

DEVELOPMENT OF AN EVALUATION METHOD USING A COMBINED CAT SWARM OPTIMIZATION ALGORITHM

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The object of the study is complex dynamic objects with a hierarchical structure. The problem solved in the study is to increase the efficiency of decision-making while ensuring the given reliability. The subject of the study is the process of decision-making in management problems using an improved cat swarm optimization algorithm (CSO), an improved genetic algorithm and evolving artificial neural networks.

The proposed method, due to additional and improved procedures, allows you:

– to take into account the type of uncertainty of the initial data for setting CA for the local search procedure;

– to implement adaptive strategies for finding food sources by CA;

– to take into account the experience of the most authoritative CA while conducting local and global search;

– to take into account the available computing resources of the state analysis system of complex dynamic objects and determine their required amount for involvement;

– to take into account the CA search priority;

– to determine the best CA using an improved 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 architecture of individual elements and the architecture of the artificial neural network as a whole;

– to avoid the local extremum problem by using the jump procedure.

The proposed method was tested on the example of solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure. An example of using the method showed an increase in the efficiency of data processing at the level of 14–19 % by using additional improved procedures.

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

Keywords: mentor cats, combined approach, genetic algorithm, global and local optimization

Received date 04.03.2024

Accepted date 30.05.2024

Published date 28.06.2024

How to Cite: Tarkhan, A. B., Kuchuk, H., Stanovska, I., Golian, V., Golian, N., Zharova, O., Kryzhanivskiy, Y., Liubarets, A., Zvershkhovskiy, I., Fysiuk, A. (2024). Development of an evaluation method using a combined cat swarm optimization algorithm. *Eastern-European Journal of Enterprise Technologies*, 3 (4 (129)), 55–63. <https://doi.org/10.15587/1729-4061.2024.305363>

1. Introduction

The constant volume of information circulating in various information, information-analytical, and automated systems requires the search for new approaches to increase the efficiency of processing information that circulates in them.

This applies to both the security and defense sector and commercial systems. This refers to typical optimization problems [1–3]. An optimization problem involves finding the best solution among several possible solutions, usually defined by decision variables, constraints and an objective function. Optimization is aimed at identifying the optimal

solution to a given problem among all possible alternatives. Optimization methods can be classified into deterministic and stochastic approaches [4–6].

Along with exploration and exploitation, achieving the desired performance of metaheuristic algorithms relies on maintaining a balance between these two aspects during the search process [5–8]. This was shown in the analysis of the radio-electronic situation of groups of troops (forces), creation (refinement) of knowledge bases and processing of various types of data of information (information-analytical) systems of various functional purposes [1–8].

The no free lunch theorem (NFL) states that achieving acceptable performance with a metaheuristic algorithm for a specific set of optimization problems does not guarantee similar performance for other optimization problems. An algorithm that has shown success in solving specific optimization problems may fail when applied to others. The NFL theorem emphasizes that no metaheuristic algorithm can claim to be the best optimizer for all optimization problems. The NFL theorem is a catalyst for ongoing research in the field of metaheuristic algorithms to develop more efficient algorithms.

Given the above, an urgent scientific task is to develop an evaluation method using a combined cat swarm optimization algorithm, which would increase the efficiency of decisions made to control the parameters of complex dynamic objects with a given reliability.

2. Literature review and problem statement

The work [9] presents a cognitive modeling algorithm. 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 analysis object.

The work [10] disclosed the essence of cognitive modeling and scenario planning. A system of complementary principles of building and implementing scenarios is proposed, different 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 take into account the type of uncertainty about the state of the analysis object and the noise of the initial data.

The work [11] carried out an analysis of the main approaches to cognitive modeling. Cognitive analysis allows you to: investigate problems with fuzzy factors and relationships; take into account changes in the external environment and use objectively formed trends in the development of the situation to your advantage. 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 the operations of generating analytical baselines, reducing variables, detecting sparse features and specifying rules. The disadvantages of this method include the impossibility of taking into account different decision evaluation strategies, the lack of consideration of the type of uncertainty of the input data.

The work [13] presents a 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 disadvantages of the mentioned approach include the impossibility

of assessing the adequacy and reliability of the information transformation process and making 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 of assessing 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 based on a set of input parameters. The disadvantages of the specified method include the impossibility of assessing the adequacy and reliability of the assessment and, accordingly, determining 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 their high computational complexity and the impossibility of checking 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 consists in clustering the basic set of input data, analyzing them, after which 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. This approach allows you to process data from various sources. The disadvantages of this approach include the low accuracy of the obtained estimate and the impossibility of verifying the reliability of the obtained estimate.

The work [19] carried out a comparative analysis of existing decision support technologies, namely: the 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 under the condition of complete initial information, but due to the need for experts to compare alternatives and choose evaluation criteria, it has a high share of subjectivity. For forecasting problems 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 study 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. At the same time, the problem is defined as the non-compliance of the existing system state with the required one, which is set by the management subject. The disadvantages of the proposed method include the problem of the local optimum and the inability to conduct a parallel search.

The work [21] presents a cognitive approach to simulation modeling of 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 the computing resources of the system.

The work [22] indicated that the most popular evolutionary bio-inspired algorithms are the so-called «swarm» procedures (Particle Swarm Optimization – PSO). Among them, there are cat swarm optimization algorithms (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. Among the modifications, procedures based on harmonic search, fractional derivatives, adaptation of search parameters and, finally, «crazy cats» can be noted. At the same time, these procedures are not without some drawbacks that worsen 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 possibility of forming a hierarchical system of indicators for assessing the state of complex dynamic objects;
- the lack of consideration of computing resources of the system that evaluates the state of complex dynamic objects;
- the lack of mechanisms for adjusting the system of indicators for assessing the state of complex dynamic objects;
- the lack of consideration of the type of uncertainty and noise of data on the state of complex dynamic objects, which creates corresponding errors while assessing their 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.

3. The aim and objectives of the study

The aim of the study is to develop an evaluation method using a combined cat swarm optimization algorithm. This will increase the speed of assessing the state of dynamic objects with a given reliability and developing subsequent management decisions. This will make it possible to develop software for intelligent decision support systems.

To achieve the aim, the following objectives were set:

- to determine the algorithm for implementing the method;
- to give an example of using the method in analyzing the operational situation of a group of troops (forces).

4. Materials and methods

The object of the study is complex dynamic objects with a hierarchical structure.

The problem solved in the study is to increase the efficiency of decision-making in the problems of assessing the state of dynamic objects while ensuring the given reliability regardless of its hierarchy. The subject of the study is the process of decision-making in management problems using an improved cat swarm optimization algorithm (CSO), an improved genetic algorithm and evolving artificial neural networks.

The hypothesis of the study is the possibility of increasing the efficiency of decision-making with a given assess-

ment reliability using the improved cat swarm optimization algorithm.

The proposed method was simulated in the MathCad 14 software environment (USA). The problem solved during the simulation was to assess the elements of the operational situation of a group of troops (forces). The hardware of the research process is AMD Ryzen 5.

The object of assessment was an operational group of troops (forces). The operational group of troops (forces) formed on the basis of an operational command with a standard composition of forces and means according to the wartime state and with a range of responsibilities under current regulations.

The research is based on the cat swarm optimization algorithm to find a solution regarding the state of dynamic objects with a hierarchical structure. Evolving artificial neural networks are used to train cat agents, and an advanced genetic algorithm is used to select the best individuals of the cat swarm.

To determine the effectiveness of the proposed method, modeling of its work was carried out to solve the problem of determining the composition of the operational group of troops (forces) and elements of its operational structure in order to determine the expediency of regrouping troops (forces).

Initial data for determining the composition of the operational group of troops (forces) and elements of its operational structure using the method:

- the number of sources of information about the state of the monitoring object – 3 (radio monitoring means, earth remote sensing means and unmanned aerial vehicles). To simplify the modeling, the same number of each tool was taken – 4 tools each;
- the number of information features for determining the state of the monitoring object – 12. Such parameters include: membership, 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, number of samples of weapons and military equipment (WME), number of types of WME samples and number of communication means), type of operational structure are also taken into account;
- the variants of organizational and personnel formations
- company, battalion, brigade.

The parameters of the method:

- the number of iterations – 100;
- the number of individuals in the swarm – 100;
- the range of the feature space – $[-150,150]$.

The parameters of the advanced genetic algorithm:

- Selection – Roulette wheel (proportional);
- Crossover – probability=0.8;
- Mutation – Gaussian probability=0.05.

5. Development of an evaluation method using a combined cat swarm optimization algorithm

5.1. Algorithm of the evaluation method using the combined cat swarm optimization algorithm

Social groups of cats exist and work only in a few conditions: when members of the group know each other, when there is no competition for food or other resources. Cats can form strong social relationships with familiar individuals and in particular between kittens in the same litter, and between kittens and their mothers.

Cat colonies may have a centralized structure, with a «central» cat colony linked to the main food source and surrounded

by small «peripheral» groups that develop around the central colony while having access to the food source. Peripheral groups have worse access to food, weaker health and poorer reproduction [23].

According to the matriarchal system of social interaction of cats, catteries are mainly organized by the principle of «ten visiting cats». It is this property of gathering in matriarchal groups and forming bonds with the help of kittens that allows undamaged cats in the cattery to coexist almost without conflicts.

According to the above, individuals in the cat swarm who have authority and life experience are teachers for other, less authoritative, individuals of the cat swarm. This means the possibility of training individuals of the cat swarm by other authoritative individuals.

The proposed approach is a bio-inspired algorithm that assumes that cats form a swarm (cat swarm – CS), while each cat can be in one of two states: Seeking Mode (SM) and Tracing Mode (TM).

Each member of the cat swarm, based on its position in space, determines the values for the variables of the problem solution. Thus, each cat, as a member of the population, is a candidate for solving the problem, which is modeled mathematically using a vector.

The evaluation method using the combined cat swarm optimization algorithm consists of the following sequence of actions:

1. General procedures of the algorithm.

Step 1. Entering initial data. At this stage, the available initial data about the object of analysis and the computing power of the analysis system are entered.

Step 2. Creating a cat swarm. The initialization of the cat population X_i ($i=1, 2, \dots, n$) takes place. The set of cats form a population described by the matrix X . The location of each cat describes the i -th element of the general matrix X . Cats are set on the search plane taking into account the uncertainty about the control object, and the basic model of its state is also initialized [2, 19, 21, 24, 25].

The position of the cat in the problem space is initialized at the beginning of the algorithm run using equation (1):

$$x_{i,d} = lb_d + r \cdot (ub_d - lb_d), \tag{1}$$

X is the cat population matrix, X_i is the i -th member of the cat swarm, $x_{i,d}$ is the d -th dimension in the solution search space, regarding the state of the control object, N is the number of cats, m is the number of decision variables, r is a random number in the interval $[0, 1]$, lb_d and ub_d are the lower and upper bounds of the d -th decision variables.

Since the position of each cat in the problem-solving space represents a solution to the problem, the value of the objective function can be estimated according to the position of each cat.

Step 3. Numbering cats in the swarm, $i, i \in [0, S]$. At this stage, each cat is assigned a serial number. This makes it possible to determine the parameters of finding a solution for each individual in the swarm.

Step 4. Checking the fitness of each cat.

The relevance of each search cat is determined in each iteration using the improved genetic algorithm proposed in [26] and comparing the obtained values with standardized functions. The fitness value of each cat in the search swarm (each row in the X matrix) is measured and compared with the fitness of the remaining cats (the other rows of the X matrix).

2. Local search procedures.

The seeking mode is associated with slow movements with a small amplitude near the starting position (space scanning in the current position).

Step 5. Preliminary evaluation of the cat search area. In this procedure, the search area in natural language is determined precisely by the halo of the cat existence. Considering that food sources for cats are food of animal origin, it is advisable to sort the fitness of food sources (Step 5).

Step 6. Classification of food sources for cats.

The location of the best food source (minimum fitness) of a lizard (rodent) (FS_{ht}) that is nearby and requires the least amount of energy to find and obtain. Delicate food (birds) will be denoted as FS_{at} .

Other non-priority food sources (food that is necessary for the survival of individuals) will be designated as FS_{nt} :

$$FS_{ht} = FS(\text{sorte_index}(1)), \tag{2}$$

$$FS_{at}(1:3) = FS(\text{sorte_index}(2:4)), \tag{3}$$

$$FS_{nt}(1:NP-4) = FS(\text{sorte_index}(5:NP)). \tag{4}$$

Step 7. Updating the cat position for local optimization.

At this stage, cats update their position based on modeling the behavior of training cats and trained cats. To simulate this step, a new position is first calculated for each trained cat based on repeating steps using equation (5). This process leads to large shifts in the position of population members, which has a positive effect on research and global search in various areas of the problem-solving space.

According to equation (6), the new position calculated for each cat is acceptable if it improves the value of the objective function. Therefore, equation (6) states that the new position is acceptable for the cat if the value of the objective function improves in the new position, since the cat movement in the problem-solving space is aimed at achieving better solutions and preventing the algorithm from moving to inappropriate solutions:

$$\begin{aligned} \bar{X}_i^{p2}(t+1) &= \bar{X}_i(t+1) + \\ &+ \overline{rand} * (\bar{K}(t) - \overline{rand}_2 * \bar{X}_i(t+1)), \\ i &= 1, \dots, N, j = 1, \dots, m, \end{aligned} \tag{5}$$

$$\bar{X}_i(t+1) = \begin{cases} \bar{X}_i^{p2}(t+1), & F(\bar{X}_i^{p2}(t+1)) < F(\bar{X}_i(t+1)), \\ \bar{X}_i(t+1), & \text{else,} \end{cases} \tag{6}$$

$i = 1, \dots, N,$

where $\bar{X}_i^{p2}(t+1)$ is the new calculated position of the i -th cat based on the second training phase, $x_{i,j}^{p2}(t+1)$ is its j -th dimension, \overline{rand} is a random dimension vector drawn from a uniform distribution.

Step 8. Determining the need to involve additional hardware resources of the system.

Based on the information about the unexplored area, the need for additional network hardware resources is determined. The seeking mode is determined by three main factors: the amount of the seeking memory pool (seeking memory pool – SMP), which determines the number of copies of each cat cat_p , the change step for each space coordinate R_x^n (seeking range of the selected dimension – SRD) and changing coordinates (counts of dimension to change – CDC).

3. Tracing mode procedure (Step 9).

The tracing mode is determined by fast jumps with a large amplitude and allows you to remove the cat cat_p from the local extremum, if it got there. The combination of local scanning and sudden changes in the current state allows you to find the global extremum with a higher probability compared to traditional multiextremal optimization methods.

At this stage, the cat position is updated based on modeling the efforts of trained cats during self-awareness education. This process leads to large changes in the cat position, which play an influential role in increasing the ability of trained cats to perform a global search using equation (7). According to equation (8), the proposed computed position for each population member is acceptable if it improves the value of the objective function:

$$\bar{X}_i^{P3}(t+1) = \bar{X}_i(t+1) + \overline{rand} * (\bar{X}_i(t+1) - \bar{X}_i(t)), i = 1, \dots, N, \tag{7}$$

$$\bar{X}_i(t+1) = \begin{cases} \bar{X}_i^{P3}(t+1), F(\bar{X}_i^{P3}(t+1)) < F(\bar{X}_i(t+1)); \\ \bar{X}_i(t+1), \text{else,} \end{cases} \tag{8}$$

where $\bar{X}_i^{P3}(t+1)$ is the new calculated position of the i -th cat during the tracing phase, $x_{ij}^{P3}(t+1)$ is its j -th dimension, \overline{rand} is a random vector of dimension m drawn from

a uniform distribution in the interval $[0, 1]$, which is the tracing vector.

The tracing mode corresponds to the global search process, which allows you to «skip» the local extrema of the optimized function.

Step 10. Checking the stop criterion. The algorithm terminates when the maximum number of iterations is completed. Otherwise, the behavior of generating new locations and checking conditions is repeated.

Step 11. Training cat knowledge bases.

In this research, the learning method based on evolving artificial neural networks developed in [2] is used to train the knowledge bases of each cat. The method is used to change the movement nature of each cat, for more accurate analysis results in the future.

End of the algorithm.

5. 2. Example of applying the evaluation method using the combined cat swarm optimization algorithm

The effectiveness of the evaluation method using the combined cat swarm optimization algorithm is compared with the swarm optimization algorithms listed in Tables 1–3. Initial data for modeling, parameters of the method and individual procedures are given in section 4 of the study.

Table 1 compares bio-inspired optimization algorithms and the proposed method for 7 unimodal reference functions.

Table 1

Efficiency of optimization algorithms in solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure (for unimodal reference functions)

No. F	Value	Grey wolf optimizer algorithm	Walrus optimization algorithm	Particle swarm optimization algorithm	Monkey algorithm	Hawk optimization algorithm	Bat algorithm	Coot optimization algorithm	Proposed method
F_1	Average	0	0	5.87E-50	2.61E-47	1.69E-152	1.62E-01	1.16E-58	4.15E-74
	Best	0	0	2.84E-52	1.24E-50	2.41E-168	9.82E-02	1.12E-60	2.27E-77
	Worst	0	0	3.48E-49	3.20E-46	2.59E-151	2.27E-01	8.48E-58	7.17E-73
	Standard	0	0	8.40E-50	7.29E-47	5.84E-152	3.66E-02	2.50E-58	1.59E-73
	Median	0	0	2.42E-50	1.06E-48	1.55E-159	1.58E-01	1.43E-59	3.50E-76
F_2	Average	0	0	1.01E-27	9.02E-29	1E-103	2.56E-01	1.07E-34	7.74E-39
	Best	0	0	5.97E-30	1.72E-30	3.17E-113	1.53E-01	1.76E-35	6.07E-40
	Worst	0	0	4.31E-27	5.47E-28	1.54E-102	3.73E-01	7.83E-34	4.79E-38
	Standard	0	0	1.13E-27	1.67E-28	3.53E-103	5.40E-02	1.73E-34	1.09E-38
	Median	0	0	6.94E-28	1.96E-29	5.94E-108	2.53E-01	4.26E-35	4.56E-39
F_3	Average	0	0	1.315E-11	2.48E-10	18 858.845	1.29 E+01	2.649E-1	2.49E-25
	Best	0	0	2.652E-16	1.90E-18	2032.3297	4.20 E+00	3.816E-1	2.02E-27
	Worst	0	0	1.82E-10	4.87E-09	33 406.826	2.07 E+01	4.419E-1	1.29E-24
	Standard	0	0	4.047E-11	1.09E-09	8589.6075	4.86 E+00	9.822E-1	4.02E-25
	Median	0	0	5.931E-13	3.76E-14	18 946.43	1.29 E+01	4.75E-16	2.52E-26
F_4	Average	0	0	2.362E-19	1.37E-02	25.164909	5.60E-01	1.229E-1	1.389E-3
	Best	0	0	2.66E-20	1.57E-04	0.0159905	2.41E-01	6.529E-1	6.32E-32
	Worst	0	0	9.464E-19	2.08E-01	66.772408	1.19 E+00	5.365E-1	7.472E-3
	Standard	0	0	2.231E-19	4.59E-02	21.758362	1.99E-01	1.297E-1	1.765E-3
	Median	0	0	1.621E-19	1.62E-03	23.196445	5.23E-01	7.145E-1	7.971E-3
F_5	Average	0.00044	8.69465	23.549145	28.63252	27.239329	576.0648	26.52322	26.67888
	Best	4.577E-	1.575E-	22.951247	27.13044	26.744112	27.65624	25.53492	25.72669
	Worst	0.00320	28.9901	24.176305	29.08185	28.73628	2095.188	27.90093	27.97673
	Standard	0.00091	13.6263	0.3563753	0.451802	0.554927	747.1212	0.584281	0.680046
	Median	5.048E-	1.299E-	23.548934	28.82276	27.012342	230.1384	26.21475	26.37307
F_6	Average	0	6.63989	1.43E-09	3.828507	0.0832617	0.143322	0.508549	1.142094
	Best	0	4.16 E	5.07E-10	2.802989	0.0115735	8.98E-02	1.907E-0	0.409080
	Worst	0	7.25009	3.28E-09	5.031701	0.2700173	0.207617	1.250753	2.079622
	Standard	0	0.83696	6.47E-10	0.622201	0.0794334	0.031349	0.335495	0.403572
	Median	0	6.97578	1.38E-09	3.568478	0.040989	0.138077	0.500399	1.167196
F_7	Average	1.328E	9.22E-0	0.0006545	0.004642	0.0015207	0.012250	0.000829	0.002349
	Best	6.54E-0	1.03E-0	0.0001747	0.001663	0.0001157	0.006046	1.64E-04	0.000490
	Worst	5.028E	0.00035	0.0021105	0.016796	0.0059269	0.018080	0.001983	0.005127
	Standard	1.438E-	8.699E	0.0004314	0.003557	0.0015071	0.003276	0.000430	0.001353
	Median	3.606E	7.175E	0.0005529	0.003700	0.000804	0.012341	0.000795	0.002016

Table 2 shows the results of a comparative analysis of the proposed method with other bio-inspired optimization algorithms for 6 multidimensional multimodal reference functions in accordance with the conditions and parameters given in section 4 of the study.

Table 3 shows a comparison of the method proposed in the study with 9 high-dimensional multimodal functions while solving the problem of determining the composition of an operational group of troops (forces), in accordance with the conditions of section 4 of the study.

Table 2

Efficiency of optimization algorithms in solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure (for multidimensional multimodal reference functions)

No. F	Value	Grey wolf optimizer algorithm	Walrus optimization algorithm	Particle swarm optimization algorithm	Monkey algorithm	Hawk optimization algorithm	Bat algorithm	Coot optimization algorithm	Proposed method
F ₈	Average	-12 340.5	-5479.39	-9.76 E	-6.09 E	-10 835.7	-8.09 E	-6.02 E	-5.17 E+03
	Best	-12 569.4	-5.66 E	-1.04 E	-7.73 E	-12 569.4	-9.23 E	-7.81 E	-7.52 E+03
	Worst	-9015.580	-5255.87	-8.83 E	-5.23 E	-7160.143	-6.70 E	-3.01 E	-4.32 E+03
	Standard	792.57825	141.0296	4.03 E	6.47 E+02	1757.8744	7.09 E+02	9.25 E+02	7.25 E+02
	Median	-12 559.1	-5489.11	-9.81 E	-6.10 E	-11 531.9	-8.10 E	-6.21 E	-5.04 E+03
F ₉	Average	0	0	0.00 E	1.61 E+02	0	1.11 E+02	8.28E-01	0.00 E+00
	Best	0	0	0.00 E	8.42 E+01	0	4.09 E+01	0.00 E+00	0.00 E+00
	Worst	0	0	0.00 E	2.29 E+02	0	1.61 E+02	1.22 E+01	0.00 E+00
	Standard	0	0	0.00 E	4.21 E+01	0	2.80 E+01	2.78 E+00	0.00 E+00
	Median	0	0	0.00 E	1.67 E+02	0	1.11 E+02	0.00 E+00	0.00 E+00
F ₁₀	Average	8.882E-16	8.882E-1	4.086E-1	2.21 E+00	3.908E-15	8.18E-01	1.563E-14	4.09E-15
	Best	8.882E-16	8.882E-1	8.882E-1	7.99E-15	8.882E-16	9.40E-02	1.155E-14	8.88E-16
	Worst	8.882E-16	8.882E-1	4.441E-1	3.45 E+00	7.994E-15	2.91 E+00	1.865E-14	4.44E-15
	Standard	0	0	1.094E-1	1.33 E+00	2.647E-15	8.53E-01	1.739E-15	1.09E-15
	Median	8.882E-16	8.882E-1	4.441E-1	2.81 E+00	4.441E-15	1.58E-01	1.51E-14	4.44E-15
F ₁₁	Average	0	0	0	8.98E-03	0.0096082	3.94E-01	0.0034191	0
	Best	0	0	0.00 E	0.00 E+00	0	2.84E-01	0	0.00 E+00
	Worst	0	0	0	2.38E-02	0.1097843	5.12E-01	0.017904	0
	Standard	0	0	0	7.61E-03	0.0299058	6.04E-02	0.006312	0
	Median	0	0	0	9.92E-03	0	3.93E-01	0	0
F ₁₂	Average	3.137E-08	1.16244	1.57E-07	8.007413	0.0167428	0.6392239	0.0329332	0.0751404
	Best	4.736E-10	0.557437	3.842E-0	1.076990	0.0010716	0.000628	0.0065876	0.03806
	Worst	1.695E-07	1.668894	2.913E-0	16.99856	0.1908087	2.4615261	0.0664481	0.1133911
	Standard	4.053E-08	0.338705	6.877E-0	4.509667	0.042204	0.7935942	0.0159373	0.0184989
	Median	1.432E-08	1.106103	1.461E-0	8.009401	0.0037323	0.3815718	0.0293849	0.0756851
F ₁₃	Average	5.337E-07	0.392759	2.82E-03	2.868884	0.2466066	0.036827	0.4665474	1.111075
	Best	7.965E-11	5.35E-31	1.86E-09	1.679169	0.0158998	1.42E-02	0.2003169	0.5959632
	Worst	6.244E-06	2.9	1.31E-02	4.195679	0.6945697	0.0691117	0.8138707	1.6022415
	Standard	1.395E-06	0.963463	5.06E-03	0.663853	0.1993274	0.0180155	0.1651567	0.296759
	Median	7.624E-08	8.367E-3	3.62E-09	2.826203	0.1936396	0.0320078	0.417461	1.1361137

Table 3

Efficiency of optimization algorithms in solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure (for high-dimensional multimodal functions)

No. F	Value	Grey wolf optimizer algorithm	Walrus optimization algorithm	Particle swarm optimization algorithm	Monkey algorithm	Hawk optimization algorithm	Bat algorithm	Coot optimization algorithm	Proposed method
1	2	3	4	5	6	7	8	9	10
F ₁₄	Average	0.998003	3.453968	1.009255	7.868411	1.833185	0.998003	4.324466	1.097209
	Best	0.998003	1.992030	0.998003	0.998003	0.998003	0.998003	0.998003	0.998003
	Worst	0.998003	12.67050	1.186694	13.61860	10.76318	0.998003	12.67050	2.982105
	Standard	7.204E-1	2.876489	0.042540	5.30 E+00	2.27 E+00	5.358E-1	4.381902	0.443658
	Median	0.998003	2.929699	0.998003	10.76318	0.998003	0.998003	2.982105	0.998003
F ₁₅	Average	0.000307	0.001543	0.000307	0.011393	0.000605	0.003616	0.008375	0.001432
	Best	0.000307	0.000664	0.000307	0.000307	0.000309	0.000308	0.000307	0.000309
	Worst	0.000307	0.004743	0.000308	0.056621	0.001488	0.020363	0.020363	0.020364
	Standard	2.795E-1	0.001016	1.693E-0	0.014517	0.000365	0.007221	0.010044	0.004465
	Median	0.000307	0.001289	0.000307	0.001224	0.000497	0.000662	0.000307	0.000319
F ₁₆	Average	-1.03162	-1.02957	-1.03162	-1.02688	-1.03162	-1.03162	-1.03162	-1.03162
	Best	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162
	Worst	-1.03162	-1	-1.03162	-0.99999	-1.03162	-1.03162	-1.03162	-1.03162
	Standard	2.28E-16	6.99E-03	6.22E-09	1.16E-02	8.88E-11	9.05E-08	1.09E-08	1.689E-0
	Median	-1.03162	-1.03132	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162	-1.03162

Continuation of Table 3

1	2	3	4	5	6	7	8	9	10
F_{17}	Average	0.397887	0.652433	0.397890	0.397920	0.397888	0.397887	0.397887	0.402056
	Best	0.397887	0.398073	0.397887	0.397887	0.397887	0.397887	0.397887	0.397888
	Worst	0.397887	5.040108	0.397948	0.398011	0.397894	0.397887	0.397889	0.478014
	Standard	0	1.034473	1.361E-0	3.639E-0	1.69E-06	9.65E-08	5.91E-07	1.79E-02
	Median	0.397887	0.406863	0.397887	0.397901	0.397887	0.397887	0.397887	0.397979
F_{18}	Average	3	5.744307	3	12.45005	3.000002	3.000000	3.000008	3.000000
	Best	3	3.000000	3	3.000000	3	3	3	3
	Worst	3	30.67341	3	84.00037	3.000014	3.000002	3.000034	3.000003
	Standard	9.282E-1	8.45 E+00	6.16E-12	2.01 E+01	3.38E-06	5.23E-07	8.73E-06	6.641E-0
	Median	3	3.000062	3	3.000009	3.000000	3.000000	3.000006	3.000000
F_{19}	Average	-3.86278	-3.81393	-3.86277	-3.86233	-3.86012	-3.86278	-3.86241	-3.86123
	Best	-3.86278	-3.86029	-3.86278	-3.86277	-3.86277	-3.86278	-3.86278	-3.86272
	Worst	-3.8627821	-3.6907307	-3.8627274	-3.8548841	-3.8549006	-3.8627816	-3.8571253	-3.8547679
	Standard	2.278E-15	4.77E-02	1.33E-05	0.0017545	2.76E-03	1.44E-07	0.0012587	2.78E-03
	Median	-3.86278	-3.82697	-3.86278	-3.86274	-3.86100	-3.86278	-3.86277	-3.86240
F_{20}	Average	-3.32199	-2.45245	-3.27645	-3.24702	-3.27744	-3.26239	-3.25530	-3.25503
	Best	-3.32199	-2.90842	-3.32199	-3.32165	-3.32197	-3.32199	-3.32199	-3.31237
	Worst	-3.32199	-1.35805	-3.18713	-3.03852	-3.12472	-3.20220	-3.08381	-3.10044
	Standard	4.201E-1	0.448159	6.37E-02	0.077203	0.069983	0.061147	0.089609	0.067429
	Median	-3.32199	-2.62555	-3.32197	-3.20257	-3.32103	-3.26253	-3.32198	-3.30235
F_{21}	Average	-10.1532	-5.05519	-10.1532	-6.87371	-7.98909	-7.88059	-8.63473	-6.41227
	Best	-10.1532	-5.05519	-10.1532	-10.1174	-10.1526	-10.1531	-10.1531	-9.46395
	Worst	-10.1532	-5.05519	-10.1532	-2.64585	-2.63005	-2.63046	-5.05519	-4.27208
	Standard	2.512E-1	2.82E-07	1.911E-1	2.948936	2.761215	2.937749	2.379035	1.810375
	Median	-10.1532	-5.05519	-10.1532	-5.05311	-10.1432	-10.1531	-10.1525	-6.08448
F_{22}	Average	-10.4029	-5.08766	-10.1371	-8.39720	-7.29093	-8.96209	-10.4024	-7.57499
	Best	-10.4029	-5.08767	-10.4029	-10.3955	-10.4027	-10.4029	-10.4027	-9.07515
	Worst	-10.4029	-5.08766	-5.08767	-1.82452	-2.76585	-2.76589	-10.4019	-4.36756
	Standard	3.645E-1	1.118E-0	1.19 E+00	3.049536	2.940632	2.605068	0.000237	1.469583
	Median	-10.4029	-5.08766	-10.4029	-10.1883	-5.08767	-10.4028	-10.4025	-8.17147

As can be seen from Tables 1–3, the increase in decision-making efficiency is achieved at the level of 14–19 % by using additional procedures for various types of unimodal reference functions.

It can be seen that the state estimation method of dynamic objects using the combined swarm algorithm is able to converge to the true value for most unimodal functions with the fastest convergence rate and the highest accuracy, while the convergence results of the particle swarm optimization algorithm are far from satisfactory.

6. Discussion of the results of developing an evaluation method using the combined cat swarm optimization algorithm

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

- the initial setting of cats is carried out taking into account the type of uncertainty (Step 2), by adding appropriate correction factors, compared to [9, 14, 21];
- universality of cat food location search strategies, which allows you to classify the type of data to be processed (Steps 5, 6, expressions (2)–(4)), compared to [14, 16, 17];
- classification of cat food sources, which determines the solution search priority (Step 6, expressions (2)–(4)), compared to [11, 13, 17–19];
- while conducting a local and global search for the swarm (Step 7, Step 9, expressions (5)–(8)), the experience of the most experienced representatives of the cat swarm is taken into account, by ranking the level of knowledge of each cat, before a new iteration of the algorithm, compared to [12, 13, 15–18];

– accelerated selection of individuals for each cat due to the use of an improved genetic algorithm (Step 4), compared to [9, 12–18];

– universality of solving the problem of analyzing the state of dynamic objects of cats due to the hierarchical nature of their description (Steps 1–11, expressions (1)–(8)), compared to [9, 12–18];

– the possibility of simultaneous solution search in different directions (Steps 1–11, Tables 1–3);

– the adequacy of the obtained results (Steps 1–11, expressions (1)–(8)), compared to [9–23];

– the ability to avoid the local extremum problem (Steps 1–11), due to the use of the tracing procedure, compared to [10, 11, 15, 19];

– the possibility of deep learning of cat knowledge bases (Step 11), due to the use of the deep learning method, compared to [9–23];

– the possibility of calculating the necessary amount of computing resources, which must be involved in case of impossibility of carrying out calculations with available computing resources (Step 8), compared to [9–23].

The disadvantages of the proposed method include:

- the loss of informativeness while assessing the state of complex dynamic objects due to the construction of the membership function;
- the 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 will allow you:

- to assess the state of complex dynamic objects;
- to determine effective measures to increase the efficiency of managing complex dynamic objects;

- to increase the speed of assessing the state of complex dynamic objects;
- to reduce the use of computing resources of decision support systems.

The limitations of the study are the need to have an initial database on the state of a complex dynamic object, the need to take into account the delay time for collecting and communicating information from intelligence sources.

The proposed approach should be used to solve the problems of evaluating complex and dynamic processes characterized by a high degree of complexity. For example, solving routing problems in information networks, mapping, building routes in the interests of logistics support.

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, 27–31].

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

7. Conclusions

1. An algorithm for implementing the method was determined, which, due to additional and improved procedures, allows you:

- to take into account the type of uncertainty of the initial data for setting cat swarm agents for the local search procedure, by using correction factors at the stage of entering the initial data;
- to implement adaptive strategies for finding food sources by the cat swarm agents, by controlling the speed and direction of movement of the pack agents;
- to take into account the experience of the most authoritative individuals of the cat swarm while conducting a local and global search, by ranking the experience of the swarm representatives;
- to take into account the available computing resources of the state analysis system of complex dynamic objects and determine their required quantity;
- to determine the best agents using an advanced 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 be used as a universal tool for solving the problem of analyzing the state of complex dynamic objects due to the hierarchical nature of the description;

- to avoid the local extremum problem by using the jump procedure.

2. An example of using the proposed method in solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure is given. The specified example showed a 14–19 % 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 otherwise, that could affect the research and its results presented in this paper.

Financing

The research was conducted without financial support.

Data availability

The manuscript has associated data in the data repository.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies while creating the presented work.

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