results can be seen from the results in the last terms of Table 6, 7 as the difference of the Xie-Beni index. However, as it was already mentioned, the known methods accumulate errors, that is why the proposed method suggests the use of evolving artificial neural networks. The results of the efficiency evaluation are shown in Fig. 3.

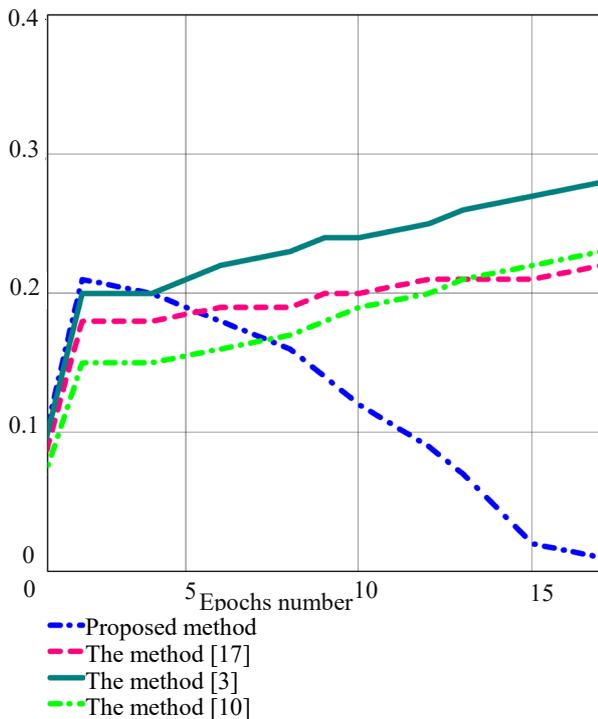


Fig. 3. Evaluation of the efficiency of evolving artificial neural networks

Fig. 3 shows that the use of evolves artificial neural networks prevents the accumulation of learning errors after 3 epochs and gradually reduces the number of learning errors.

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 estimate;
- wide scope of use (decision support systems);
- simplicity of mathematical calculations;
- no accumulation of learning errors;
- adaptability of the system of indicators in the course of 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;
- taking into account the type of uncertainty in constructing a fuzzy cognitive temporal model;
- ability to synthesize the optimal structure of the decision support system.

The disadvantages of the proposed method include:

- loss of informativeness in assessing the state of the monitored 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 electronic 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:

- assessing 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.

According to the results of the effectiveness analysis of the proposed method, its computational complexity is 15–25 % less, compared to the methods used for assessing the effectiveness of decisions presented in Table 1.

This research 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 computational costs in the processing of 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 DSS of ACS for aviation and air defense, as well as DSS of ACS for logistics of the Armed Forces of Ukraine.

This research is a further development of research aimed at developing methodological principles for improving the efficiency of data processing in special-purpose information systems, published earlier [26, 27]. Further research should be aimed at reducing computational costs in the processing of various data in special-purpose information systems.

7. Conclusions

1. A formalized description of the problem of analyzing and forecasting the object state in intelligent decision support systems 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 the process of analyzing and forecasting the object state is chosen as an efficiency criterion of this method.

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

3. The algorithm of the method allows:

- conducting multidimensional analysis and forecasting of the object state under uncertainty;
- provides a forecast estimate under non-stochastic uncertainty, nonlinearity of mutual influence, partial inconsistency and significant interdependence of components of a multidimensional time series;
- taking into account the initial type of uncertainty of the initial data while constructing the FCM;

- training artificial neural networks for intelligent decision support systems.

4. An example of using the proposed method for assessing and forecasting the operational situation of troops (forces) is given. This example showed an increase in data processing efficiency at the level of 15–25 % using additional advanced procedures.

Acknowledgments

The author's team expresses gratitude for assistance in preparing the paper to:

- Doctor of Technical Sciences, Professor Oleksiy Kuvshinov, Deputy Head of the Educational and Scientific Institute of the Ivan Chernyakhovsky National Defense University of Ukraine.

- Doctor of Technical Sciences, Senior Researcher Sova Oleg, Head of the Department of Automated Control Systems of the Military Institute of Telecommunications and Information Technologies named after Heroes of Kruty.

- Doctor of Technical Sciences, Senior Researcher Zhuravskiy Yuriy, Head of the Department of Electrical Engineering and Electronics of the Zhytomyr Military Institute named after S. P. Korolyov.

- Honored Worker of Science and Technology of Ukraine, Doctor of Technical Sciences, Professor Slyusar Vadym, Chief Researcher of the Central Research Institute of Armament and Military Equipment of the Armed Forces of Ukraine.

- Doctor of Technical Sciences, Professor Rothstein Oleksandr, Professor of the Mahon Lev Jerusalem Polytechnic Institute.

- PhD, Associate Professor Oleksandr Bashkirov, Leading Researcher at the Central Research Institute of Armament and Military Equipment of the Armed Forces of Ukraine.

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