Today's management solutions depend precisely on the successful solution of optimization problems, which are discontinuous, undifferentiated and multimodal. One of the approaches to increase the efficiency of solving optimization problems is bio-inspired algorithms. The object of the study is complex dynamic objects. The subject of the study is the decision-making process in the problems of managing complex dynamic objects. A management method using a bio-inspired algorithm is proposed. The research is based on the goose algorithm – for finding a solution to the state of dynamic objects with a hierarchical structure. Evolving artificial neural networks are used to train goose agents (GA) and an advanced genetic algorithm is used to select the best ones in the combined swarm algorithm.

The originality of the proposed method lies in setting GA taking into account the uncertainty of the initial data, improved global and local search procedures. Also, the originality of the study lies in determining GA food locations, which allows choosing the priority of search in a given direction. The next element in the originality of the study is the ability to determine the indicators of guard GA, which allows adjusting the amount of time during which the GA flock will be located. Another original element of the study is the determination of the initial velocity of each GA. This makes it possible to optimize the speed of conducting exploration by each GA in a certain research direction. The method allows increasing the efficiency of data processing at the level of 10–12 % by using additional improved procedures. The proposed method should be used to solve problems of evaluating complex dynamic objects

Keywords: deep learning, complex processes, genetic algorithm, complex and dynamic objects

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DEVELOPMENT OF A METHOD FOR MANAGING TECHNICAL SYSTEMS USING A BIO-INSPIRED ALGORITHM

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1. Introduction

Optimization is a complex process of determining multiple solutions for a variety of functions. Many of today's management decisions depend precisely on the successful solution of optimization problems, especially in the problems of intellectualization of troops (forces) management [1–3]. While solving optimization problems, solution variables are defined in such a way that complex dynamic objects work at their best point (mode) according to a certain optimization criterion.

In essence, optimization problems of complex dynamic objects are discontinuous, undifferentiated and multimodal. Thus, classical gradient deterministic algorithms [4–6] are not useful for solving optimization problems of complex dynamic objects, as shown in solving the problems of analyzing the radio-electronic situation and processing various types of data.

To overcome the drawbacks of classical optimization algorithms for solving optimization problems of complex dynamic objects, a significant number of stochastic optimization algorithms, known as bio-inspired algorithms, were created [7–9].

One type of stochastic optimization algorithms for complex dynamic objects is swarm intelligence algorithms (swarm algorithms) [9–11]. Swarm intelligence algorithms are based on swarm movement and simulate interactions between the swarm and its environment to improve knowledge about the environment, such as new food sources [10–13]. The most well-known swarm algorithms are the particle swarm optimization algorithm, the artificial bee colony algorithm, the ant colony optimization algorithm, the wolf pack algorithm and the sparrow search algorithm [14–17].

However, most of the basic bio-inspired algorithms mentioned above cannot balance exploration and exploitation, resulting in poor performance for real-world complex optimization problems [16–19].

This prompts the introduction of various strategies to improve the convergence rate and accuracy of basic bio-inspired algorithms.

Given the above, an urgent scientific task is to develop a management method using a bio-inspired algorithm, which would increase the efficiency of decisions made to manage 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 for 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. This method is aimed at 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. This 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 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 priority of the search in a certain direction.

3. The aim and objectives of the study

The aim of the study is to develop a management method using a bio-inspired algorithm. This will increase the efficiency 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 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 a given reliability regardless of its hierarchy. The object of the study is complex dynamic objects with a hierarchical structure. The subject of the study is the process of decision-making in management problems using an improved goose algorithm (GA), 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 assessment reliability using a bio-inspired algorithm.

The advantage of this method in the study is the ability to conduct gradient search, with restriction elements in certain directions and the necessary search speed, which is an undeniable advantage in the analysis of hierarchical and non-uniform dynamic objects [22–27].

In the work of bio-inspired algorithms, there is a need to select the best individuals that meet the optimal criteria in the study – an improved genetic algorithm was chosen to solve this partial problem in the study. This advanced algorithm has all the necessary procedures, such as selection, mutation, etc.

In order to reduce the number of errors that accumulate during the work of the bio-inspired algorithm, it is necessary to adjust the knowledge bases (in the natural language of optimization, this is the accumulation of experience). For this, the method of training artificial evolving neural networks is used. This approach is due to the fact that it allows you to create the necessary number of connections for a specific task.

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.

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 tools and unmanned aerial vehicles). To simplify the modeling, the same amount of each tool was taken – 4 tools each;

– the number of informational features for determining the state of the monitoring object – 12. Such parameters include: affiliation, type of organizational and staff formation, priority, minimum width along the front, maximum width along the front. The number of personnel, minimum depth along the flank, maximum depth along the flank, the number of samples of weapons and military equipment (WME), the number of types of WME samples and the number of communication devices), type of operational construction are also taken into account;

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

Operating parameters of the method:

– the number of iterations – 100;

– the number of individuals in the flock – 50 (the number of flock guard GA – 5, the number of forager GA – 45);

– pebble weight for guard GA – 2 kg;

– the feature space range – [–150, 150].

Parameters of the improved genetic algorithm:

– Selection – Roulette wheel (proportional);

– Crossover – probability=0.8;

– Mutation – Gaussian probability=0.05.

The data processing procedure is as follows:

– input of initial data on the group of troops (forces) for calculations (available initial situation – calculation of the degree of uncertainty about the object state);

– input of initial parameters of the method;

– processing of the data obtained.

5. Development of a management method using a bio-inspired algorithm

5. 1. Algorithm of the management method using a bio-inspired algorithm

The proposed approach is a bio-inspired algorithm that assumes that GA form a flock. This approach can provide appropriate solutions for optimization problems (for subsequent management) in a multiple iterative process based on the ability to search for its members (GA) in the problem-solving space.

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

The management method using a bio-inspired algorithm consists of the following sequence of steps:

Step 1. Input of initial data. At this stage, the following is determined:

– the number of GA in the flock;

– the maximum value of the fitness function;

– the number of alpha individuals (leaders), a function that describes the management object;

– basic positions of each GA in the search space;

– he number of iterations of the search algorithm;

– pebble weight (GA used by the guards).

Step 2. Creating a GA flock. Initialization of the GA population X_i (i=1, 2, ..., n) is performed. A set of GA form a population described by the matrix X. The location of each GA describes the i-th element of the general matrix X. GA are set on the search plane taking into account the uncertainty about the management object, and the basic model of its state is also initialized [2, 19, 21].

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

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

X is the population matrix of GA, X_i is the i-th member of the GA flock, $x_{i,d}$ is the d-th dimension in the solution search space, regarding the state of the management object, N is the number of GA, m is the number of solution 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 solution variables.

Since the position of each GA 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 GA.

Step 3. Numbering GA in the flock, i, $i \in [0, S]$. At this stage, each GA is assigned a serial number. This allows you to determine the parameters of finding a solution for each individual in the flock.

Step 4. Dividing GA by functional purpose. At this stage, GA are divided according to purpose. In this case, the available GA are divided into two categories: flock guard GA (up to 10 % of the flock size), the remaining GA are foragers.

Step 5. Determining the initial velocity of GA.

The initial velocity v_0 of each GA is determined by the following expression:

$$v_i = \left(v_1, v_2 ... v_S\right), v_i = v_0. \tag{2}$$

In the planning of the proposed approach, the position of the GA flock members in the problem-solving space is updated based on modeling the GA foraging strategy in the wild. Accordingly, in each iteration, the position of the population members is updated in two stages: exploration based on modeling the GA movement towards the food source and exploitation based on simulating the behavior of feeding GA. Updating of the guard GA position is determined according to the position of the main flock.

Step 6. Preliminary evaluation of the GA search area. In this procedure, the search area in natural language is determined precisely by the halo of the GA existence. Given that food sources for GA are plant food, it is advisable to sort the fitness of food sources (Step 7).

Step 7. Classification of food sources for GA.

The location of the best food source (minimum fitness) is considered to be (FS_{ht}) plant food (watercress), which is nearby and requires the least amount of energy to find and obtain it. Delicacy food of plant origin is denoted as FS_{at}.

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

$$FS_{ht}=FS(\text{sorte\_index}(1)), \tag{3}$$

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

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

Step 8. Forming a flock of guards and their parameters. As indicated in Step 4 of the algorithm, a certain part of the flock remains as guards. The ability to protect the flock is a necessary condition for the exploitation phase.

Step 8. 1. Calculating the weight of the pebble that the GA keeps in its paws. The pebble is intended to alert the resting GA about the predator approaching the flock. Accordingly, the pebble size determines the time of its fall and the propagation of sound. In the natural environment, the weight of a pebble kept by an individual ranges from 1 to 25 kg. Expression (6) describes the procedure for finding the weight of a pebble randomly for any iteration:

$$W_{it}=\text{rand}([1, 25],1,1). \tag{6}$$

Step 8. 2. Calculating the time for the pebble to reach the ground.

Expression (7) allows you to calculate the time Tst_{it} required for a falling pebble to reach the ground. This is a random value between 1 and the number of measurements for each iteration in the loop:

$$Tst_{it}=\text{rand }(1, \text{dim}). \tag{7}$$

Step 8. 3. Calculating the time the pebble hits the ground.

Expression (8) allows you to calculate the time Tas_{it} when the pebble hits the ground and a sound is heard, which is transmitted to each GA in the flock:

$$Tas_{it}=\text{rand }(1, \text{dim}). \tag{8}$$

Step 8. 4. Calculating the sound propagation time.

Expression (9) describes the procedure for calculating the total time T_{total} required for sound propagation and reaching an individual GA in the flock during the iterations of the algorithm:

$$T_{total} = \frac{\sum (Tas_{it})}{\dim}. \tag{9}$$

To get the average required time T_a, the total time is divided by 2:

$$T_a = \frac{T_{total}}{2}. \tag{10}$$

Step 9. Forming the GA search flock. Alpha GA that are not flock guards go in search of food sources and lead the rest of the flock.

Step 10. Checking the fitness of each GA.

The correspondence of each search GA is determined in each iteration using the improved genetic algorithm proposed in [26–30] and comparing the obtained values with standardized functions. The fitness value of each GA in the search flock (each row in the X matrix) is measured and compared to the fitness of the remaining GA (the other rows of the X matrix).

Step 11. Checking the presence of a predator near the flock. To protect and awaken the GA in the group, the pebble falling speed should be calculated:

$$V_{FFS} = T_{ait} * \frac{\sqrt[2]{W_{it}}}{9.81}. \tag{11}$$

In equation (12), to find the sound propagation distance S_{it}, it must be the speed of sound V_{ss} in air multiplied by the sound propagation time Tas_{it}. The speed of sound in air is 343.2 meters per second:

$$S_{it} = V_{ss} \cdot Tas_{it}. \tag{12}$$

At this step, the distance D_{it} between the guard GA and another GA that is resting or feeding is found. Equation (13) uses the sound propagation distance S_{it} multiplied by 1/2 because only time for sound travel is needed, not time for the sound to return:

$$D_{it} = 1/2 * S_{it}. \tag{13}$$

To awaken an individual in the flock, $BestX_{it}$ must be found, as shown in equation (14). This equation consists of the pebble falling velocity V_{FFS}, added to the GA distance D_{it}, multiplied by the average value in the square of time T_a:

$$\left(X_{it+1}\right) = V_{FFS} + D_{it} * T_a^2. \tag{14}$$

Step 12. 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 13. Training GA knowledge bases.

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

Step 14. Determining the amount of necessary computing resources of the intelligent decision support system.

In order to prevent looping of calculations on Steps 1–13 of this method and increase the efficiency of calculations, the system load is additionally determined. When a certain threshold of computational complexity is exceeded, the amount of software and hardware resources that must be additionally involved is determined using the method proposed in [31].

The end of the algorithm.

5. 2. Example of applying the management method using a bio-inspired algorithm

The management method using a bio-inspired algorithm is proposed. To determine the effectiveness of the proposed method, a simulation 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 feasibility of rearranging troops (forces).

The efficiency of the management method using a bio-inspired algorithm is compared with the swarm optimization algorithms listed in Tables 1–4. The comparison was made with unimodal and multimodal functions.

The statistical results given in Table 1 allow us to conclude that the proposed method provides an increase in the efficiency of initial data processing while saving the cost of calculations. At the same time, the level of computational complexity is approximately equal compared to the walrus optimization, ant colony optimization and flying squirrel search optimization algorithms.

Table 1

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

Name of the algorithm	T_s	Optimal variables T_h R		L	Optimal value
Walrus optimization algorithm	0.7280271	0.3845792	40.312284	200	5,882.8955
Particle swarm optimization algorithm	0.7480269	0.3845797	40.312282	200	5,882.9013
Flying squirrel search optimization algorithm	0.7690308	0.384581	40.312476	199.99732	5,882.9077
Artificial bee colony algorithm	1.1950157	0.64038	60.549321	48.031984	7,759.8234
Ant colony optimization algorithm	0.7780271	0.3845792	40.312284	200	5,882.9013
The proposed method	0.7194994	0.385819	40.386517	200	5,809.3749
Monkey search algorithm	0.911517	0.4510723	46.230782	133.83941	6,270.8621
Bat algorithm	0.8344267	0.4164052	43.217775	163.90679	6,003.8497
Locust swarm optimization algorithm	0.7784599	0.385813	40.320627	199.96442	5,890.2105
Genetic algorithm	1.5622593	0.481302	47.695987	124.64823	10,807.366
Cat swarm optimization algorithm	1.1300127	1.157634	44.110061	190.7876	11,984.417
Invasive weed optimization algorithm	1.55006	0.623124	63.139483	49.78495	9,998.6395
Firefly algorithm	1.406417	0.783276	58.253368	73.964478	10,920.286

Table 2

Comparative analysis of the efficiency of optimization algorithms in solving the problem of determining the composition of the operational group of troops (forces) and elements of its operational structure

Name of the algorithm	Average	Best	Worst	Standard	Median	Rank
Walrus optimization algorithm	59.8955	5,882.8955	5,884.8955	1.87E-12	5,882.8955	1
Particle swarm optimization algorithm	59.226	5,882.9013	5,967.0365	22.218932	5,882.9017	3
Flying squirrel search optimization algorithm	622.5386	5,882.9077	7,047.3206	352.35848	6,047.6955	5
Artificial bee colony algorithm	12,41.586	776.8234	19,991.769	3137.065	11,403.338	9
Ant colony optimization algorithm	588.901	5,880.9013	5,882.9013	3.68E-06	5,882.9013	2
The proposed method	6271.132	5,909.3749	6,948.3792	333.1584	6,143.6153	6
Monkey search algorithm	7998.6372	6,270.8621	12,805.388	1,681.8974	7,579.6333	8
Bat algorithm	6518.1019	6,003.8497	7,050.4059	320.31898	6,572.19	7
Locust swarm optimization algorithm	6012.3675	5,890.2105	6,670.9945	239.38549	5,898.5494	4
Genetic algorithm	28,273.334	10,81.366	60,311.64	13,795.65	24,975.491	12
Cat swarm optimization algorithm	20,643.589	11,98.417	32,105.445	6711.6675	19,830.394	10
Invasive weed optimization algorithm	29,687.575	9998.64	50,712.307	12,915.318	32,709.339	13
Firefly algorithm	25,427.766	10,920.27	45,530.922	10,828.815	22,551.255	11

Table 3

Comparative analysis of the efficiency of optimization algorithms in determining the operational group of troops (forces)

No. *F*	Value	Grey wolf optimization algorithm	Walrus optimization algorithm	Monkey search algorithm	Hawk optimization algorithm	Bat algorithm	Coot optimization algorithm	The proposed method
F_1	Average	2.22E–27	7.92E–72	9.73E–48	5.75E–98	6.49E–06	4.99E–07	1.22E–22
	Standard	5.43E–27	4.22E–71	4.80E–47	2.87E–97	1.28E–05	6.71E–07	6.6E–22
F_2	Average	8.23E–17	4.46E–51	0.00E+00	1.51E–50	3.39E–05	1.26E–05	2.21E–14
	Standard	6.13E–17	1.30E–50	0.00E+00	5.19E–50	4.15E–05	2.54E–05	6.57E–14
F_3	Average	1.43E–05	4.3E+04	4.04E–03	3.50E–72	9.74E+01	1.29E–01	4.06E–26
	Standard	3.47E–05	1.2E+04	7.64E–03	1.79E–71	1.57E+02	2.52E–01	1.98E–26
F_4	Average	1.08E–06	5.3E+01	3.02 E–02	3.14E–49	2.87E–01	5.03E–02	2.14E–13
	Standard	1.26E–06	2.7E+01	1.77E–02	1.47E–48	3.48E–01	8.79E–02	9.39E–13
F_5	Average	2.70E+01	2.8E+01	2.85E+01	8.34E–03	2.89E+01	2.8E+01	4.52E+01
	Standard	8.74E–01	5.51E–01	3.06E–01	1.36E–02	1.26E–01	4.E–01	3.22E+01
F_6	Average	7.66E–01	4.69E–01	3.27E+00	1.02E–04	3.72E+00	2.6E+00	1.97E–01
	Standard	3.53E–01	2.86E–01	2.36E–01	1.16E–04	4.53E–01	4.64E–01	1.23E–01
F_7	Average	2.19E–03	2.54E–03	9.03E–05	1.28E–04	2.09E–03	6.91E–03	5.77E–03
	Standard	1.22E–03	2.76E–03	8.86E–05	1.01E–04	2.80E–03	5.71E–03	5.24E–03
F_8	Average	–6E+03	–1E+04	–5.4E+03	–1.24E+04	–5.74E+03	–5.9E+03	–7.44E+03
	Standard	1E+03	1.7E+03	4.29E+02	5.03E+02	7.42E+01	5.1E+02	7.55E+02
F_9	Average	1.9E+00	1.7E+00	0.00E+00	0.00E+00	1.66E+01	1.1E+01	1.47E–04
	Standard	2.74E+00	7E+00	0.00E+00	0.00E+00	2.01 E+01	1.6E+01	9.49E–04
F_{10}	Average	1.00E–13	4.56E–15	8.88E–16	8.88E–16	2.00E+01	2.0E+01	2.77E–09
	Standard	1.4E–14	2.38E–15	0.00E+00	0.00E+00	1.20E–03	1.20E–03	1.42E–08
F_{11}	Average	4.2E–03	6.89E–03	1.76E–01	0.00E+00	2.57E–02	2.59E–02	1.28E–16
	Standard	1E–02	2.77E–02	1.34E–01	0.00E+00	6.67 E–02	4.07E–02	2.78E–16
F_{12}	Average	4.2E–02	2.20E–02	5.10E+06	1.02E–05	5.41E–01	2.41E–01	3.77E–01
	Standard	2.1E–02	1.08E–02	4.63E+07	1.58E–05	2.24E–01	1.61E–01	8.26E–01
F_{13}	Average	6.8E–01	5.70E–01	2.83E+00	9.94E–05	2.72E+00	1.9E+00	4.12E–01
	Standard	2.5E–01	2.52E–01	1.02E–01	1.54E–04	1.27E–01	2.51E–01	5.26E–01
F_{14}	Average	4.3E+00	3.48E+00	9.80E+00	1.72E+00	1.32E+00	1.2E+00	9.98E–01
	Standard	4.2E+00	3.66E+00	4.28E+00	1.97E+00	1.78E+00	5.64E–01	6.60E–16
F_{15}	Average	3.1E–03	8.30E–04	1.18E–02	3.74E–04	1.30F.–03	1.09E–03	1.32E–03
	Standard	6.8E–03	5.59E–04	1.76E–02	1.71E–04	5.13E–05	3.35E–04	3.64E–03
F_{16}	Average	–1E+00	–1E+00	–1E+00	–1.03E+00	–1.03E+00	–1E+00	–1.08E+00
	Standard	2.6E–08	3.12E–09	1.24E–07	8.85E–10	1.46E–05	3.45E–06	3.22E–12
F_{17}	Average	4E–01	3.98E–01	4.14E–01	3.98E–01	5.54E–01	3.98E–01	4.31E–01
	Standard	3.1E–06	3.57E–05	1.54E–02	2.30E–05	8.47E–01	4.95E–04	8.85E–07

The analysis of statistical data given in Tables 2, 3 allows us to conclude that the method for estimating the state 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.

Table 4

Results of the GA algorithm for the test functions

Function	Function dimension	Number of GA	Number of iterations	Result	Average time, s.
Benchmark (global optimum: 0)	2	4	100	0	0
	5	14		0	0.1
	10	28		0.005	3.11
	30	50		0.007	30.42
Rastrigin (global optimum: 0)	2	6	100	0	0
	5	30		0	18,22
	10	50		0.03	62.2
	30	50		0.92	527.6
Griewank (global optimum: 0)	2	6	100	0	0
	5	16		0.002	0.16
	10	30		0.004	4.55
	30	50		0.024	89.01
Ackley (global optimum: 0)	2	6	100	0	0
	5	24		0.001	0.15
	10	42		0.012	3.15
	30	50		0.021	65.92
Bukin (global optimum: 0)	2	8	100	0	0
	5	20		0.002	1.94
	10	50		0.02	3.97

As can be seen from Tables 1–4, the increase in decision-making efficiency is achieved at the level of 10–12 % by using additional procedures.

6. Discussion of the results of developing a management method using a bio-inspired algorithm

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

– the initial setting of GA is carried out taking into account the type of uncertainty (Step 2), compared to [9, 14, 21];

– the initial velocity of each GA is taken into account (Step 4), compared to [9–15];

– the fitness of the GA search location is determined, which reduces the solution search time (Step 5), compared to [14, 16, 17];

– the universality of strategies for searching for GA food locations, which allows classifying the type of data to be processed (Steps 6, 7), compared to [14, 16, 17];

– classification of GA food sources is carried out, which determines the solution search priority (Step 6), compared to [11, 13, 17–19];

– taking into account the presence of a predator during GA foraging, which allows avoiding local optima (Step 11), compared to [12, 13, 15–18];

– accelerated selection of individuals for each GA by using an improved genetic algorithm (Step 10), compared to [9, 12–18];

– the universality of solving the problem of analyzing the state of dynamic objects by flock agents of the combined swarm algorithm due to the hierarchical nature of their description (Steps 1–14), compared to [9, 12–18];

– the possibility of simultaneous solution search in different directions (Steps 1–14, Tables 1–3);

– the adequacy of the obtained results (Steps 1–14), compared to [9–23];

– the ability to avoid the local extremum problem (Steps 1–14);

– the possibility of deep learning of GA knowledge bases (Step 14), compared to [9–23];

– the possibility of calculating the necessary amount of computing resources, which must be involved if it is impossible to perform calculations with available computing resources (Step 14), 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;

– lower accuracy of assessment by a single assessment parameter for the state of complex dynamic objects;

– 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 management efficiency of 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 problems of evaluating complex and dynamic processes characterized by a high degree of complexity.

This study is a further development of research aimed at developing methodological principles for increasing the efficiency of processing various types of data, published earlier [2, 4–6, 21–23].

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

7. Conclusions

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

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

– to implement adaptive strategies of searching for GA food sources;

– to take into account the presence of a predator while choosing food sources by the flock agents of the combined swarm algorithm;

– to take into account the available computing resources of the state analysis system of complex dynamic objects of GA;

– to change the search area by individual GA;

– to change the speed of GA movement;

– to take into account the search priority of the flock agents of the combined swarm algorithm;

– to carry out the initial setting of GA taking into account the type of uncertainty;

– to determine the best GA using an improved genetic algorithm;

– to conduct a local and global search taking into account the noise degree of data on the state of complex dynamic objects;

– to conduct training of knowledge bases, carried out by training the synaptic weights of the artificial neural network, the type and parameters of the membership function, 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 check the adequacy of the obtained results;

– to combine various swarm algorithms for mutual verification of the adequacy and reliability of the obtained results;

– to avoid the local extremum problem.

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 10–12 % 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.

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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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