A method of complex analysis and multidimensional forecasting of the state of intelligence objects is proposed to increase the accuracy of their state assessment. The object of research is decision support systems. The subject of research is the process of decision-making in management problems using artificial intelligence methods. The hypothesis of research is to increase the efficiency of decision-making with a given assessment reliability. The proposed method is based on a combination of fuzzy cognitive and temporal models, an advanced cat swarm optimization algorithm and evolving artificial neural networks. The method has the following sequence of actions:

– input of initial data;

– processing of initial data taking into account uncertainty about the state of heterogeneous intelligence objects;

– construction of a fuzzy temporal ontological model of heterogeneous intelligence objects;

– conclusion on the state of heterogeneous intelligence objects;

– correction of the fuzzy temporal ontological model;

– building a fuzzy relational temporal cognitive model of heterogeneous intelligence objects and forecasting the state of the intelligence object;

– training knowledge bases on heterogeneous intelligence objects.

The training procedure consists in learning 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 method makes it possible to increase the efficiency of data processing at the level of 18–25 % by using additional improved procedures. The proposed method should be used to solve the problems of evaluating complex and dynamic heterogeneous intelligence objects, characterized by a high degree of complexity

Keywords: multidimensional forecasting, artificial intelligence, bio-inspired algorithms, heterogeneous intelligence objects

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DEVELOPMENT OF A METHOD OF COMPLEX ANALYSIS AND MULTIDIMENSIONAL FORECASTING OF THE STATE OF INTELLIGENCE OBJECTS

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1. Introduction

Currently, methods of computational intelligence are widely used to solve a variety of complex problems, both purely scientific and in the field of engineering, business, finance, medical and technical diagnostics, and other fields related to information processing, including, of course, traditional data mining and new directions such as dynamic data mining, data stream mining, big data mining, web-mining, text mining, etc. [1–6].

The increase in the amount of information circulating in various information collection, processing and transmission systems leads to a significant use of hardware computing resources. The armed forces of technically developed countries have integrated decision-making architectures based on the works [7–15]:

– artificial intelligence and nanotechnology;

– effective processing of large amounts of information;

– data compression technologies to increase processing speed.

At the same time, the use of information systems with elements of artificial intelligence will increase the efficiency of planning, conducting operations (combat operations) and their comprehensive support, affect the doctrine, organization and methods of application of groups of troops (forces).

Also, the increase in the dynamism of operations (combat operations), the growth of the number of various sensors and the need to integrate them into a single information space create a number of problems:

– implemented algorithms for determining correlations between events do not fully take into account the reliability of intelligence sources and the reliability of information in the dynamics of operations (combat operations);

– forms of information presentation complicate its transmission through communication channels;

– limited computing power of hardware;

– radio-electronic suppression of short-wave (SW) and ultrashort-wave (USW) radio communication channels and cybernetic impact on information systems;

– transition to the principle of monitoring object assessment «everything affects everything at once», which covers the aggregate network and computing resources of all types of armed forces.

Artificial intelligence is actively used in the analysis of the state, nature of actions, life cycle of heterogeneous objects, their energy, technical, combat and operational characteristics change significantly. At the same time, the complexity of solving problems of forecasting the state of heterogeneous objects is determined by [1–5]:

– multidimensional and heterogeneous space of interdependent parameters, their non-linear dependence;

– uniqueness of application conditions, instability of external factors;

– insufficient volume, uncertainty and fuzziness of data about their condition during operation, significant costs and increased complexity of experimental research.

Given the above, an urgent scientific task is to develop a method of complex analysis and multidimensional forecasting of the state of intelligence objects, which would increase the efficiency of decisions made to control the parameters of the control object with a given reliability.

2. Literature review and problem statement

The topological approach to the comprehensive research of heterogeneous objects proposed in the works [5, 6] is based on recording the reactions of heterogeneous objects to the influence of pulsed functions. At the same time, the reactions of heterogeneous objects are determined by the parameters of their vector space, which change during application. Periodic testing of the vector space of heterogeneous objects provides reliable information about their current state.

The topological approach and the created generalized topological theory of heterogeneous objects [5–7] are, in turn, the basis for theoretical generalization and development of promising intelligent methods, models and technologies for the research of heterogeneous objects. This approach makes it possible to substantiate the expediency of combining fuzzy ontological and cognitive models for complex analysis and multidimensional forecasting of the state of heterogeneous objects in order to manage them.

At the same time, fuzzy ontological modeling of heterogeneous objects provides an interoperable representation and comprehensive analysis of heterogeneous objects at all stages of the life cycle, their combat use in conditions of uncertainty [8].

The work [9] presents an algorithm for cognitive modeling. The main advantages of cognitive tools are determined. The shortcomings of this approach include the lack of consideration of the type of uncertainty about the state of the object of analysis.

The work [10] reveals the essence of cognitive modeling and scenario planning. A system of complementary principles of building and implementing scenarios is proposed, various approaches to building scenarios are highlighted, the procedure for modeling scenarios based on fuzzy cognitive maps is described. The approach proposed by the authors does not allow taking into account the type of uncertainty about the state of the object of analysis and does not take into account the noise of initial data.

The work [11] analyzes the main approaches to cognitive modeling. Cognitive analysis allows one: to investigate problems with fuzzy factors and relationships; to take into account changes in the external environment and use objectively formed trends in the development of the situation in one's interests. At the same time, the issue of describing complex and dynamic processes remains unexplored in this work.

The work [12] presents a method of analyzing large data sets. The specified method is focused on finding hidden information in large data sets. The method includes generating analytical baselines, reducing variables, detecting sparse features and specifying rules. The disadvantages of this method include the impossibility to take into account various decision evaluation strategies, the lack of taking into account the type of uncertainty of input data.

The work [13] shows the mechanism of transformation of information models of construction objects to their equivalent structural models. This mechanism is designed to automate the necessary conversion, modification and addition operations during such information exchange. The shortcomings of the mentioned approach include the impossibility to assess the adequacy and reliability of the information transformation process and to make an appropriate correction of the obtained models.

The work [14] developed an analytical web platform to study the geographical and temporal distribution of incidents. The web platform contains several information panels with statistically significant results by territory. The disadvantages of the specified analytical platform include the impossibility to assess the adequacy and reliability of the information transformation process and high computational complexity. Also, one of the shortcomings of the mentioned research is that the search for a solution is not unidirectional.

The work [15] developed a method of fuzzy hierarchical assessment of library service quality. The specified method allows you to evaluate the quality of libraries by a set of input parameters. The disadvantages of the specified method include the impossibility to assess the adequacy and reliability of the assessment and, accordingly, determine the assessment error.

The work [16] carried out an analysis of 30 algorithms for processing large data sets. Their advantages and disadvantages are shown. It was found that the analysis of large data sets should be carried out in layers, take place in real time and have the opportunity for self-learning. The disadvantages of these methods include high computational complexity and the impossibility to check the adequacy of the obtained estimates.

The work [17] 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 the system is trained based on the analysis. The disadvantages of this approach are the gradual accumulation of assessment and training errors due to the lack of an opportunity to assess the adequacy of decisions made.

The work [18] presents an approach to processing data from various sources of information. The disadvantages of this approach include the low accuracy of the obtained estimate and the impossibility to verify the reliability of the obtained estimate.

The work [19] carried out a comparative analysis of existing decision support technologies, namely: analytic hierarchy process, 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. It is shown that the analytic hierarchy process works well if the initial information is complete, but due to the need for experts to compare alternatives and choose evaluation criteria, it has a high share of subjectivity. For problems of forecasting under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

The work [20] developed a method of structural and objective analysis of the development of weakly structured systems. An approach to the research of conflict situations caused by contradictions in the interests of subjects that affect the development of the studied system and methods of solving poorly structured problems based on the formation of scenarios for the development of the situation are given. At the same time, the problem is defined as the non-compliance of the existing state of the system with the required one, which is set by the management entity. The disadvantages of the proposed method include the problem of local optimum and the inability to conduct a parallel search.

The work [21] presents a cognitive approach to modeling complex systems. The advantages of the specified approach, which allows you to describe the hierarchical components of the system, are shown. The shortcomings of the proposed approach include the lack of consideration of system computing resources.

The work [22] indicates that the most popular evolutionary bio-inspired algorithms are the so-called «swarm» procedures (Particle Swarm Optimization – PSO). Among them, there are optimization algorithms based on cat swarms (Cat Swarm Optimization – CSO), which are very promising both in terms of speed and ease of implementation. These algorithms have proven their effectiveness in solving a number of rather complex problems and have already undergone a number of modifications, including procedures based on harmonic search, fractional derivatives, adaptation of search parameters and, finally, «crazy cats». At the same time, these procedures are not without some shortcomings that impair the properties of the global extremum search process.

An analysis of the works [9–22] showed that the common shortcomings of the above studies are:

– the lack of the possibility to form a hierarchical system of indicators;

– the lack of consideration of computing resources of the system;

– the lack of mechanisms for adjusting the system of indicators during the assessment;

– the failure to take into account the type of uncertainty and noise of data on the state of the control object, which creates corresponding errors while assessing its real state;

– the lack of deep learning mechanisms for knowledge bases;

– high computational complexity;

– the lack of consideration of computing (hardware) resources available in the system;

– the lack of search priority in a certain direction.

Therefore, it is proposed to jointly use fuzzy temporal ontological cognitive models while solving tasks of complex analysis and multidimensional forecasting of the state of heterogeneous objects for their management. At the same time, bio-inspired algorithms are proposed to be used for learning (correcting) parameters. The joint use of the proposed approaches is due to:

– the correspondence of attributes of the ontological model and concepts of the cognitive model;

– the correspondence of relationships between attributes of the ontological model and between concepts of the cognitive model;

– the correspondence of the values of attributes and concepts and the values of relationships in the ontological and cognitive models;

– the possibility to adjust the values of time lags and values of fuzzy interactions of concepts in order to ensure the necessary accuracy of modeling and multidimensional forecasting of vector space parameters.

For this purpose, it is proposed to develop a method of complex analysis and multidimensional forecasting of the state of heterogeneous intelligence objects.

3. The aim and objectives of the study

The aim of the study is to develop a method of complex analysis and multidimensional forecasting of the state of intelligence objects. This will increase the efficiency of assessment and multidimensional forecasting with a given reliability and development of subsequent management decisions. This will make it possible to develop software for intelligent decision support systems for combat management of the actions of troops (forces).

To achieve the aim, the following objectives were set:

– to determine the algorithm for implementing the method;

– to give an example of the application of the proposed method in the analysis of the operational situation of a group of troops (forces).

4. Research materials and methods

The problem that is solved in the study is to increase the efficiency of decision-making in management problems while ensuring a given reliability, regardless of the hierarchical nature of the object. The object of the research is decision support systems. The subject of the research is the decision-making process in management problems using artificial intelligence methods. The hypothesis of the research is to increase the efficiency of decision-making with a given assessment reliability. In the course of the research, the general provisions of artificial intelligence theory were used to solve the problem of analyzing the state of heterogeneous intelligence objects in intelligent decision support systems. Thus, artificial intelligence theory is the basis of the research. The research uses fuzzy temporal ontological models, improved cat swarm optimization algorithm and evolving artificial neural networks. The simulation was carried out using MathCad 2014 software (USA) and an Intel Core i3 PC (USA).

5. Development of a method of complex analysis and multidimensional forecasting of the state of intelligence objects

5. 1. Algorithm for implementing the method of complex analysis and multidimensional forecasting of the state of intelligence objects

The method of complex analysis and multidimensional forecasting of the state of intelligence objects consists of the following sequence of actions (Fig. 1):

1. Input of initial data (Step 1 in Fig. 1). At this stage, available initial data on the heterogeneous intelligence object to be analyzed are entered. The basic model of the heterogeneous intelligence object is also initialized.

2. Processing of the initial data taking into account uncertainty (Step 2 in Fig. 1).

At this stage, the type of uncertainty about the state of the heterogeneous intelligence object is taken into account and the basic model of the object state is initialized [19, 21]. At the same time, the degree of uncertainty can be: full awareness; partial uncertainty and total uncertainty.

3. Construction of a fuzzy temporal ontological model of heterogeneous intelligence objects (Step 3 in Fig. 1).

While presenting loosely structured information resources about the state of complex technical systems, methods of fuzzy ontological modeling are used with the possibility of displaying the dynamics of attribute changes [19]. At the same time, the applied methods do not take into account the possibility of setting and recording the interaction of attributes with each other with different time lags (delay intervals).

For the presentation, comprehensive analysis and display of the dynamics of changes in heterogeneous intelligence objects, a procedure for building a fuzzy temporal ontological model is proposed.

A feature of the proposed procedure is that the attributes corresponding to the parameters of its vector space and state indicators are characterized by time series of the corresponding clear/fuzzy values, obtained measurements/estimates and based on their multidimensional forecasting.

In this case, fuzzy granulation of the ontological model of heterogeneous intelligence objects is performed at the level of fuzzy values of the time series of these attributes. In addition, the specified action is performed at the level of fuzzy values of binary relations between the attributes of this model with different time lags.

The attributes of the ontological model of heterogeneous intelligence objects, which are carriers of diagnostic information about the state of heterogeneous intelligence objects, are the normalized parameters of Green's matrices:

$$G=\begin{vmatrix} C_1 & C_4 & C_3 \\ C_1 & C_2 & C_5 \\ C_6 & C_2 & C_3 \end{vmatrix}, \qquad (1)$$

where C_1–C_3 are the parameters characterizing the reaction of heterogeneous intelligence objects to impacts along three symmetric axes of the working area of the vector space of heterogeneous intelligence objects; C_4–C_6 are the parameters characterizing the reaction of heterogeneous intelligence objects and the same impacts along the axis of the orthogonal working area of heterogeneous intelligence objects.

The proposed fuzzy temporal ontological model presents the dynamics of changes in the considered parameters in the form of values of component time series forming a multidimensional time series:

$$C=\left\{C_i \middle| i=1,...,I\right\},$$

$$C_i=\left\{\tilde{c}_i(t) \middle| t=1,...,T,...\right\},\ i=1,...,I,$$

$$\forall t\in\left\{1,...,T,...\right\},$$

$$\tilde{C}(t)=\left\{\begin{matrix} \tilde{c}_1(t)=F_1\left(\phi_{1,1}\left(\tilde{c}_1(t-1),...,\tilde{c}_1\left(t-L_1^1\right)\right),...,\right. \\ \left.\phi_{1,I}\left(\tilde{c}_I(t),...,\tilde{c}_I\left(t-L_1^I\right)\right)\right), \\ \tilde{c}_i(t)=F_i\left(\phi_{i,1}\left(\tilde{c}_1(t-1),...,\tilde{c}_1\left(t-L_i^1\right)\right),...,\right. \\ \left.\phi_{i,I}\left(\tilde{c}_I(t),...,\tilde{c}_I\left(t-L_i^I\right)\right)\right), \\ \tilde{c}_I(t)=F_I\left(\phi_{I,1}\left(\tilde{c}_1(t-1),...,\tilde{c}_1\left(t-L_I^1\right)\right),...,\right. \\ \left.\phi_{I,I}\left(\tilde{c}_I(t),...,\tilde{c}_I\left(t-L_I^I\right)\right)\right), \end{matrix}\right\}, \qquad (2)$$

where C is the multidimensional time series characterizing the vector space of heterogeneous intelligence objects; C_i is the component (one-dimensional) time series of the multidimensional time series; I is the number of considered components of the multidimensional time series (analyzed attributes of the ontological model of heterogeneous intelligence objects); $\tilde{C}(t)=\left\{\tilde{c}_1(t),...,\tilde{c}_I(t)\right\}$ is the «time slice» of fuzzy values of the multidimensional time series at time t; $\tilde{c}_i(t)$ is the fuzzy value of C_i at time t; L_j^i is the maximum time lag taken into account (delay interval) $\tilde{c}_j(t)$ relative to $\tilde{c}_i(t)$; ϕ_{ij} is the operator to account for the impact of $\left\{\tilde{c}_j(t-1),...,\tilde{c}_j\left(t-L_j^i\right)\right\}$ on $\tilde{c}_i(t)$; F_i is the conversion to calculate $\tilde{c}_i(t)$.

4. Conclusion on the state of heterogeneous intelligence objects (Step 4 in Fig. 1).

Based on the construction of fuzzy temporal ontological expressions, a conclusion is drawn regarding the state of heterogeneous intelligence objects.

In addition to the presentation and display of the dynamics of heterogeneous intelligence objects considered above using the procedure in Step 3 in Fig. 1, the following tasks must be solved:

– to develop a model and carry out modeling and forecasting of a multidimensional time series, the components of which correspond to the parameters of the vector space of heterogeneous intelligence objects;

– to carry out a predictive state assessment based on the results of forecasting a multidimensional time series corresponding to the multidimensional vector space of heterogeneous intelligence objects;

– to monitor and adapt the multidimensional time series forecasting model under changes in actual data during the application of heterogeneous intelligence objects.

5. Adjustment of the FOM (Steps 5, 6 in Fig. 1).

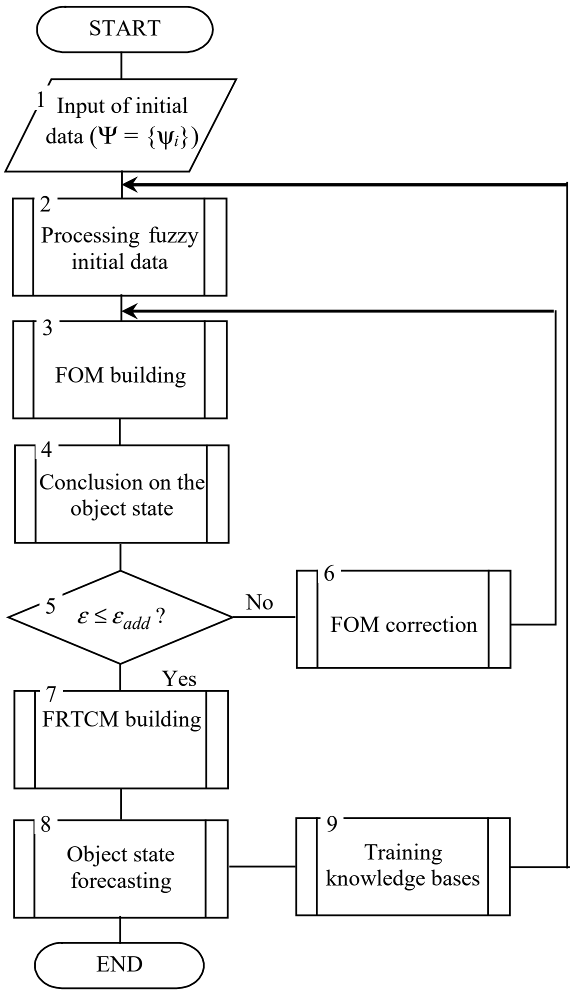

Fig. 1. Algorithm for implementing the object state analysis method

The adaptation of the FCM consists in the structural and parametric adjustment (time lags and values of fuzzy relations of concepts) in order to ensure the necessary accuracy of modeling and multidimensional forecasting of the parameters of the vector space of heterogeneous intelligence objects, taking into account the accumulated data about them when external factors change. As a method of adjustment, an enhanced firefly algorithm is used. The advantages of the evolutionary adjustment of the FCM parameters are as follows:

– independence from the FCM topology;

– the possibility to determine whether a given individual shows low adaptability due to a poorly formed topology or incorrectly selected weights;

– selective optimization of the parameters of recently changed or added connections in the FCM without changing the structure already modified in previous iterations of the algorithm.

6. Building a fuzzy relational temporal cognitive model of heterogeneous intelligence objects and forecasting the state of the intelligence object (Steps 7, 8 in Fig. 1).

In this study, an improved fuzzy relational temporal cognitive model is proposed for multidimensional forecasting of the parameters of the vector space of heterogeneous intelligence objects, which allows typing the settings of operators ϕ_{ij} and transformations $F(i,j=1,...I)$ due to:

– first, «personifications» of system dynamics models (for each pair of directly interacting concepts – parameters of the vector space of heterogeneous intelligence objects);

– second, setting of fuzzy relationships of influence between concepts based on learning algorithms using generated training samples for component time series of a multidimensional time series;

– third, calculation of dependencies between fuzzy parameters in vector-matrix form.

The proposed type of fuzzy relational temporal cognitive model (FRTCM) is presented as follows:

$$\begin{aligned}
&FRTCM = \langle C, R\rangle,\\
&C = \left\{C_i \middle| i=1,...,I\right\},\ R = \left\{R_i \middle| i=1,...,I\right\},\\
&R_i = \left\{\tilde{r}_{ij}(t-l) \middle| l=0,...,L_j^i,\ j=1,...,J^i\right\},\\
&c_i : \tilde{c}_i(t) =\\
&= \tilde{F}_i\left(\begin{gathered}\left\{\tilde{c}_i(t-k), \tilde{r}_{ii}(t-k) \middle| k=1,...,L_i^i\right\},\\ \left\{\tilde{c}_j(t-l), \tilde{r}_{ii}(t-l) \middle| j=1,...,J^i, l=1,...,L_j^i\right\}\end{gathered}\right),\\
&i=1,...,I,
\end{aligned} \tag{3}$$

where C is the set of FRTCM concepts; I is the number of FRTCM concepts; R is the set of fuzzy relations of the influence of concepts on each other; R_i is the subset of fuzzy binary relations of the impact of concepts that directly affect the concept c_i; J^i is the number of concepts that directly influence the concept c_i; $\tilde{r}_{ij}(t-k)$ is the fuzzy relation of influence of the concept c_i on itself at time $(t–k)$; L_i^i is the maximum value of the time lag (delay interval) when the concept c_i affects itself; $\tilde{r}_{ij}(t-l)$ is the fuzzy relation of influence of the concept c_j on the concept c_i at time $(t–l)$; L_j^i is the maximum value of the time lag (delay interval), taken into account when thEe concept c_j affects the concept c_i; $\tilde{c}_i(t), \tilde{c}_i(t-k), \tilde{c}_j(t-l)$ is the fuzzy values of the concepts c_i and c_j at the corresponding time points.

In multidimensional forecasting of the parameters of the vector space of heterogeneous intelligence objects, it is better to use fuzzy compositional rules for the transfer of influence between FRTCM concepts, according to which the system dynamics models take the following form:

$$\begin{aligned}
&\tilde{c}_i(t) = \bigoplus_{j=1}^{J^i}\left(\bigoplus_{l=1}^{L_j^i}\left(\tilde{c}_j(t-l)\circ\tilde{r}_{ij}(t-l)\right)\right),\\
&\tilde{c}_i(t) = \left(\bigoplus_{k=1}^{L_j^i}\left(\tilde{c}_i(t-k)\circ\tilde{r}_{ij}(t-k)\right)\right)\oplus\\
&\oplus\left(\bigoplus_{j=1}^{J^i}\left(\bigoplus_{l=1}^{L_j^i}\left(\tilde{c}_j(t-l)\circ\tilde{r}_{ij}(t-l)\right)\right)\right),\\
&\tilde{c}_i(t) = \left(\bigoplus_{k=1}^{L_j^i}\left(\Delta\tilde{c}_i(t-k)\circ\tilde{r}_{ij}(t-k)\right)\right)\oplus\\
&\oplus\left(\bigoplus_{j=1}^{J^i}\left(\bigoplus_{l=1}^{L_j^i}\left(\Delta\tilde{c}_j(t-l)\circ\tilde{r}_{ij}(t-l)\right)\right)\right),
\end{aligned} \tag{4}$$

where $\Delta\tilde{c}_i(t-k)$ is the fuzzy increase in the value of the concept C_i at time $(t-k)$; $\Delta\tilde{c}_j(t-l)$ is the fuzzy increase in the value of the concept C_i at time $(t-l)$; $\circ$ is the operation of fuzzy composition; $\overset{L_j^i}{\underset{k=1}{\oplus}}$ is the operation of fuzzy aggregation of individual impacts of the concept c_i on itself in the range of the time lag, which are taken into account $\left(k=1,...,L_i^i\right)$; $\overset{L_j^i}{\underset{l=1}{\oplus}}$ is the operation of fuzzy aggregation of individual effects of the concept c_i on the concept c_j in the range of the time lag, which is taken into account $\left(l=1,...,L_j^i\right)$; $\overset{J^i}{\underset{j=1}{\oplus}}$ is the operation of fuzzy aggregation of individual effects of concepts c_j $(j=1, ..., J^i)$, which directly affect the concept c_i; $\oplus$ is the operation of fuzzy aggregation of cumulative effects.

To define ranges of time lags L_i^i and L_j^i with the mutual influence of concepts, the influence of fuzzy relations of mutual influence $\tilde{r}_{ii}(t-k)$, $\tilde{r}_{ij}(t-l)$ of the subsets R_i $(i=1,..., I)$ is significant, and statistical (expert) methods are used to adjust these relations. Thus, in the presence of training samples in the components of a multidimensional time series, we apply the method of fuzzy multiple linear regression to determine fuzzy relations of mutual influence:

$$\tilde{c}_i(t)=\sum_{j=1}^{J^i}\sum_{l}^{L_j^i}\left(\tilde{a}_{ij}(t-l)\tilde{c}_j(t-l)+\tilde{b}_{ij}(t-l)\right), i=1,...,I, \qquad (5)$$

where $\tilde{a}_{ij}(t-l)$ are the fuzzy regression coefficients; $\tilde{b}_{ij}(t-l)$ are the fuzzy free terms (usually equal to 0).

The obtained values of fuzzy regression coefficients $\tilde{a}_{ij}(t-l)$ are normalized $\tilde{a}'_{ij}(t-l)$ in the range [0, 1]. Thus, on their basis, subsets $R_i=\{\tilde{r}_{ij}(t-l)=\tilde{a}'_{ij}(t-l)\,|\,l=0,...,L_j^i, j=1,...,J^i\}$ of fuzzy relations of mutual influence of FRTCM concepts are defined. Then those relations whose modal values are less than a given threshold (for example, less than 0.1) are excluded.

The results of modeling and multidimensional forecasting of the parameters of the vector space of heterogeneous intelligence objects using FRTCM are the basis for a predictive assessment of the state of heterogeneous intelligence objects.

9. Training knowledge bases (Step 9 in Fig. 1).

In the study, the learning method based on evolving artificial neural networks developed in [2] is used for training knowledge bases.

The end of the algorithm.

5. 2. Example of the application of the proposed method in analyzing and forecasting the state of an operational group of troops (forces)

A method of complex analysis and multidimensional forecasting of the state of heterogeneous intelligence objects is proposed. To evaluate the effectiveness of the developed method of complex analysis and multidimensional forecasting of the state of heterogeneous intelligence objects, a comparative evaluation was performed based on the results of research presented in [3–6, 23, 24–37].

Modeling of the solution search processing method according to the algorithm in Fig. 2 and expressions (1)–(5) was carried out. Simulation of the proposed method of complex analysis and multidimensional forecasting of the state of heterogeneous intelligence objects was carried out in the MathSad 14 software environment (USA). The task that was solved during the simulation was to assess the elements of the operational situation of the group of troops (forces).

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

– the number of sources of information about the state of the monitoring object – 3 (radio monitoring tools, remote earth sensing tools and unmanned aerial vehicles). To simplify the modeling, the same number of each tool was taken – 4 tools each;

– the number of informational signs to determine the state of the monitoring object – 12. These parameters include: affiliation, type of organizational and staff formation, priority, minimum width along the front, maximum width along the front. The number of personnel, minimum depth along the flank, maximum depth along the flank, the number of samples of weapons and military equipment (WME), the number of types of WME samples and the number of communication means, type of operational structure are also taken into account;

– options of organizational and staff formations – company, battalion, brigade.

The forecasting of the operational situation of the group took place 3 days ahead based on a training sample of 10 days of operation for each with a modal value of fuzzy degrees of influence of one concept on another. The results of forecasting the operational situation of the group are shown in Fig. 2.

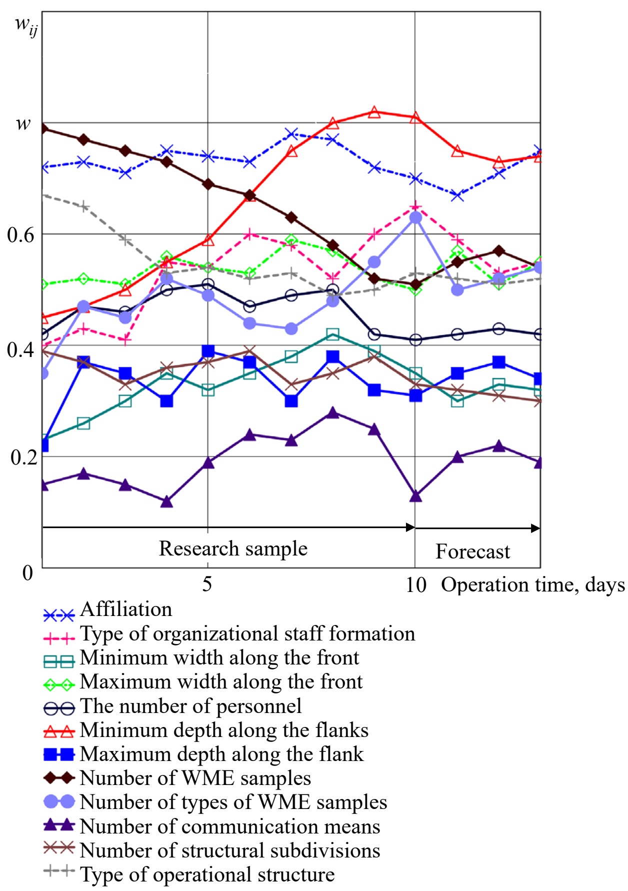

Fig. 2. Results of forecasting changes in the operational situation of the group of troops for 3 days of the operation

We evaluate the multidimensional analysis of heterogeneous intelligence objects, which is the operational group of troops (forces) using the developed method (Table 1).

The results of estimating the forecasting error are given in Table 2. The comparison was based on the MAPE criterion.

Table 3 shows the comparative results of evaluating the training efficiency of evolving artificial neural networks.

Before training, the features of observations were normalized at the interval [0, 1].

To determine the effectiveness of the simultaneous search procedure based on the cat swarm optimization algorithm, research was conducted compared to other swarm methods, namely the ant colony optimization algorithm (ACO), the particle swarm optimization (PSO) method and the classic cat swarm optimization algorithm. The results of the experiments are given in Table 4 to solve the task of analyzing the operational situation.

Table 1

Comparative assessment of evaluation errors while using different approaches for heterogeneous intelligence objects

No.	Time series components	Evaluation error, MAPE (mean absolute percentage error), %		
		Fuzzy cognitive models (FCM)	Artificial neural networks (ANN)	Developed method
1	Affiliation	15	9.4	5.8
2	Type of organizational staff formation	9.3	8.2	6.8
3	Minimum width along the front	2.3	2	1.5
4	Maximum width along the front	2	1.2	0.8
5	Number of personnel	2	1.87	1.7
6	Minimum depth along the flank	1.94	1.7	1.4
7	Maximum depth along the flank	1.6	1.33	1.75
8	Number of WME samples	1.4	1.5	1.3
9	Number of types of WME samples	1.7	1.32	1.2
10	Number of communication means	0.6	0.41	1.77
11	Number of structural subdivisions	1.2	0.66	0.5
12	Type of operational structure	1.1	0.78	0.55

Table 2

Comparative assessment of forecasting errors while using different approaches

No.	Time series components	Evaluation 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 along the front	8.5	8.3	8.1
4	Maximum width along the front	2.5	2.2	2
5	Number of personnel	2	1.87	1.7
6	Minimum depth along the flank	2.34	2.1	1.8
7	Maximum depth along the flank	2.1	1.95	1.75
8	Number of WME samples	1.9	1.76	1.6
9	Number of types of WME samples	1.7	1.52	1.42
10	Number of communication means	2	1.84	1.77
11	Number of structural subdivisions	1.6	1.4	1.25
12	Type of operational structure	1.69	1.52	1.3

Table 3

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

System	Algorithm parameters	XB (Xie-Beni Index)	Time, sec
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

Table 4

Comparative analysis of bio-inspired algorithms

Number of intermediate solution points	Particle swarm optimization method	Ant colony optimization algorithm	Classic cat swarm optimization method	Improved cat swarm optimization procedure
N	T, s	T, s	T, s	T, s
5	0.282	0.276	0.232	0.19
10	0.723	0.4	0.423	0.34
15	6.641	0.999	1.1	0.88
20	10.7	2.5	2.7	2.16
30	21.3	4.5	4.7	3.76
40	42	7.9	7.4	5.92
50	56	10.1	9.2	7.36
100	120	17.6	19.6	15.68
200	727	74.2	80.2	64.2
Complexity	$O\left(\frac{(N-1)!}{4}\right)=O(N!)$	$O(N^2+N)=O(N^2)$	$O(n^2)$	$O(n^2\times 0.8)$

6. Discussion of the results of the development of a complex analysis and forecasting method

Based on the results of the evaluation error analysis presented in Table 1, it was found that the assessment accuracy of the specified method is higher by an average of 14 % compared to artificial neural networks and fuzzy cognitive models.

According to the analysis of the data in Table 2, it was found that the assessment accuracy of the specified method is higher by 15 % on average compared to the above approaches.

From the analysis of the data presented in Fig. 2, it can be seen that the presented method has a smaller number of calculations compared to known estimation and forecasting approaches.

The advantage of the specified method in comparison with the known ones lies in the reduction of computational complexity, which in turn increases the efficiency of decision-making regarding the state of the operational situation of a group of troops (forces).

The research showed that the specified training procedure provides an average of 10–18 % higher training efficiency of artificial neural networks and does not accumulate errors during training (Table 3).

These results can be seen in the last lines of Table 3, as the difference in the Xie-Beni index. At the same time, as already mentioned, known methods accumulate errors, which is why we propose to use evolving artificial neural networks.

In addition, the method operates with fewer parameters and, accordingly, does not require high computational costs.

The main advantage of the procedure based on the behavior of the cat flock is that while using it, the probability of getting into the local optimum and global optimum is sharply reduced and due to parallelization, the time is reduced. At each iteration, it is equal to the search time in the most promising block (Table 4).

The analysis of the data given in Table 4 shows that the proposed procedure has acceptable computational complexity.

In the range from 50 to 100, the proposed procedure becomes more efficient in terms of algorithm operating time compared to other algorithms (faster than the particle swarm optimization method by 82–90.6 %, the ant colony optimization method by 27–29.1 and the classic cat swarm optimization algorithm by 20 %. The proposed procedure gives adequate solutions with a complex hierarchical structure of the monitoring object. The effectiveness of the proposed procedure is on average from 15 to 23 % at different hierarchies of construction of the monitoring object, which is an operational grouping of troops (forces), as can be seen from the analysis of the results in Table 4.

The limitations of the research are the need for an initial database on the state of heterogeneous intelligence objects, the need to take into account the delay time for collecting and reporting information from intelligence sources.

The advantages of the proposed method are as follows:

– while correcting a fuzzy cognitive model, the type of uncertainty is taken into account (Step 2 in Fig. 1), compared to studies [9–11];

– universality of solving the problem of analyzing the state of heterogeneous intelligence objects due to the hierarchical nature of their description (expressions (1)–(5)), compared to studies [11–13];

– the possibility to quickly build models due to the simultaneous search for a solution by several individuals (Steps 5, 6 in Fig. 1), compared to studies [15, 19, 21];

– the adequacy of the obtained results (expressions (1)–(5));

– the ability to avoid the problem of a local extremum (Steps 5, 6 in Fig. 1), compared to studies [14, 16, 19];

– the possibility of deep learning of knowledge bases (Step 9 in Fig. 1), compared to studies [13, 15].

The main advantages of the proposed method are:

– a 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 obtained assessment of the state of a heterogeneous intelligence object;

– universality of application due to adaptation of the system of indicators during operation;

– does not accumulate learning errors due to the use of the training procedure;

– the possibility of comprehensive learning of the architecture and parameters of artificial neural networks;

– takes into account the type of uncertainty of initial data while building models of a heterogeneous intelligence object;

– the possibility of finding a solution in several directions;

– high reliability of the obtained solutions while searching for a solution in several directions;

– no falling into the local optimum trap.

The disadvantages of the proposed method include:

– the loss of informativeness while assessing the state of a heterogeneous intelligence object due to the construction of the membership function;

– lower accuracy of assessment by a single parameter of assessment of the state of a heterogeneous object;

– loss of credibility of the obtained solutions while searching for a solution in several directions at the same time;

– lower assessment accuracy compared to other assessment methods.

This method allows you:

– to assess the state of a heterogeneous intelligence object;

– to determine effective measures to improve management efficiency;

– to increase the speed of assessment of the state of a heterogeneous intelligence object;

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

The proposed approach should be used to solve problems of evaluating complex and dynamic processes characterized by a high degree of complexity.

This study is a further development of research aimed at developing methodological principles for increasing the efficiency of processing various types of data, published earlier [2, 4–6, 23].

Areas of further research should be aimed at reducing computing costs while processing various types of data in special-purpose systems.

7. Conclusions

1. The algorithm for implementing the method is defined, which allows you:

– to take into account the type of data uncertainty;

– to take into account available computing resources of the system for analyzing the state of a heterogeneous intelligence object;

– to take into account the priority of searching by individuals from the cat flock;

– to conduct an initial display of individuals of the cat flock;

– to carry out accurate training of individuals of the cat flock;

– to take into account the type of uncertainty and noise of data;

– to carry out the correction of fuzzy cognitive models using a genetic algorithm;

– to conduct training of knowledge bases, which is carried out by training the 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;

– to use as a universal tool to solve the problem of analyzing the state of heterogeneous intelligence objects due to the hierarchical description of heterogeneous intelligence objects;

– to check the adequacy of the obtained results;

– to avoid the problem of local extremum.

2. An example of using the proposed method is given using the example of assessing and forecasting the state of the operational situation of a group of troops (forces). The specified example showed an 18–25 % increase in the efficiency of data processing by using additional improved procedures.

Conflict of interest

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

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Data availability

The manuscript has associated data in the data repository.

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References

1. Bashkyrov, O. M., Kostyna, O. M., Shyshatskyi, A. V. (2015). Rozvytok intehrovanykh system zviazku ta peredachi danykh dlia potreb Zbroinykh Syl. Ozbroiennia ta viyskova tekhnika, 1, 35–39. Available at: http://nbuv.gov.ua/UJRN/ovt_2015_1_7
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskyi, R., Repilo, I. et al. (2020). Development of a method for training artificial neural networks for intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (2 (105)), 37–47. doi: https://doi.org/10.15587/1729-4061.2020.203301
3. Sova, O., Shyshatskyi, A., Salnikova, O., Zhuk, O., Trotsko, O., Hrokholskyi, Y. (2021). Development of a method for assessment and forecasting of the radio electronic environment. EUREKA: Physics and Engineering, 4, 30–40. doi: https://doi.org/10.21303/2461-4262.2021.001940
4. Pievtsov, H., Turinskyi, O., Zhyvotovskyi, R., Sova, O., Zvieriev, O., Lanetskii, B., Shyshatskyi, A. (2020). Development of an advanced method of finding solutions for neuro-fuzzy expert systems of analysis of the radioelectronic situation. EUREKA: Physics and Engineering, 4, 78–89. doi: https://doi.org/10.21303/2461-4262.2020.001353

5. Zuiev, P., Zhyvotovskyi, R., Zvieriev, O., Hatsenko, S., Kuprii, V., Nakonechnyi, O. et al. (2020). Development of complex methodology of processing heterogeneous data in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (9 (106)), 14–23. doi: https://doi.org/10.15587/1729-4061.2020.208554
6. Shyshatskyi, A. (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. Yeromina, N., Kurban, V., Mykus, S., Peredrii, O., Voloshchenko, O., Kosenko, V. et al. (2021). The Creation of the Database for Mobile Robots Navigation under the Conditions of Flexible Change of Flight Assignment. International Journal of Emerging Technology and Advanced Engineering, 11 (5), 37–44. doi: https://doi.org/10.46338/ijetae0521_05
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, 33–47. doi: doi: https://doi.org/10.17308/meps.2017.10/1754
11. Zhaldak, H. (2021). Determination of features of development of modern theories of management. Technology Audit and Production Reserves, 1 (4 (57)), 10–13. doi: https://doi.org/10.15587/2706-5448.2021.225380
12. 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
13. 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
14. 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
15. 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
16. 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
17. 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
18. Gödri, I., Kardos, C., Pfeiffer, A., Váncza, 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
19. 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
20. Papa, A., Shemet, Y., Yarovyi, A. (2021). Analysis of fuzzy logic methods for forecasting customer churn. Technology Audit and Production Reserves, 1 (2 (57)), 12–14. doi: https://doi.org/10.15587/2706-5448.2021.225285
21. Chapran, S. (2021). Analysis of methodological approaches to the construction of dynamic systems of investment in information development. Technology Audit and Production Reserves, 6 (4 (62)). doi: https://doi.org/10.15587/2706-5448.2021.248312
22. Chandar, K. S., Punjabi, H. (2022). Cat Swarm Optimization Algorithm Tuned Multilayer Perceptron for Stock Price Prediction. International Journal of Web-Based Learning and Teaching Technologies, 17 (7), 1–15. doi: https://doi.org/10.4018/ijwltt.303113
23. Koshlan, A., Salnikova, O., Chekhovska, M., Zhyvotovskyi, 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
24. 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
25. Emel'yanov, V. V., Kureychik, V. V., Kureychik, V. M., Emel'yanov, V. V. (2003). Teoriya i praktika evolyutsionnogo modelirovaniya. Moscow: Fizmatlit, 432.
26. Gorokhovatsky, V., Stiahlyk, N., Tsarevska, V. (2021). Combination method of accelerated metric data search in image classification problems. Advanced Information Systems, 5 (3), 5–12. doi: https://doi.org/10.20998/2522-9052.2021.3.01
27. Levashenko, V., Liashenko, O., Kuchuk, H. (2020). Building Decision Support Systems based on Fuzzy Data. Advanced Information Systems, 4 (4), 48–56. doi: https://doi.org/10.20998/2522-9052.2020.4.07

28. Meleshko, Y., Drieiev, O., Drieieva, H. (2020). Method of identification bot profiles based on neural networks in recommendation systems. Advanced Information Systems, 4 (2), 24–28. doi: https://doi.org/10.20998/2522-9052.2020.2.05
29. Kuchuk, N., Merlak, V., Skorodelov, V. (2020). A method of reducing access time to poorly structured data. Advanced Information Systems, 4 (1), 97–102. doi: https://doi.org/10.20998/2522-9052.2020.1.14
30. Shyshatskyi, A., Tiurnikov, M., Suhak, S., Bondar, O., Melnyk, A., Bokhno, T., Lyashenko, A. (2020). Method of assessment of the efficiency of the communication of operational troop grouping system. Advanced Information Systems, 4 (1), 107–112. doi: https://doi.org/10.20998/2522-9052.2020.1.16
31. Raskin, L., Sira, O. (2016). Method of solving fuzzy problems of mathematical programming. Eastern-European Journal of Enterprise Technologies, 5 (4 (83)), 23–28. doi: https://doi.org/10.15587/1729-4061.2016.81292
32. Lytvyn, V., Vysotska, V., Pukach, P., Brodyak, O., Ugryn, D. (2017). Development of a method for determining the keywords in the slavic language texts based on the technology of web mining. Eastern-European Journal of Enterprise Technologies, 2 (2 (86)), 14–23. doi: https://doi.org/10.15587/1729-4061.2017.98750
33. Stepanenko, A., Oliinyk, A., Deineha, L., Zaiko, T. (2018). Development of the method for decomposition of superpositions of unknown pulsed signals using the second-order adaptive spectral analysis. Eastern-European Journal of Enterprise Technologies, 2 (9 (92)), 48–54. doi: https://doi.org/10.15587/1729-4061.2018.126578
34. Gorbenko, I., Ponomar, V. (2017). Examining a possibility to use and the benefits of post-quantum algorithms dependent on the conditions of their application. Eastern-European Journal of Enterprise Technologies, 2 (9 (86)), 21–32. doi: https://doi.org/10.15587/1729-4061.2017.96321
35. Lovska, A. (2015). Peculiarities of computer modeling of strength of body bearing construction of gondola car during transportation by ferry-bridge. Metallurgical and Mining Industry, 1, 49–54.
36. Lovska, A., Fomin, O. (2020). A new fastener to ensure the reliability of a passenger car body on a train ferry. Acta Polytechnica, 60 (6). doi: https://doi.org/10.14311/ap.2020.60.0478
37. Koval, M., Sova, O., Orlov, O., Shyshatskyi, A., Artabaiev, Y., Shknai, O. et al. (2022). Improvement of complex resource management of special-purpose communication systems. Eastern-European Journal of Enterprise Technologies, 5 (9 (119)), 34–44. doi: https://doi.org/10.15587/1729-4061.2022.266009