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DEVELOPMENT OF A COMPLEX METHOD FOR FINDING A SOLUTION FOR NEURO-FUZZY EXPERT SYSTEMS

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Artificial intelligence has become the backbone of modern decision support systems. This is why a complex method for finding solutions for neuro-fuzzy expert systems has been developed. The proposed complex method is based on a mathematical model for the analysis of the operational situation. The model makes it possible to determine the parameters of the analysis of the operational situation, their influence on the quality of assessment of the operational situation and to determine their number with units of measurement. An increase in the efficiency of information processing (error reduction) of the assessment is achieved by the use of evolving neuro-fuzzy artificial neural networks. Training of evolving neuro-fuzzy artificial neural networks is carried out by training not only synaptic weights of the artificial neural network, the type, parameters of the membership function, but also by applying the procedure for reducing the dimension of the feature space. The efficiency of information processing is also achieved by training the architecture of artificial neural networks; accounting for the type of uncertainty in the information to be assessed; work with both clear and fuzzy data. We achieved a reduction in computational complexity while making decisions; the absence of errors in training artificial neural networks as a result of processing information entering the input of artificial neural networks. The analysis of the operational situation as a whole occurs due to the improved clustering procedure, which allows working with both static and dynamic data. The proposed complex method was tested on the example of assessing the state of the operational situation. The mentioned example showed an increase in assessment efficiency at the level of 20–25 % in terms of information processing efficiency

Keywords: artificial intelligence, operational situation, intelligent systems, decision support systems

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1. Introduction

Nowadays, many areas of human activity use artificial intelligence approaches to solve important practical problems. Expert systems have been successfully used in complex technical systems to solve informal or poorly formalized tasks, such as training, diagnostics, forecasting, control and measurement [1–6].

This class of intelligent information systems is characterized by the fact that they are able to model the expert's thinking process in making a decision and explain why this or that result was obtained. This is achieved by implementing the procedure of logical inference on formalized knowledge about the subject area, the processes that take place in it and the laws that govern these processes [2, 7].

However, there are a number of difficulties and problems in analyzing the operational situation:

1. The assessment of the operational situation takes place against the background of intentional and natural obstacles.
2. The obtained data do not coincide with the standards due to the influence of different types of interference and incomplete intelligence.
3. Interpretation of the operational situation depends on the decision maker's experience, completeness of additional information on a particular task (conditions of uncertainty).
4. High dynamics of combat operations.
5. A large number of features of the operational situation.
6. Limited time for the analysis and decision making in conditions of uncertainty.
7. A large number of different types of objects that simultaneously perform operational tasks (combat tasks) and affect each other.

The best solution in this situation is integration with the data of the analysis of the operational situation and artificial neural networks (ANN).

These circumstances lead to recourse to the theory of expert systems, where one of the important limitations in their use is the difficulty of formulating rules for machine processing. And when used in conjunction with the system of analysis of the operational situation, it is difficult to formulate rules for the transfer and transformation of the expertise of territory assessment from the source of knowledge to the program. In this form, an effective methodology for recording, storing and using expert knowledge should be developed in the expert system for the operational sampling of knowledge [4].

An alternative method of recording expert knowledge without using rules is to use artificial neural networks, using their ability to generalize, self-train and retrain. Their advantage is also the ability to work in real time and quick adaptation to specific situations [8, 9].

These circumstances cause uncertainty in the task of recognizing the operational situation and vague statements in its interpretation, when the involved additional information may be incomplete and the official makes decisions based on his experience.

That is why the urgent task is to increase the speed (efficiency) of decision-making while maintaining the necessary reliability.

2. Literature review and problem statement

In [10], it is proposed to use neuro-fuzzy systems to predict the efficiency of building structures. This approach allows predicting the efficiency of building structures in conditions of probabilistic and non-probabilistic uncertainty. The disadvantages of this approach include the inability to train the architecture and parameters of the artificial neural network, as well as the accumulation of errors during system operation.

In [11], it is proposed to use fuzzy expert systems for estimating the creative abilities of the person. This approach is based on the use of fuzzy logic to assess the creative abilities of the person in the selection of personnel. The disadvantages of this approach include the accumulation of errors during the procedures of fuzzification and defuzzification.

In [12], it is proposed to use fuzzy expert systems for forecasting the load on electric networks. The genetic algorithm and the ant colony algorithm are used to speed up the decision. The disadvantages of this approach include the accumulation of errors in the procedures of fuzzification and defuzzification, also there is no reduction in the dimensionality of the feature space.

The paper [13] proposes an intelligent evaluation methodology based on fuzzy logic and expert systems. The principle of this methodology is to transform abstract concepts of human expertise into a numerical engine of inference applied to evaluation. Therefore, it reproduces the cognitive mechanisms of evaluation experts. An example of implementation is given to compare this method with the classical one and make conclusions about its effectiveness. In addition, due to its flexibility, various types of extensions became possible by updating the basic rules and adapting to possible new architectures and new types of evaluation. The disadvantages of this approach include the accumulation of errors in the procedures of fuzzification and defuzzification, also there is no reduction in the dimensionality of the feature space.

In [14], it is proposed to use an adaptive neuro-fuzzy inference system to control the speed of the direct current motor, optimized by the collective swarm intelligence. The controller is designed according to fuzzy rules, has an advantage in the expert knowledge of the fuzzy inference system and the ability to train neural networks. However, this neuro-fuzzy system implements the training mechanism only by adjusting synaptic weights and does not take into account the uncertainty about the state of the object.

The paper [15] presents the results of analytical review and comparison of the most common technologies to support management decision-making: hierarchy analysis method, 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 hierarchy analysis method works well under the condition of complete initial information, but due to the need for experts to compare alternatives and choose evaluation criteria has a high degree of subjectivity. The use of fuzzy set theory and neural networks is justified for forecasting problems in conditions of risk and uncertainty. The technology of collective decision-making, which is used both in general elections and in a group of experts, is also considered. It reduces the time for conciliation meetings to reach a consensus by pre-analyzing all opinions presented on the plane in the form of points. The consistency of opinions is determined by the distances between them.

In [16], the development of a fuzzy expert system for the diagnosis of cystic fibrosis was carried out. The results showed that the proposed system can be used as a powerful diagnostic tool with an accuracy of 93.02 %, specificity of 89.29 %, sensitivity of 95.24 % and accuracy of 92.86 % for the diagnosis of cystic fibrosis. However, the proposed fuzzy expert system does not implement the training mechanism and does not take into account the uncertainty about the state of the object.

In [17], the method of information security risk assessment was developed. The method is based on an attack tree model with fuzzy set theory and risk probability estimation technology used in a ship management system risk scenario. Fuzzy numbers and expert knowledge are used to determine the factors that affect the probability of a leaf node, and leaf nodes are quantified to obtain the probability of an interval. The disadvantages of the proposed method include the accumulation of errors during operation and failure to take into account the uncertainty about the state of the object.

In [18], a fuzzy expert system for early diagnosis of infections in newborns was created. This fuzzy expert system allows the early diagnosis of infections by many indicators. However, this system does not reduce the feature space, which in turn requires significant computing resources of the system.

In [19], a fuzzy expert system with a soft expert set was created, which allows checking the adequacy of the information provided by the expert and increasing the accuracy of the assessment. However, the disadvantages of this approach include the accumulation of evaluation errors and the inability to take into account the uncertainty about the state of the evaluation object. The analysis showed that the known methods (techniques) [6–19]:

– do not adjust the results taking into account the evaluation error;

– train only by adjusting synaptic weights;

– require significant computing resources;

– do not reduce the dimensionality of the feature space;

– do not take into account uncertainty about the state of the evaluation object;

– are not able to adapt the architecture of the artificial neural network depending on the amount of information received at the input of the artificial neural network;

– are not able to assess the individual object and the situation as a whole.

Therefore, it is necessary to develop a complex method of finding a solution for neuro-fuzzy expert systems that can effectively search for solutions in conditions of uncertainty and shortage of computing resources, as well as assess not only the individual object, but the situation as a whole.

3. The aim and objectives of the study

The aim of the study is to develop a complex method of finding a solution for neuro-fuzzy expert systems to increase the efficiency of decision-making while maintaining a given degree of reliability.

To achieve this goal, the following objectives were set:

– to carry out a mathematical statement of the problem of analyzing an operational situation;

– to develop an approach for finding solutions for neuro-fuzzy expert systems;

– to evaluate the effectiveness of the proposed approach.

4. Mathematical statement of the problem of the operational situation analysis

Let it be that a vector model is obtained as a result of classifying the operational situation. The model determines the type of monitoring object, so the studied monitoring objects are divided into elementary components according to the characteristics that make up the set V of elementary components of the analyzed monitoring object. The obtained information is also interpreted to a particular structural unit (group).

The operational situation is stored in the computer's memory in digital form, will be represented as a matrix R of dimension (M*N), and has the form [2, 4]:

$$R = \left\| r_{i,j} \right\|, \tag{1}$$

where $i = 1,...,M;\ j = 1,...,N.$

Each element of the matrix R is a vector of parameters that characterize each (i, j)-th elementary parameter of the operational situation on some m-th $m=(1,...,T)$ set of thematic properties of the structural unit (group):

$$r_{i,j} = \left(r_{i,j}^{1},...,r_{i,j}^{T} \right), \tag{2}$$

the nature of the components of the vectors $r_{i,j}$ in the general case does not play a fundamental role.

A set of thematic properties $\{P_n\}$, $(n=1, ..., K)$, which classify the studied information and threshold values of restrictions, is set. It is necessary for each P_n according to their threshold constraints to match the set P_n, $V_t \in V$, $\left(1 \le t \le \left(M \times N\right)\right)$ of elementary components of the object, which have the property P_n. Then, showing all sorts of options of the feature values within the thresholds of the constraints for each of the k-th reference table, we have the evaluation matrix G^{kl}:

$$\Gamma^{kl} = \left\| q_{u,v}^{kl} \right\|, \quad q_{u,v}^{kl} \in \left[0,1\right], \tag{3}$$

where the answer 1 means that the set of features and their restriction thresholds are used to make a decision about belonging to one of the membership classes and 0 is otherwise, l is the number of options.

However, even with all the advantages of neuro-fuzzy expert systems, they have certain disadvantages. Here are the main ones [6–9]:

– accumulation of evaluation errors during fuzzification and defuzzification procedures;

– the architecture of the artificial neural network used to form knowledge bases has a rigid architecture, and is not able to adapt during calculations;

– training of an artificial neural network is limited only to training synaptic weights between neurons;

– low productivity of solution search methods even with a small volume of rules;

– great computational complexity of solution search methods;

– large dimension of the feature space.

Therefore, it is necessary to develop an approach for finding solutions for neuro-fuzzy expert systems.

5. Development of a solution search approach for neuro-fuzzy expert systems

The proposed complex method of finding solutions for fuzzy expert systems consists of two major procedures: finding a solution for the object of monitoring; finding a solution to the operational situation as a whole.

We will consider the first procedure of the proposed method. This procedure consists of actions 1-6 on the algorithm scheme (Fig. 1).

The Rete method was chosen as the basis for the development of the first procedure [5, 10, 11]. The main disadvantage of the Rete method is its work only with clear products, which does not allow it to be used while processing different types of data.

The algorithm for implementing the proposed search method is shown in Fig. 1.

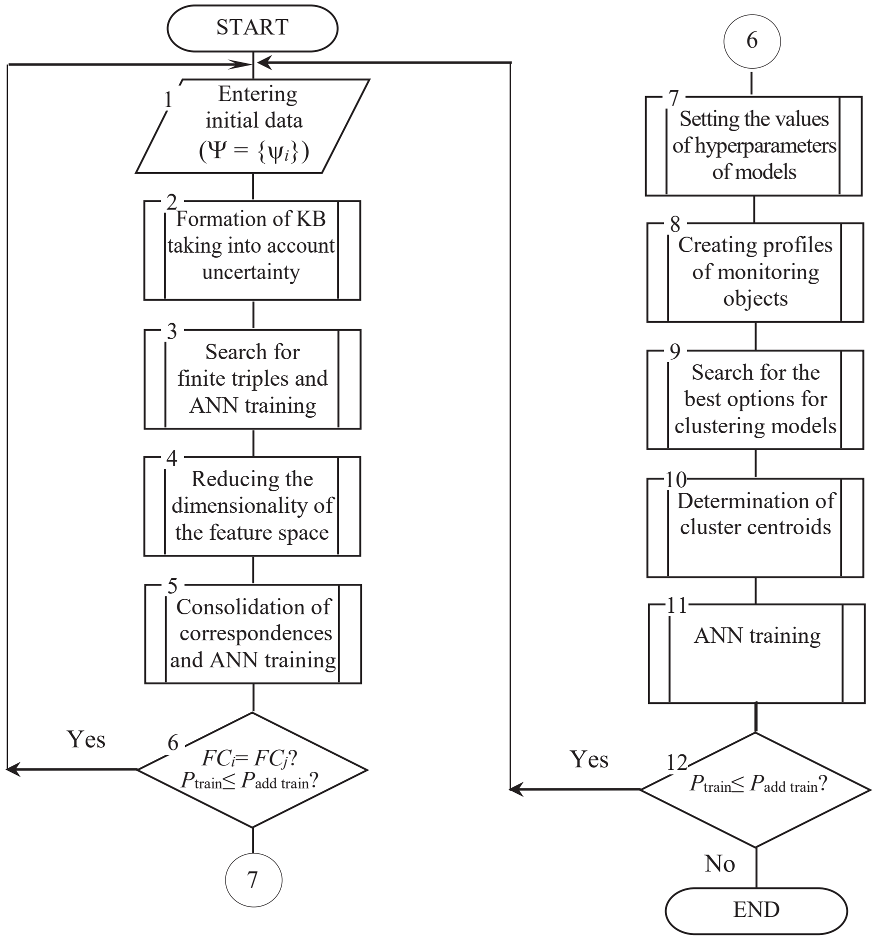

Fig. 1. Algorithm for implementing the proposed complex method

where C_l is the left node of the rule condition, R is the relationship between rule nodes, C_r is the right node of the rule condition.

Then, we will consider the following parameters.

$$C_l = FC_l \| \text{Null} \| C, \tag{7}$$

$$C_r = FC_r \| \text{Null} \| C, \tag{8}$$

where FC_l is the left finite triple of the rule condition, FC_r is the right finite triple of the rule condition.

Formulas (7) and (8) allow us to describe conditions with different degrees of nesting.

$$FC_l = < L, Z, W >, \tag{9}$$

$$FC_r = < L, Z, W >, \tag{10}$$

where L is the linguistic variable, Z is the sign of the condition $Z = \{<,>,<=,>=,=,!=\}$; W is the value of the condition, which is determined as follows (11):

$$W = L \| V, \tag{11}$$

where L is the linguistic variable, V is the fixed value (12).

$$V = T_i \| \text{const}, \tag{12}$$

where T_i is the value of a fuzzy variable from the term sets of a linguistic variable, const is a constant. This model allows the use of not only linguistic variables but also classical variables. In this case, their values can also be compared with constants [5]. R is the set of relations between the nodal vertices $R \subset (C_l \times C_r)$ or $R : C_l \to C_r$. The parameter S – the consequence of the rule is determined similarly to the parameter C.

$$S = < S_l, R, S_r >, \tag{13}$$

where S_l is the left node of the rule consequence, R is the relationship between the nodes of the rule consequence, S_r is the right node of the rule consequence.

$$S_l = FS_l \| \text{Null} \| S, \tag{14}$$

$$S_r = FS_r \| \text{Null} \| S, \tag{15}$$

where FS_l is the left finite triple of the rule consequence, FS_r is the right finite triple of the rule consequence. Formulas (14) and (15) allow us to describe the consequences with different degrees of nesting.

$$FS_l = < L, \text{Op}, W >, \tag{16}$$

$$FS_r = < L, \text{Op}, W >, \tag{17}$$

where L is the linguistic variable, Op is the operation, $\text{Op} = \{:=\}$, W is the value of the consequence.

Step 1. Entering source data for the analysis of the operational situation (step 1 in Fig. 1).

At this stage, the introduction of the initial radioelectronic-operational and radioelectronic environment, which is typical to the region.

Step 2. Formation of the knowledge base (KB) taking into account uncertainty.

At this stage, the KB is formed on the basis of expressions (4)–(17). While converting the values of REE into fuzzy rules, the value of uncertainty about the radiation sources is taken into account, according to expressions (10)–(12) [23].

The formal model of the neuro-fuzzy rule base will look like (4):

$$\{P_n\} = \{\text{Rule}\}, \tag{4}$$

where Rule is a rule of the neuro-fuzzy expert system. Each rule is defined as follows (5):

$$\text{Rule} = < C \to S >, \tag{5}$$

where C is the condition of the rule, S is the consequence of the rule. Since the model must provide a representation of the grammatical structure of rules with various types of nested conditions, a recursive mechanism will be used to describe the nodes and end vertices of the rule condition tree. Parameter C is defined as follows (6):

$$C = < C_l, R, C_r >, \tag{6}$$

Step 3. Search for finite triples and ANN training (step 3 on the algorithm diagram).

At this stage of the Rete method, the search for close finite triples in all the rules of the production knowledge base is performed. The matches found between the finite triples are denoted. The rules set out the references of such finite triples to ensure their one-time processing. In contrast to the classical neuro-fuzzy expert systems, in this neuro-fuzzy expert system it is proposed to use a neuro-fuzzy evolutionary network as an artificial neural network, the architecture of which is given in [3, 10]. Also at this stage, training of parameters and architecture of the artificial neural network is performed in accordance with the method of training proposed in [3].

Let's consider the algorithm for finding the correspondences of the finite triples of the decision tree.

Input data: Rule is a database of rules, presented in the form of a decision tree.

Output dat: Rule' is a shortened database of rules represented as a decision tree. Intermediate data: FC_i and FC_j are the current finite triples.

Step 3. 1. At the beginning of the algorithm, all finite triples are not noted (not checked), m is the number of finite triples. Set the initial value of $i=1$.

Step 3. 2. If $i>m$ is typed in text, not a formula, then move to step 3. 10.

Step 3. 3. If FC_i is noted, then $i=i+1$ and move to step 3. 2.

Step 3. 4. Select FC_i. Set $j=j+1$.

Step 3. 5. If $j>m$, then note FC_i as the viewed finite triple and move to step 3. 2.

Step 3. 6. If FCj is noted, then $j=j+1$and move to step 3. 5.

Step 3. 7. Select FC_j. Follow the procedure to check the proximity of the end nodes and finite triples FC_i and FC_j.

Step 3. 8. If the result is successful, add FC_j to the list of matches for FC_i, and FC_j, the finite triple that has been checked.

Step 3. 9. Determination of the training error. Making a decision about ANN training taking into account the type of uncertainty.

Step 3. 10. Move to step 3. 2.

Step 3. 11. End.

Step 4 Reducing the dimension of the feature space (step 4 in Fig. 1).

The proposed procedure for aggregating features works as follows. Initially, based on the initial set of characteristics of the considered objects, the initial characteristics are combined into groups of criteria with verbal ordinal scales with a small number of gradations (3–5).

The criteria should have scales that, on the one hand, will reflect the aggregate qualities of the objects and, on the other hand, will be clear while the final selection of the object or their classification.

Formally, the task of reducing the dimensionality of the feature space is as follows:

$$X_1 \times \ldots \times X_m \to Y_1 \times \ldots \times Y_n, \quad n < m, \tag{18}$$

where X_1, ..., X_m is the output set of features, Y_1, ..., Y_n is the new set of features, m is the dimension of the original feature space, n is the dimension of the new feature space. Each of the features has its own scale $X_i = \left\{x_i^1,\ldots,x_i^{g_i}\right\}$, $i=1,\ldots,m$, $Y_i = \left\{y_i^1,\ldots,y_i^{h_i}\right\}$, $j=1,\ldots,n$, with an orderly gradation of estimates.

All gradations of estimates on the scales of features act as objects of classification. Grades of decisions of the i-th level are gradations of estimates on the scale of the compiled criterion. In the classification block of the $(i+1)$-th level of hierarchy, the constituent criteria of the i-th level are considered to be features. Many gradations of estimates are new objects of classification in the reduced feature space, and the classes of solutions will now be gradations of estimates on the scale of the compiled criterion of the $(i+1)$-th level. The procedure is repeated until there is a single compiled upper-level criterion, the scale of which forms the necessary ordered classes of solutions C_1, ..., C_q.

This establishes a mutually unambiguous correspondence between the classes of solutions C_1, ..., C_q and a set of initial indicators – a set $X_1 \times \ldots \times X_m$ of all possible gradation combinations of estimates on the scales of criteria $X_i = \left\{x_i^1,\ldots,x_i^{g_i}\right\}$, $i=1,\ldots,m$, K_1, ..., K_m and boundaries of the classes are found, which makes it easy to build a classification of real alternatives A_1, ..., A_p, evaluated by many criteria.

Step 5. Consolidation of correspondences and ANN training (step 5 on the algorithm scheme).

At this stage, a recursive procedure is performed to check the proximity of intermediate nodes of decision trees. This procedure provides aggregation of correspondences between conditions in the rules of the knowledge base. Also at this stage, training of the ANN architecture and parameters is performed.

Then, we consider the algorithm for finding the aggregation of the matches found.

Input data: Rule' is a shortened base of rules, presented in the form of a decision tree, with the same finite triples combined.

S_p is typed – a list of finite triples for which matches are found; k is the number of items in the list S_p. S_{pi} is the list of the finite triple FC_i, containing the corresponding finite triples with indexes; k_i is the number of items in the list S_{pi}.

Output data: Rule' is a shortened database of rules, which combines all similar conditions.

Intermediate data: FC_i and FC_j are the current finite triples, C_i and C_j are the parental nodes for FC_i and FC_j.

Step 5. 1. Set $i=1$.

Step 5. 2. Choose FC_i in the decision tree, which is on the i-th place in the list S_p.

Step 5. 3. Set $j=1$.

Step 5. 4. Choose the finite triple FC_j from the list S_{pi}, which is on the j-th place. Remove the parental nodes C_i and C_j for FC_i and FC_j.

Step 5. 5. Perform a recursive procedure to check intermediate nodes C_i and C_j.

Step 5. 6. If the result of the function is successful, match the nodes C_i and C_j, otherwise move to step 5. 7.

Step 5. 7. $j=j+1$. If $j>k$, then move to step 5. 8, otherwise move to step 5. 4.

Step 5. 8. $i=i+1$. If $i>k$, then move to step 5. 10, otherwise move to step 5. 2.

Step 5. 9. Determination of a training error. Making a decision about ANN training taking into account the type of uncertainty.

Step 5. 10. End.

Step 6. Checking the proximity assessment metrics and determining the error of ANN training (step 6 in Fig. 1).

At this stage, the metrics of the proximity of the obtained decisions are determined and the training error is determined in order to make management decisions.

The procedure for the analysis and decision-making regarding the operational situation consists of steps 7–12.

The procedure of the analysis and decision-making on the operational situation is designed to assign monitoring objects to the group of monitoring objects that are similar in identification characteristics. It should be noted that this task is known as the segmentation of monitoring objects, but in this case there is a fundamental difference. Typically, segmentation uses static data to perform partitioning, such as: type of the monitored object, affiliation to a unit, etc. However, as practice shows, it is necessary to take into account the behavior of the monitored object as an element of the operational situation.

In this case, the same group may include monitoring objects of different units, but with similar behavioral dynamics. In this case, it is difficult or impossible to determine the number of such groups.

In machine learning, this task belongs to clustering tasks, due to the specifics of the initial uncertainty about the number and structure of groups (clusters). We formulate the problem of clustering taking into account the specifics of the subject area: automation of the analysis of the operational situation.

Step 7. Setting the values of hyperparameters of clustering models:

$[t_s,t_k]$ is the observation interval, where t_s is the timestamp of the observation beginning, t_k is the timestamp of the observation end;

h is the length of a short observation interval into which the interval is evenly divided $[t_s, t_k]$;

b is the number of breakdowns in the short observation interval;

k is the number of clusters.

Hyperparameter is a parameter, which is set a priori to the model setting, the value of which affects the quality of structural-parametric optimization of the model.

Thus, at the stage of observation, short models of observation are formed: $[t_s,t_s+h)$, $[t_s+h,t_s+2h)$, ..., $[t_s+lh,t_k)$, where l is the integer that is divided into b equal intervals.

The values of hyperparameters can be specified as a single value, as well as in the form of a value grid with a step.

Table 1 presents examples of methods for setting hyperparameters (setting either one value or interval of the value change) and values of hyperparameters (for different methods).

Step 8. Forming profiles of monitoring objects.

Generate profiles of monitoring objects in accordance with expression (1) and values of hyperparameters $[t_s, t_k]$, h, b.

It should be noted that the resulting matrix contains rows, each of which is an input vector for clustering algorithms for each short observation interval.

Step 9. Construction of an ensemble of clustering models: k-means, MiniBatch, MeanShift (no number is required for the last task).

The k-means algorithm is applied to objects that are represented by points in a d-dimensional vector space. Thus, clusters consist of d-dimensional vectors, $D=\{x_i,|i=1,...,N\}$, where $x_i \in R^d$ denotes the i-th object or «data point». The algorithm divides D points into k clusters so that each point falls into only one cluster of k. You can track which point is in which cluster by assigning a cluster number to each point. The value of k is the main parameter of the algorithm.

Typically, the choice of the value of k is based on prior knowledge of how many clusters will actually appear in D. How many clusters are required for the current program or what number of clusters is detected during the experiment with different values of k. In the k-means algorithm, each of the k clusters is represented by one point in R^d. Denote the set of clusters as a set $C=\{c_j|j=1,...,k\}$. This is also called cluster states, or cluster centroids.

In clustering algorithms, points are grouped according to the measure of «proximity» or «similarity». In k-means, the measure of proximity by default is the Euclidean distance.

In particular, we can say that the k-means algorithm tries to minimize such a non-negative loss function:

$$\text{cost}=\frac{1}{n}\sum_{i=1}^{k}\sum_{j=1}^{n}\left\|x_j-\mu_i\right\|^2. \tag{19}$$

Mini Batch k-means algorithm. In Mini Batch k-means is a modification of the algorithm to k-means, which uses a mini-package to reduce the computation time while optimizing the objective function. Mini-packets are subsets of input data randomly selected in each training iteration. These mini-packages will dramatically reduce the amount of computation required to converge to a local solution. Unlike other algorithms, this method allows reducing the convergence time of the k-means method.

Step 10. Search for the best options for clustering models using multiple launches and evaluate the quality of clustering.

Quality assessment of each model is carried out according to the coefficient of silhouette:

$$s(i)=\frac{b(i)-\alpha(i)}{\max(\alpha(i),b(i))}.$$

The formula can be written in another form:

$$s(i)=\begin{cases}1-\alpha(i)/b(i), \text{ if } \alpha(i)<b(i),\\ 0, \text{ if } \alpha(i)=b(i),\\ \alpha(i)/b(i)-1, \text{ if } \alpha(i)>b(i).\end{cases} \tag{20}$$

The average value of $s(i)$ for all cluster data is a measure of how «strongly» the data in the cluster is grouped.

Step 11. Determining cluster centroids and comparing the identifiers of the cluster label monitoring objects.

It is necessary to pay attention to characteristic features of the proposed method compared to existing approaches.

In step 8, in addition to information on the dynamics of changes in the monitored object in a certain period, statistics were used to include information on changes in the operational situation in a certain period of time.

In step 10, based on the analysis, it was decided to use an ensemble of models. The models are set up on the basis of a selected training sample based on a certain number of models.

To find the best model, the grid search of hyperparameters with a check on cross-validation samples with the set number of partitions (10 by default).

For the new monitoring object (data about which did not participate in the configuration of the clustering algorithm), the following algorithm for determining the cluster label is proposed.

Table 1

Example of methods to set hyperparameters

Hyper-parameter	One value	Grid of parameters	
		Change interval	Change step
$[t_s, t_k]$	[01.01.2020 00:00; 31.12.2020 23:59]	[01.01.2019 00:00; 31.12.2019 23:59], [01.01.2020 00:00; 31.12.2020 23:59]	[2018,2019,2020]
h	01:00:00 (DD:MM:YYYY)	[01:00:00], [07:00:00]	1
b	4	[4,24]	1
k	3	[3;35]	1

Step 1. For each cluster, load the centroid values.

Step 2. Convert the data on the classification of the monitored object into a functional structure (similar to step 2 of the clustering method).

Step 3. Calculate the distances from the profile of the classified monitoring object to the centroid of each cluster $\left\{d_1^*, d_2^*, \ldots, d_k^*\right\}$.

Step 4. Define the cluster label as $l' = \arg\min\left\{d_1^*, d_2^*, \ldots, d_k^*\right\}$, $l' \in [1, \ldots, k]$.

Step 12. Determining the ANN training error (step 6 in Fig. 1).

At this stage, the training error is determined in order to make management decisions.

6. Evaluation of the effectiveness of a complex solution search method

So, the simulation of the complex method of processing the search for solutions in accordance with the algorithm in Fig. 1 and expressions (4)–(20) was performed. The simulation of the proposed complex method was performed in the Umbrello UML Modeller software environment (Germany) (in terms of processing different types of data) and MathCad 14 (USA) (in terms of estimating computational complexity).

The standard notation for modeling large information systems based on object-oriented methodology is the Unified Modeling Language (UML). One of the tools available is the Umbrello UML Modeller environment, which meets two key requirements: free and cross-platform. This application is free software designed to build Uml charts and supports all their standard types. Using the Umbrello UML Modeller environment (Germany), a frame knowledge base was built to identify monitoring objects. The frame knowledge base was built as a UML class diagram, where each frame is represented as a class with its own attributes and procedures.

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

– the number of sources of information on the state of the monitoring object is 3 (radio monitoring devices, earth remote sensing devices and unmanned aerial vehicles);

– the number of information features used to determine the state of the monitored object is 13. The following parameters include: affiliation, type of organizational and staff formation, priority, minimum width on the front, maximum width on the front. Also, 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 types of the weapons sample, the number of communication devices, the type of communication devices are taken into account;

– options for organizational and staff formations, for example: company, battalion, brigade.

To conduct the experiment, 8 sample frames were used: «Monitoring object», «Unit», «Operational and tactical grouping of troops», «Brigade», «Battalion», «Company», «Detected object», «Dedicated cluster». Each of the sample frames (except for «Monitoring object» and «Subdivision») corresponds to the instance frames in the form of information about specific units. The constructed dependence has a clear hierarchical structure and 3 types of relations between frames: generalization, association and dependence.

The «Unit» frame is related to the generalization relationship with the «Monitoring object» frame and its descendant. The «Operational and tactical grouping of troops», «Brigade», «Battalion», «Company» frames are connected with the «Unit» frame and its descendants. While filling the knowledge base, instance frames with a structure that is similar to the mentioned frames are created, but the slots of which are filled according to the information about the specific units.

The «Detected object» frame is a generalized form that is filled in at the points (posts) of monitoring and contains information about the class, type, coordinates and number (in the case of a group object). The specified frame is related by a relationship to the «Dedicated cluster» frame. The slots of the «Dedicated cluster» frame are filled as a result of performing the procedure of clustering the territorially combined information sources of monitoring, in accordance with actions 6–12, which are given above. The associated procedures centerKoordFinding (finding the coordinates of the center of the selected cluster) and clusterSizeFinding (finding the size of the selected cluster) are used to determine the values of the slots. The resulting set of selected clusters, the information of which is represented by a set of instance frames of the «Dedicated cluster» type, is subjected to the procedure of identification of the monitored objects. During identification, the frames corresponding to the selected clusters are compared with the reference frames that are contained in the knowledge base.

The result is a conclusion that the cluster corresponds to a specific unit (or the discovery of a new monitoring object) and its current state. Primary processing of information from information sources of monitoring, filling the frames of the «Detected object» type. Clustering of identified monitoring information sources in accordance with filling the frames of the «Dedicated cluster» type. Identification of selected clusters and formation of conclusions. Based on these initial data, we obtain the distances between the points, which are given in Table 2.

Table 2

Fragment of the matrix of distances between objects

Fragment of the matrix of distances between points	1	2	3	4	5	6	7	8	9	10
1	0	6,18E+08	2,58E+08	2,08E+08	5,18E+08	1,35E+09	2,29E+08	2,85E+06	1,21E+09	2,01E+08
2	0	0	5,50E+08	1,10E+08	4,16E+08	7,28E+08	1,04E+09	5,61E+08	3,63E+08	1,20E+08
3	0	0	0	2,77E+08	1,10E+09	2,06E+09	9,70E+08	2,88E+08	1,63E+09	2,28E+08
4	0	0	0	0	3,08E+08	8,33E+08	5,45E+08	1,75E+08	5,69E+08	3,17E+06
5	0	0	0	0	0	1,98E+08	3,43E+08	4,46E+08	2,25E+08	3,72E+08
6	0	0	0	0	0	0	9,79E+08	1,23E+09	8,98E+07	9,38E+08
7	0	0	0	0	0	0	0	2,07E+08	1,12E+09	5,88E+08
8	0	0	0	0	0	0	0	0	1,10E+09	1,73E+08
9	0	0	0	0	0	0	0	0	0	6,47E+08
10	0	0	0	0	0	0	0	0	0	0

Fig. 2 shows graphical estimates of the efficiency of data processing by the criterion of the number of computational operations. The comparison of the developed complex method was performed by comparing the efficiency of the complex method with the known ones, which are presented in [9, 10, 12]. We denote these works, respectively, 1, 2 and 3.

However, as it was already mentioned, in the course of work, 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.

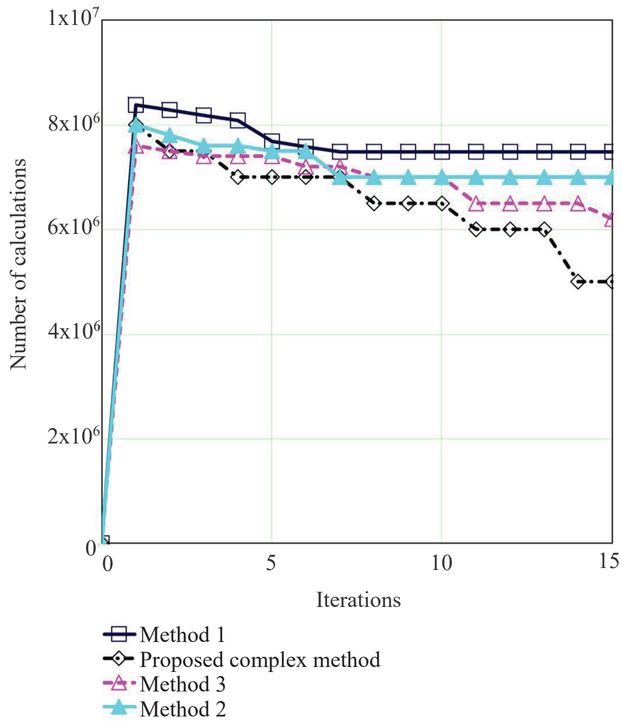

Fig. 2. Results of evaluating the effectiveness of the proposed complex method

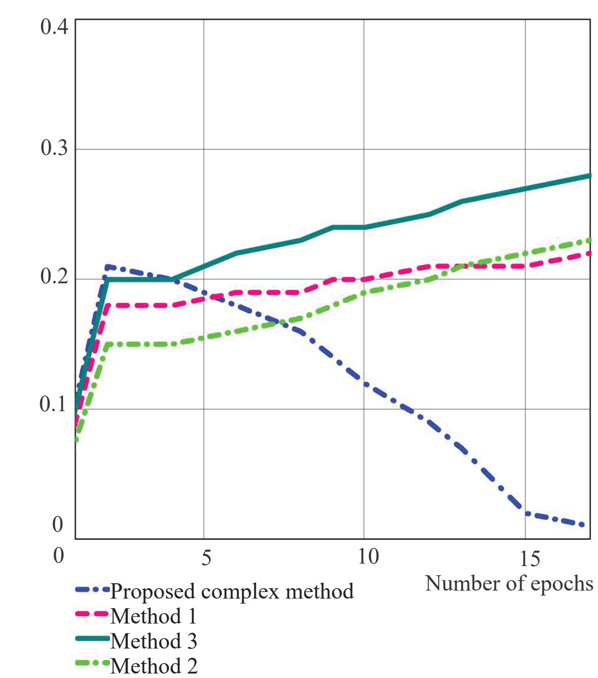

Fig. 3. Evaluation of the effectiveness of evolving artificial neural networks

The proposed complex method allows increasing the efficiency of information processing (reducing the number of computational operations) from 20 to 25 % depending on the amount of information about the monitoring object.

7. Discussion of the results of evaluating the effectiveness of a complex solution search method

This gain is explained by the complex consideration of various types of data on the state of the monitored object; such as uncertainty about the state of the monitored object, the use of evolving ANN, but also the clustering of objects with similar behavior. The difference of the proposed complex method is as follows:

– allows high-quality processing of large arrays of different types of data that have a numerical and quantitative nature;

– while clustering the monitored objects, takes into account not only the dynamics of changes in the state of the monitored object, but also the use of resources;

– allows training of a complex method in the course of its work;

– takes into account the degree of awareness of the monitored object state;

– allows complex processing of information about the state of the monitored object;

– allows you to get a complex assessment of the operational situation for each unit.

The advantages of the complex method include:

– minimization of the total time required to perform the response task;

– limiting the degree of human participation in the cycle of resource management of complex processing, as well as automatic determination of the option of forming scenarios for solving monitoring tasks.

Fig. 3 shows that the use of evolving artificial neural networks allows not to accumulate training errors after 3 epochs and there is a gradual reduction of training errors.

The limitations of this complex method include the need for communication channels with high reliability of information and minimal delay. This is due to the need to process information in close to real-time mode and high requirements for the reliability of information circulating in special-purpose decision support systems.

The disadvantages of this complex method include the need to process large data sets to determine the state of the monitoring object and the operational situation as a whole.

The practical significance of the developed complex method is that the efficiency of complex data processing in automated control systems is significantly increased. The proposed complex method allows solving the following tasks, which are useful from the standpoint of analysis of the operational situation:

– having a set of clusters and information about new monitoring objects, the new monitoring object should be assigned to one or another cluster;

– having a set of clusters, it is possible to assess changes in the «position» of the monitored object in the cluster and possibly its transition to another cluster;

– having a set of clusters, it is possible to estimate changes in the size, structure of clusters (absolute values of differences between «old» and «new» centroid of a cluster);

– having the obtained centroids for each cluster, to estimate their dynamics of changes;

– to estimate the deviation between the set values and the centroids for the typical average profiles of the monitoring objects specified by the official.

It is proposed to use the proposed methodology in decision support systems for automated control systems (ACS DSS for artillery units, special-purpose geographic information systems, ACS DSS for aviation and air defense and ACS DSS for logistics of the Armed Forces of Ukraine in software development for processing data and various types by the persons, who receive them.

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]. Areas of further research should be aimed at reducing computational costs in the processing of various types of data in special-purpose information systems.

8. Conclusions

1. The mathematical formulation of the problem of the analysis of the operational situation is carried out.

In the course of the specified mathematical statement of the problem of the analysis of the operational situation, parameters of the analysis of the operational situation, their influence on the quality of assessing the operational situation are defined. Their number and units of measurement are determined.

2. An approach for finding solutions for neuro-fuzzy expert systems is developed.

The difference between the proposed complex method and the known ones, which determines its novelty, is as follows:

– while assessing the operational situation, the type of uncertainty in accordance with expressions (10)–(12) [23] is additionally taken into account;

– to increase the efficiency of information processing, evolving artificial neural networks with the algorithm of their training are used [24];

– the ability to work with both clear and fuzzy products through the use of evolving artificial neural networks;

– the ability to reduce the feature space by applying the procedure of reducing the feature space;

– no error accumulation in training artificial neural networks as a result of processing information arriving on the input of artificial neural networks by training architecture and parameters;

– the ability to conduct a complex assessment of the operational situation due to the advanced clustering procedure, which allows clustering both static and dynamic data.

3. Evaluation of the effectiveness of the proposed method on the example of assessing the state of the radio-electronic environment is performed. This example showed an increase in assessment efficiency at the level of 20–25 % in terms of information processing efficiency.

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