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DEVELOPMENT OF OBJECT STATE EVALUATION METHOD IN INTELLIGENT DECISION SUPPORT SYSTEMS

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Accurate and objective object analysis requires multi-parameter estimation with significant computational costs. A methodological approach to improve the accuracy of assessing the state of the monitored object is proposed. This methodological approach is based on a combination of fuzzy cognitive models, advanced genetic algorithm and evolving artificial neural networks. The methodological approach has the following sequence of actions: building a fuzzy cognitive model; correcting the fuzzy cognitive model and training knowledge bases. The distinctive features of the methodological approach are that the type of data uncertainty and noise is taken into account while constructing the state of the monitored object using fuzzy cognitive models. The novelties while correcting fuzzy cognitive models using a genetic algorithm are taking into account the type of data uncertainty, taking into account the adaptability of individuals to iteration, duration of the existence of individuals and topology of the fuzzy cognitive model. The advanced genetic algorithm increases the efficiency of correcting factors and the relationships between them in the fuzzy cognitive model. This is achieved by finding solutions in different directions by several individuals in the population. The training procedure consists in learning 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. The use of the method allows increasing the efficiency of data processing at the level of 16–24 % using additional advanced procedures. The proposed methodological approach should be used to solve the problems of assessing complex and dynamic processes characterized by a high degree of complexity

Keywords: decision support system, artificial neural networks, genetic algorithm, population

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1. Introduction

The growth of information circulating in various information transmission systems leads to a significant complication of the tasks of collecting, processing and summarizing information. Solving management problems is impossible without the use of information and management systems. The basis of any modern information and management systems are decision support systems (DSS). DSS are used in the processing of large data sets in databases, process forecasting, providing information support for decision-makers in the decision-making process.

Intelligent DSS have become a natural continuation of the widespread use of the classical type DSS through the use of artificial intelligence methods.

Analysis of intelligent DSS creation shows that the most promising for their construction are information technologies based on a combination of different approaches [1–8]. One such approach is a combination of neuro-fuzzy cognitive models (NFCM), artificial neural networks (ANN) and genetic algorithms (GA). The combination of different approaches to artificial intelligence minimizes the individual shortcomings of each approach, thereby increasing the efficiency of data processing.

The use of evolutionary methods compared to traditional approaches gives the following advantages:

– rapid adaptation of the model structure to the subject of research, which almost without any transformations allows forming the structure of NFCM and ANN that corresponds to a specific process;

– the ability to conduct a parallel search for a solution in several directions;

– avoiding the problem of falling into the trap of the local optimum;

– the ability to work in conditions of uncertainty, nonlinearity, stochasticity, chaos and various disturbances;

– have universal approximating properties and fuzzy inference capabilities;

– the ability to work with different sizes.

Despite the relatively successful application of evolutionary approaches, these systems have a number of disadvantages. The most significant ones are as follows:

1. The complexity of choosing the system architecture.

2. Problems with taking into account indicators that have a complex structure of relationships and contradict each other.

3. The difficulty of taking into account the indirect influence of interdependent components in conditions of uncertainty.

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

There is an urgent scientific task to develop an evaluation method in intelligent decision support systems using NFCM, GA and ANN.

2. Literature review and problem statement

The work [9] presents a cognitive modeling algorithm. The main advantages of cognitive tools are determined. The disadvantages of this approach include the lack of consideration of the type of uncertainty about the analysis object state and the lack of mechanisms for NFCM correction.

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

The work [11] carries out the analysis of the main approaches to cognitive modeling. Cognitive analysis allows you to explore problems with fuzzy factors and relationships, take into account changes in the external environment and take advantage of objectively formed trends in the situation. However, in this work, the issue of describing complex and dynamic processes remains unexplored.

The work [12] presents the method of large data sets analysis. This method focuses on finding hidden information in large data sets. The method includes the operations of generating analytical baselines, reducing the number of variables, detecting sparse features and specifying rules. The disadvantages of this method include the inability to take into account different decision evaluation strategies, the lack of consideration of the type of uncertainty about the 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 operations for conversion, modification and addition during such information exchange. The disadvantages of this approach include the inability to assess the adequacy and reliability of the information transformation process and make appropriate adjustments to the obtained models.

The work [14] carries out the development of 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 this analytical platform include the inability to assess the adequacy and reliability of the information transformation process and high computational complexity. Also, the disadvantages of this research should not include a unidirectional solution search.

The work [15] develops a method of fuzzy hierarchical evaluation of the library services quality. This method allows evaluating the quality of libraries by a set of input parameters. The disadvantages of this method include the inability to assess the adequacy and reliability of assessment and, accordingly, to determine the error of assessment.

The work [16] performed an analysis of 30 algorithms for processing large data sets. Their advantages and disadvantages are shown. It is found that the analysis of large data sets should be carried out by layers, in real time and have the opportunity for self-study. The disadvantages of these methods include high computational complexity and the inability to verify the adequacy of the estimates.

The work [17] presents an approach to the evaluation of 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 train the system on the basis of the analysis. The disadvantages of this approach are the gradual accumulation of evaluation and training errors due to the inability to assess the adequacy of decisions.

The work [18] presents the approach to processing data from different sources of information. The disadvantages of this approach include the low accuracy of assessment and the inability to verify the reliability of assessment.

The work [19] carries 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. The analytic hierarchy process has been shown to work well with complete initial data, but it has a high degree of subjectivity due to the need for experts to compare alternatives and select evaluation criteria. The use of fuzzy set theory and neural networks is justified for forecasting problems in conditions of risk and uncertainty.

The work [20] develops a method of structural-targeted analysis of the development of poorly structured systems: an approach to studying conflict situations caused by contradictions in the interests of actors influencing the development of the investigated system and methods of solving poorly structured problems based on scenarios. The problem is defined as the mismatch of the existing system state to the required one, which is set by the subject of management. However, the disadvantages of the proposed method include the problem of local optimum and the impossibility of conducting a parallel search.

The work [21] presents a cognitive approach to the simulation of complex systems. The advantages of this approach, which allows describing the hierarchical composition of the system, are shown. The disadvantages of the proposed approach include a unidirectional solution search.

The analysis of the works [9–21] showed the following common shortcomings of the above studies:

– lack of multidirectional search;

– high probability of falling into the trap of the local optimum;

– lack of mechanisms for correcting fuzzy cognitive models during assessment;

– lack of mechanisms for in-depth learning of knowledge bases;

– lack of consideration of computing resources available in the system.

Thus, it is proposed to develop an evaluation method in intelligent decision support systems based on NFCM, ANN and GA.

3. The aim and objectives of the study

The aim of the study is to develop a method of evaluation in intelligent decision support systems, which would allow the analysis of the object state with given reliability under resource constraints.

To achieve this aim, the following objectives were set:

– to formulate the concept of presentation of the evaluation method in intelligent decision support systems;

– 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 research used the general provisions of artificial intelligence theory to solve the problem of object state analysis in intelligent decision support systems. Thus, artificial intelligence theory is the basis of the research. The research used fuzzy cognitive models, advanced genetic algorithm, and evolving artificial neural networks. The simulation was performed using MathCad 2014 software (USA) and Intel Core i3 PC (USA).

5. Results of research on the development of the evaluation method in intelligent decision support systems

5. 1. The concept of presenting the evaluation method in intelligent decision support systems

The control system of the object state analysis process can be represented as an NFCM, which is a sign-oriented graph, where the vertices represent the essences, concepts, factors, goals and events, and the arcs set their influence on each other. Influence is characterized by some limiting function, which can be determined in different ways. In general, the task of determining the state of the monitoring object is reduced to calculations according to the formula:

$$A_i(k+1)=f\left(\left(A_i(k)+\sum_{j\neq i,j=1}^{N}A_j(k)W_{ij}\right)\times\iota_{ij}\right)\times\zeta_{ij}, \qquad (1)$$

where $A_i(k+1)$ is the new state of the NFCM vertex;

$A_i(k)$ is the previous NFCM state;

w_{ij} is the weight matrix;

f is the threshold NFCM function;

ι_{ij} is the operator that takes into account the degree of awareness of the object state;

ζ_{ij} is the operator to take into account the degree of noise of the object state data.

The calculation process is iterative – after setting the initial states of the vertices, the values of the states are recalculated until the difference between the current and previous states is less than some given value.

From expression (1), it can be concluded that it allows describing the processes in the monitoring object. This description is universal and allows describing the analysis object, taking into account the hierarchy and individual specifics of each monitoring object. While writing expression (1) as a multidimensional time series, the description process can be given for a dynamic system. Expression (1) while constructing a mathematical description of the monitoring object state takes into account the degree of awareness of the object state and data noise. Also, expression (1) allows describing the processes that have both quantitative and qualitative units of measurement and the processes occurring in Fig. 1.

5. 2. Algorithm for implementing the evaluation method in intelligent decision support systems

The evaluation method in intelligent decision support systems consists of the following steps (Fig. 1). It should be noted that the main procedures of the proposed method are described in detail in [23]. A distinctive feature of this method is that at step 6, the genetic algorithm improved by the authors is used, the main stages of which are given in Fig. 2. The key idea of improving the method is to increase the efficiency of the NFCM architecture search by a multidirectional search for individuals in the population, taking into account the fine for the NFCM size and computing resources. Let's consider them in more detail.

Step 6. NFCM correction.

Step 6. 1. Entering initial data. At this stage, the initial available data about the analysis object are entered.

Step 6. 2. Processing initial data taking into account uncertainty.

At this stage, the type of uncertainty about the analysis object state is taken into account and the basic model of the object state is initialized [22–25].

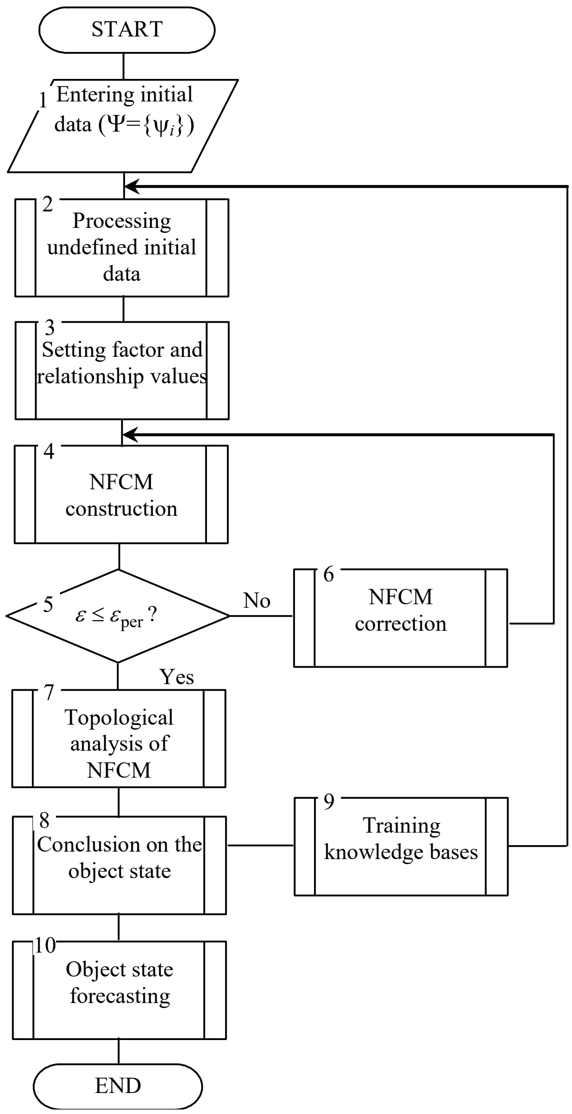

Fig. 1. Algorithm for implementing the object state analysis method

Step 6. 3. Determination of the necessary optimization conditions: at this stage, the appropriate objective function and constraints are set.

Step 6. 4. Formation of the initial population of P^0 with a sufficient variety of individuals.

Problems of initial size and topological innovations are solved by limiting the number of NFCM concepts. For the adjacency list, the operation of deleting the NFCM concepts is implemented, and the adaptability function, which imposes a fine on the NFCM size, ensures that the number of NFCM nodes will not increase strictly during evolution.

Step 6. 5. Transformation of genotype into phenotype: decoding of chromosomes of individuals into a set of NFCM vertices.

Step 6. 6. Assessment of adaptation.

For the adaptation function $F(x)$ of the search space X, we need to find the value of the argument x^*, at which $F(x)$ reaches its largest value:

$$x^* = \arg\max_{x\in X} F(x). \quad (2)$$

The adaptability F_i^t of an individual i to the iteration of t, $t\epsilon[0, +\infty]$ is calculated based on the assessment of the NFCM work, the fine for the NFCM size, the fine for such genotypes and the duration of the individual existence in the population.

The penalty for the NFCM size Φ_i^t is calculated based on the number of NFCM vertices and the relationships between them:

$$\Phi_i^t = N_i^t + \frac{M_i^t}{M_{\max}^t}, \quad (3)$$

where N_i^t is the number of NFCM vertices of the individual; M_i^t is the number of relationships between the NFCM vertices of the individual; $M_{\max}^t$ is the maximum number of relationships between the NFCM vertices.

The fine for such genotypes ρ_i is calculated on the basis of $\rho_{\min}(i, j)$ of the minimum distance between the i-th chromosome and other chromosomes of the population:

$$\rho_i = \frac{\rho_{\min}(i,j)}{1+\rho_{\min}(i,j)}. \quad (4)$$

Taking into account ρ is necessary to maintain population diversity and prevent premature convergence. The value of adaptation is also influenced by the value of κ_i, which is inverse to the existence period of the individual in the population:

$$\kappa_i = \frac{1}{1+T_i}, \quad (5)$$

where T_i is the evolution period of each individual.

Addition with the value of adaptability helps to solve the problem of insecurity of innovations by significantly reducing the risk of removal of the individual in the initial periods of existence. In the following periods κ_i, it does not significantly affect the adaptability [27].

Taking into account the RMS errors calculated by this method, the values of fines and the duration of the existence of the individual, the adaptation function F_i^t is calculated by the formula:

$$\tilde{F}_i^t = \frac{\overline{\omega}_E\left(1-E_i^t\right)+\overline{\omega}_V\left(1-V_i^t\right)}{\Phi_i^t+\rho_i} + \kappa_i, \quad (6)$$

where $\overline{\omega}_E$, $\overline{\omega}_V$ are the weight coefficients that reflect the relative importance of RMS errors,

$$\overline{\omega}_E = \frac{1-V_i^t}{2-V_i^t-E_i^t}, \overline{\omega}_V = 1-\overline{\omega}_E. \quad (7)$$

In real conditions, when it is impossible to obtain complete and reliable initial information about the state of the monitoring object, it is advisable to use the concept of indirect assessment of f_c to assess the NFCM effectiveness. Indirect assessment should be used in conditions of a priori uncertainty and in solving difficult formalized problems. While using the indirect evaluation function, the adaptation function of individuals will look like:

$$\tilde{F}_i^t = \frac{f_c}{\Phi_i^t+\rho_i} + \kappa_i, \quad (8)$$

f_c is the function of assessing the NFCM effectiveness.

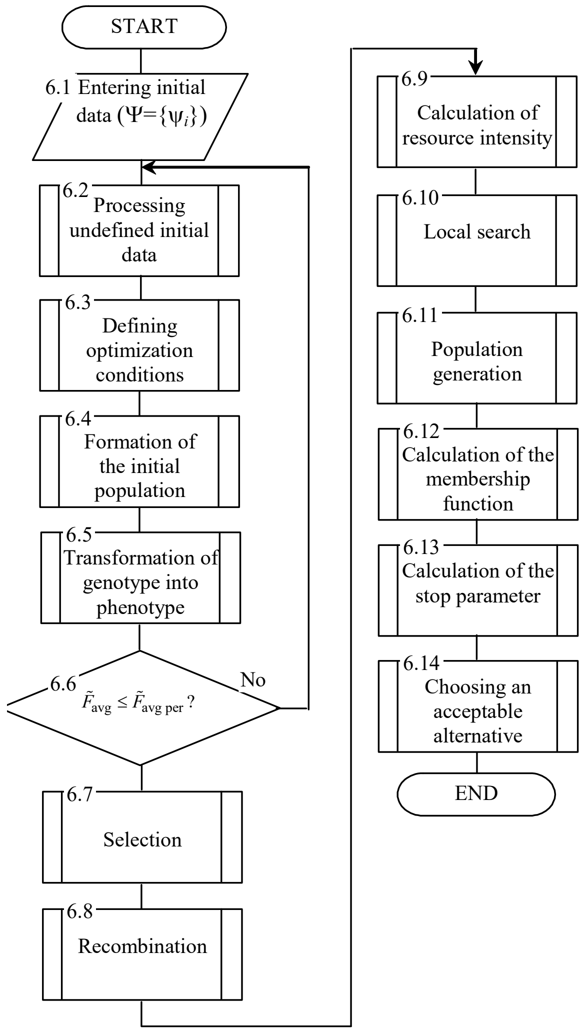

Fig. 2. Algorithm of the adjustment procedure of fuzzy cognitive models

To prevent premature convergence and a situation in which the average and best individuals form approximately the same number of offspring, the value $\tilde{F}$ is scaled by the formula:

$$F=\left(\tilde{F}+\tilde{F}_{avg}-c\sigma\right)^{\vartheta}, \tag{9}$$

$\tilde{F}_{avg}$ is the average population adaptation; c=const∊[1,5];

σ is the standard deviation of population adaptation; ϑ∊[1, 1.5] is the coefficient selected taking into account the tasks to be solved.

The lack of changes in the adaptation of the best individual in the population indicates the stagnation of the search.

Step 6. 7. Checking the condition of evolution completion.

Independent termination conditions can be as follows:

– on the exhaustion of the evolution time (or the number of calls to the optimization function);

– to achieve the best combination of genes; after the adaptation function achieves the "plateau" – in the absence of its change during a given number of iterations.

If any of the conditions are met, the algorithm is terminated. Otherwise, the next step is performed.

Step 6. 8. Selection.

The search strategy consists of selection and recombination mechanisms. These are probabilistic processes that underlie the process of neuroevolution [28, 29]. The chromosome SL (selection) operator for the new population is implemented by the probabilistic method in combination with the "elite" method: the most successful individuals are entered into the pool of "good" decisions; other individuals are selected for recombination with a probability of P_{SL}:

$$P_{SL}(i)=\frac{F_i}{\sum_{j=1}^{N}F_j}, \tag{10}$$

where i, j are the indices of individuals.

A pool of "good" solutions is necessary to maintain population diversity and prevent rapid convergence of the algorithm to a suboptimal solution (local optimum). The chromosome for the phenotype ρ^* is stored in the pool if the condition is met

$$(\forall\rho\in P)\left(\rho\left(\rho,\rho^*\right)=\rho_{\max}\right)\cap\left(F\left(\rho^*\right)=F_{\max}\right), \tag{11}$$

ρ_{max} is the maximum distance between individuals in the population for iteration of the setting; F_{max} is the maximum adaptability of individuals in the population for iteration of settings.

Step 6. 9. Recombination.

Recombination is the application of genetic operators of crossingover and mutation to individuals selected in the previous step. Crossingover is a genetic operator that affects the size of a population. In this implementation of neuroevolution, a two-stage multipoint CR (crossingover) is proposed [4].

The first stage of crossingover is to determine the number D and coordinates d_k, k∊[1, D] points of intersection, followed by crossing the original genotypes at given points. In the general case, for points the result of crossing individuals $\rho_i^t=\{\alpha_1,\alpha_2,...,\alpha_n\}$, $\rho_i^t=\{b_1,b_2,...,b_n\}\in P^t$, iteration t are two genotypes of iteration t+1:

$$\rho_i^{t+1}=\left\{\alpha_1,...,\alpha_{d_1},b_{d_{1+1}},...,b_{d_2},\alpha_{d_{2+1}},...,\alpha_{d_D},...,\right\},$$

$$\rho_i^{t+1}=\left\{b_1,...,b_{d_1},\alpha_{d_{1+1}},...,\alpha_{d_2},b_{d_{2+1}},...,b_{d_D},...,\right\}\in P^{t+1}, \tag{12}$$

d_k, k∊[1, D] are the intersection points of genotypes;

D is the number of intersection points.

The number of intersection points is defined as a random number on the segment [1, min{N_1, N_2}], N_1 and N_2 are respectively, the number of NFCM vertices in the first and second genotypes selected for crossingover. Points d_k are selected according to the condition:

$$d_k=j:\left(IN_1(j)=IN_2(j)\right)\cup\left(OUT_1(j)=OUT_2(j)\right), \tag{13}$$

j is the index that positions the peak of NFCM in the first and second genotype;

($IN_1(j)$, $IN_2(j)$, $OUT_1(j)$, $OUT_2(j)$) are the corresponding values of the parameters IN and OUT for the j-th vertex in these genotypes.

If there are several indices with equal parameter values, the indices with the closest values are selected. Thus, indexing of neurons in the genotype in combination with the use of IN and OUT parameters reduces the risk of competition of representations and prevents the crossing of areas of genotypes that carry different functional load.

The second stage of crossingover is to remove and redistribute the links associated with those missing in the new NFCM configuration change. The stage is necessary to guarantee the viability of new individuals.

MT (mutation) is a genetic operator, in this procedure implemented in eight modifications. The possibility of using a mutation for a single P_{MT} gene in the iteration of t is calculated by the formula:

$$P_{MT}(g_i) = \frac{\alpha}{L} \frac{e^{-\frac{\beta t}{2}}}{N}, \tag{14}$$

α, β=const; L is the chromosome length; N is the population size.

The choice of this type of formula is due to the fact that for effective evolution, the probability of mutation must be inversely dependent on the size of the population. This reduces the possibility of mutation over time.

One of the main purposes of using a mutation operator is to maintain the diversity of individuals, but in small populations, frequent mutations have a negative effect on the ascent to the optimum. Long chromosomes provide population variability, so the value of P_{MT} is higher the fewer parameters the chromosome contains. The parameters α, β of the formula are selected before the beginning of evolution and are necessary for fine-tuning the mutation process.

Features of the operator's modifications and the probability of application of each of the modifications are presented in Table 1. Indexing nodes in the genotype prevents the risk of removing new elements from the population. When the condition $i=i_{\max}$, where i is the index of this node, $i_{\max}$ is the index of the last node added to the genotype, the probability of using removal operators is zero. The introduction of this condition allows solving the problem of insecurity of innovations. The probability coefficients, which are multiplied by the probability for each modification of the operator, are fixed and selected based on the requirement to change existing parameters more often than adding new or deleting previously configured elements.

Table 1

Description of the mutation procedure

Markings	Description	Probability of execution
MT_{s_ADD}	Sequential adding of a relationship to the NFCM	$P_{S\_ADD} = 0.1\, P_{MT}(g_i)$
MT_{p_ADD}	Parallel adding of a relationship to the NFCM	$P_{P\_ADD} = 0.1\, P_{MT}(g_i)$
MT_{DEL}	Deleting a relationship in the NFCM	$P_{DEL} = \begin{cases} 0, i = i_{\max} \\ 0.1 P_{MT}(g_i)\, i \neq i_{\max} \end{cases}$
MT_{L_ADD}	Adding an internal relationship in the middle of the NFCM	$P_{L\_ADD} = 0.1\, P_{MT}(g_i)$
MT_{L_DEL}	Deleting the internal relationship in the middle of the NFCM	$P_{L\_DEL} = \begin{cases} 0, i = i_{\max} \\ 0.1 P_{MT}(g_i)\, i \neq i_{\max} \end{cases}$
MT_{I_ADD}	Adding an input according to a parameter from the pool	$P_{I\_ADD} = 0.05\, P_{MT}(g_i)$
MT_{I_DEL}	Deleting an input according to a parameter from the pool	$P_{L\_DEL} = \begin{cases} 0, i = i_{\max} \\ 0.05 P_{MT}(g_i)\, i \neq i_{\max} \end{cases}$

The described selection and recombination operators in combination with the adaptation function and the pool of "good" individuals are designed for the self-adaptation of the algorithm to the level of problem complexity.

Step 6. 10. Calculation of the resource intensity of the obtained values and checking conditions for non-exceeding res_{add} for each individual in the initial population:

$$res_i = f(U_{eff}), \tag{15}$$

where U_{eff} is the key efficiency indicator.

Step 6. 11. Local search. This stage of optimization of individuals of the population endows the algorithm with memetic properties and justifies the use of the direct method of chromosome coding. The stage is implemented using a local search algorithm.

Step 6. 12. Generation of P^{t+1} population and transition to a new iteration of t+1 evolution:

$$P^{t+1} = MT\Big(CR\big((SL)(P^t, F^t)\big)\Big). \tag{16}$$

The stage of local search consists of the following steps: evolutionary adjustment of the population individuals, at the previous step transformed into phenotypes; recalculation of adaptation functions; return to the previous values of the parameters in case of reduced fitness.

The advantages of evolutionary adjustment of NFCM parameters are as follows:

– independence of NFCM topology;

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

– selective optimization of parameters of recently changed or added relationships in the NFCM without change of the structure already modified on previous iterations of the algorithm.

Step 6. 13. Calculation of the membership function of the level of target $\Lambda_{ij}^{\text{targ}}$ achievement, which consists in the implementation of an iterative procedure for recalculating target indicators based on the developed fuzzy cognitive model:

$$\Lambda_{ij}^{\text{targ}} = f(U_{eff}), j = \overline{1,k}. \tag{17}$$

Step 6. 14. Calculation of the stop parameter of the algorithm based on the minimum deviation of the level of target achievement relative to the required value:

$$\Delta\Lambda_{ij}^{\text{targ}} = \Lambda_{ij}^{\text{targ}} - \Lambda_{irequired}^{\text{targ}},$$

$$\Delta\Lambda = \min_i \min_j \Delta\Lambda_{ij}^{\text{targ}}. \tag{18}$$

Step 6. 15. Choosing an acceptable alternative. An acceptable alternative is the one in which the generalized utility is the greatest.

End of the algorithm.

Procedures (1)–(5), (7)–(10) of the proposed method are described in detail in [23].

5. 3. An example of using the proposed method to analyze the operational situation of a group of troops (forces)

Simulation of the solution search method according to the algorithm in Fig. 2 and expressions (1)–(18) is carried out. The simulation of the proposed evaluation method is performed in the MathCad 14 software environment (USA). The task to be solved during the simulation was to assess the elements of the operational situation of the group of troops (forces).

Initial data for assessing the operational situation using the proposed method:

– the number of object state data sources – 3 (radio monitoring devices, remote earth sensing devices and unmanned aerial vehicles). To simplify the simulation, the same number of each device was taken – 4;

– the number of information features that determine the state of the monitoring object – 12. These parameters include: affiliation, type of organizational and staff formation, priority, minimum width on the front, maximum width on the front. The number of personnel, minimum depth on the flank, maximum depth on the flank, total number of personnel, number of weapons samples, number of types of weapons samples and number of radio communication devices are also taken into account;

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

We indicate which parameters for each type of operator were considered. The method was tested in proportional selection (volume 18 %); recombination: average. To determine the most effective combination of settings for each individual scheme considered, all other search parameters must be left the same. The size of the population was chosen equal to 50, the number of population individuals is 50. These data are taken in accordance with the approximate number of command posts of the operational and tactical grouping of troops (forces). The comparison of algorithms is carried out according to the criterion of suitability of the obtained solutions. The number of independent runs in the experiments is 100. The speed was estimated as the average generation at which the algorithm finds the global optimum.

Several different optimization algorithms for solving the extremal problem were compared (15). Among them: the classical binary genetic algorithm; valid genetic algorithm; the proposed method and genetic algorithm with the Population-Level Dynamic Probabilities (PDP) tuning algorithm. The number of calculations of the objective function for the operation of genetic algorithms was chosen equal to the number of measurements of the objective function, in the cycles of which local improvement was used [24].

Table 2 shows the results of the comparison for the proposed method and known in the search in one direction, search in two directions and search in three directions.

Table 2

Estimation of the probability of finding a solution that is close to the true one for different solution search algorithms

Iteration	Proposed method	Classical binary genetic algorithm	Valid genetic algorithm	Genetic algorithm with PDP configuration algorithm
	Average suitability for group search in one direction			
1	0.959344	0.66	0.79	0.79
2	0.957950	0.678	0.82	0.8
3	0.957798	0.69	0.823	0.825
4	0.945785	0.713	0.83	0.83
5	0.956173	0.728	0.836	0.839
6	0.964235	0.735	0.84	0.843
7	0.978653	0.746	0.845	0.858
8	0.983865	0.754	0.849	0.869
9	0.992892	0.763	0.853	0.873
10	1.000000	0.78	0.89	0.89
Average suitability for group search in two directions				
1	0.93	0.58	0.7	0.71
2	0.9359	0.63	0.7165	0.72
3	0.9401	0.66	0.7288	0.729
4	0.94397	0.689	0.73	0.738
5	0.946	0.7	0.735	0.74
6	0.951	0.71	0.75	0.755
7	0.9533	0.723	0.764	0.758
8	0.962	0.7287	0.78	0.776
9	0.9803	0.74	0.793	0.79
10	0.987	0.752	0.8	0.81
Average suitability for group search in three directions				
1	0.85	0.5	0.61	0.68
2	0.854	0.51	0.6168	0.69
3	0.859	0.516	0.62	0.7
4	0.86	0.52	0.623	0.706
5	0.862	0.531	0.628	0.711
6	0.869	0,535	0.63	0.702
7	0.87	0.539	0.64	0.71
8	0.874	0.54	0.647	0.713
9	0.88	0.546	0.649	0.716
10	0.888	0.549	0.65	0.72

From the data in Table 2, it is seen that with an increasing number of search directions, the suitability of the solution obtained by genetic algorithms decreases. As the number of solution search areas increases, the moment comes when the obtained solutions will not meet the reliability requirements. The proposed method provides adequate solutions for multidirectional search. The effectiveness of the proposed method is very significant in the multidirectional solution search on average from 16 to 24 %.

6. Discussion of the results of the development of the evaluation method

The advantages of the proposed method are due to the following factors:

– while correcting the fuzzy cognitive model, the type of uncertainty is taken into account (step 6. 2 in Fig. 2, (1) and (8));

– taking into account the adaptability of individuals and the population as a whole ((2), (9));

– efficiency of decision-making due to the use of fines for the NFCM size and the duration of the existence of individuals and the population as a whole ((4)–(6));

– taking into account the degree of data noise (1);

– universality of the solution of the object state analysis problem due to the hierarchical description of the object (1);

– the ability to quickly build a fuzzy cognitive temporal model by simultaneously finding a solution by several individuals (1)–(8);

– the adequacy of the results obtained ((15)–(17));

– taking into account the resource intensity of the obtained evaluation values (15);

– the ability to avoid the problem of local extremum (2)–(18).

The main advantages of the proposed evaluation method are:

– it has 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 object state estimate;

– universality of application due to adaptation of the system of indicators in the course of work;

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

– possibility of complex training of architecture and parameters of artificial neural networks;

– taking into account the type of uncertainty and noise of the original data while constructing a fuzzy cognitive model;

– the ability to find a solution in several areas of individuals in the population;

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

– no local optimum trap.

The limitations of the research are the need to have an initial database on the state of the monitoring object, the need to take into account the delay in collecting and proving information from intelligence sources.

The disadvantages of the proposed method include:

– loss of informativeness in the object state evaluation due to the construction of the membership function;

– lower estimation accuracy based on a separate object state estimation parameter;

– loss of reliability of the obtained solutions in solution search in several directions simultaneously;

– lower estimation accuracy compared to other estimation methods.

This method allows:

– assessing the object state;

– identifying effective measures to improve management efficiency;

– increasing the speed of object state assessment;

– reducing the use of computing resources of decision support systems.

The proposed approach should be used to solve the problems of assessing 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 improving the efficiency of information and analytical support, published earlier [2, 4–6, 23].

Further research should be aimed at reducing computational costs in processing various types of data in special-purpose systems.

7. Conclusions

1. A formalized description of the problem of object state analysis in intelligent decision support systems was carried out. This formalization allows describing the processes implemented in intelligent decision support systems in solving object state analysis problems. The efficiency of the object state analysis process is chosen as an efficiency criterion for this method. In the course of the research, the concept of presentation of the evaluation method in intelligent decision support systems is formulated. In this concept, the analysis process is presented as a multidimensional time series. This allows creating a hierarchical description of a complex process by levels of generalization and conducting appropriate analysis of its state.

2. The algorithm for implementing the method allows:

– taking into account the type of uncertainty and noise in the data;

– carrying out a correction of fuzzy cognitive models using a genetic algorithm;

– training knowledge bases by learning 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;

– taking into account the adaptability of individuals and the population as a whole;

– increasing the efficiency of decision-making using fines for the NFCM size and the duration of the existence of individuals and the population as a whole;

– applying as a universal tool for solving the problem of object state analysis due to the hierarchical description of the object;

– checking the adequacy of the obtained results;

– taking into account the resource intensity of the obtained evaluation values;

– avoiding the problem of local extremum.

3. An illustrative example of using the proposed method on the example of assessing the operational situation of a group of troops (forces) is given. This example showed an increase in the efficiency of data processing at the level of 16–24 % using additional advanced procedures.

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