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DEVELOPMENT OF A METHOD OF INCREASING THE EFFICIENCY OF DECISION-MAKING IN ORGANIZATIONAL AND TECHNICAL SYSTEMS

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The object of the study is organizational and technical systems. The subject of the study is the decision-making process in the problems of management of organizational and technical systems. A method of increasing the efficiency of decision-making in organizational and technical systems using artificial intelligence is proposed. The research is based on the giant armadillo swarm algorithm to find a solution regarding the state of organizational and technical systems. Giant armadillo agents (GAA) are trained using evolving artificial neural networks, and an advanced genetic algorithm is used to select the best GAA. The method has the following sequence of actions:

– input of initial data;
– setting GAA on the search plane;
– numbering GAA in the swarm;
– determining the initial velocity of GAA;
– preliminary evaluation of the GAA search area;
– classification of food sources for GAA;
– sorting the best GAA individuals;
– attack on termite mounds by GAA;
– digging termite mounds by GAA;
– updating GAA positions;
– checking for the presence of a GAA predator;
– escape and fight against GAA predators;
– checking the stop criterion;
– training GAA knowledge bases;
– determining the amount of necessary computing resources of the intelligent decision support system.

The originality of the proposed method lies in setting GAA taking into account the uncertainty of the initial data, advanced procedures of global and local search taking into account the noise degree of data on the state of organizational and technical systems. The method makes it possible to increase the efficiency of data processing at the level of 14–19 % using additional advanced procedures. The proposed method should be used to solve the problems of evaluating complex and dynamic processes

Keywords: management efficiency, complex processes, giant armadillo swarm algorithm, hierarchical systems

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1. Introduction

Optimization is a complex process of identifying a set of solutions for a variety of functions.

Many calculation problems today relate specifically to optimization problems [1–3]. While solving optimization problems, the solution variables are determined in such a way that the organizational and technical system works at its best point (mode) according to the optimization criterion determined.

The problems of optimization of organizational and technical systems are discontinuous, undifferentiated and also multimodal. Thus, it is impractical to use classic gradient deterministic algorithms [4–6] to solve optimization problems of organizational and technical systems.

To overcome the shortcomings of classical optimization algorithms for solving optimization problems of organizational and technical systems, a significant number of stochastic optimization algorithms, known as metaheuristic algorithms, have been created [7–11].

One of the types of algorithms for stochastic optimization of organizational and technical systems are swarm intelligence algorithms (swarm algorithms). Swarm intelligence algorithms are based on swarm movement and simulate interactions between the swarm and its environment to improve knowledge of the environment, such as new food sources. The most well-known swarm algorithms are the particle swarm optimization algorithm, artificial bee colony algorithm, ant colony optimization algorithm, wolf optimization algorithm and sparrow search algorithm [12–18].

Unfortunately, most of the basic metaheuristic algorithms mentioned above are unable to balance exploration and exploitation, resulting in poor performance for real-world complex optimization problems.

This encourages the implementation of various strategies to improve the convergence rate and accuracy of the basic metaheuristic algorithms. One of the options for increasing the efficiency of decision-making using metaheuristic algorithms is to combine them, that is, add the basic procedures of one algorithm to another.

Given the above, an urgent scientific task is to develop a method of increasing the efficiency of decision-making in organizational and technical systems using artificial intelligence, which would increase the efficiency of decisions made.

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: to investigate problems with fuzzy factors and relationships; to take into account changes in the external environment and use objectively formed trends in the development of the situation 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 an appropriate correction of the obtained models.

The work [14] developed an analytical web platform to study the geographical and temporal distribution of incidents. The web platform, contains several information panels with statistically significant results by territory. The disadvantages of the specified analytical platform include the impossibility 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 impossibility of assessing 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 provided 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. At the same time, 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, 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, which worsen the properties of the global extremum search process.

However, GAA still suffers from premature convergence and is easily trapped in the local optimal solution, especially while solving very complex problems.

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;

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

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

– the lack of consideration of the type of uncertainty and noise of data on the state of the analysis object, which creates corresponding errors while assessing its real state;

– the lack of deep learning mechanisms for knowledge bases;

– high computational complexity;

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

– the lack of search priority in a certain direction.

3. The aim and objectives of the study

The aim of the study is to develop a method of increasing the efficiency of decision-making in organizational and technical systems using artificial intelligence. This will increase the efficiency of assessing the state of organizational and technical systems 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 when 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 managing organizational and technical systems while ensuring the given reliability regardless of its hierarchy. The object of the study is organizational and technical systems. The subject of the study is the decision-making process in management problems using an advanced giant armadillo swarm algorithm, advanced genetic algorithm and evolving artificial neural networks. The giant armadillo swarm algorithm is used for a gradient search for a solution in different directions, which increases the efficiency of decisions made. An advanced genetic algorithm is used to select the best individuals in the swarm, which increases the reliability and efficiency of decisions made. Artificial neural networks are used to train individuals of the giant armadillo swarm to reduce the solution search time.

The hypothesis of the study is the possibility of increasing the efficiency of decision-making with a given reliability of assessment.

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 operational group of troops (forces) was considered as an object of assessment and management. 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 giant armadillo swarm algorithm for finding a solution regarding the state of the organizational and technical system. Evolving artificial neural networks are used to train GAA, and an advanced genetic algorithm is used to select the best GAA.

5. Development of a method of increasing the efficiency of decision-making in organizational and technical systems

5. 1. Algorithm of the method of increasing the efficiency of decision-making in organizational and technical systems

The proposed approach is based on a population metaheuristic algorithm, which assumes that giant armadillos form a swarm. The proposed approach can provide appropriate solutions to optimization problems in an iterative process based on the ability to search for its members (armadillo agents) in the problem-solving space.

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

The method of increasing the efficiency of decision-making in organizational and technical systems consists of the following sequence of actions:

Step 1. Input of initial data. At this stage, available initial data on the organizational and technical system to be analyzed are entered.

Step 2. Setting GAA on the search plane.

Giant armadillos together form a population of the algorithm, which can be modeled mathematically using a matrix according to the equation. The GAA setting is carried out taking into account the uncertainty about the organizational and technical system to be analyzed, and the basic model of its state is initialized [2, 19, 21] (1):

$$X=\begin{bmatrix} X_1 \\ \cdot \\ \cdot \\ \cdot \\ X_i \\ \cdot \\ \cdot \\ \cdot \\ X_N \end{bmatrix}_{N\times m} = \begin{bmatrix} x_{1,1}\times\iota_{1,1} & \cdots & x_{1,d}\times\iota_{1,d} & \cdots & x_{1,m}\times\iota_{1,m} \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ x_{i,1}\times\iota_{i,1} & \cdots & x_{i,d}\times\iota_{i,d} & \cdots & x_{i,m}\times\iota_{i,m} \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ \cdot & & \cdot & & \cdot \\ x_{N,1}\times\iota_{N,1} & \cdots & x_{N,d}\times\iota_{N,d} & \cdots & x_{N,m}\times\iota_{N,m} \end{bmatrix}_{N\times m}. \quad (1)$$

The main position of giant armadillos in the problem-solving space is initialized at the beginning of the algorithm execution using equation (2):

$$x_{i,d}=lb_d+r\cdot\left(ub_d-lb_d\right), \quad (2)$$

where X is the population matrix of the GAA, X_i is the i-th member of the GAA (solution candidate), $x_{i,d}$ is the d-th dimension in the search space (solution variable), N is the number of giant armadillos, 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, respectively.

Since the position of each giant armadillo in the problem-solving space represents a solution to the problem, the value of the objective function can be estimated according to each giant armadillo. Accordingly, the set of estimated values for the objective function can be represented by equation (3):

$$F=\begin{bmatrix} F_1 \\ \cdot \\ \cdot \\ \cdot \\ F_i \\ \cdot \\ \cdot \\ \cdot \\ F_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} F(X_1) \\ \cdot \\ \cdot \\ \cdot \\ F(X_i) \\ \cdot \\ \cdot \\ \cdot \\ F(X_N) \end{bmatrix}_{N\times 1}, \quad (3)$$

where F is the vector of the estimated objective function, F_i is the estimated objective function based on the i-th member of GAA.

The estimated values of the objective function provide valuable information about the quality of solution options proposed by the population members. The best value obtained for the objective function corresponds to the best member (i.e., the best possible solution) and the worst value obtained for the objective function corresponds to the worst member of GAA (the worst possible solution). As the position of giant armadillos in the solution space is updated at each iteration, the best member must also be updated based on a comparison of the updated values for the objective function. At the end of the algorithm implementation, the position of the best GAA member obtained during iterations of the algorithm is presented as a solution to the problem.

Step 3. Numbering GAA in the swarm, i, $i\in[0,S]$. At this stage, each GAA is assigned a serial number.

Step 4. Determining the initial velocity of GAA.

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

$$v_i=\left(v_1,v_2...v_S\right), v_i=v_0. \quad (4)$$

When planning the proposed GAA approach, the position of the population members in the problem-solving space is updated based on modeling the hunting strategy of giant armadillos in the wild. In this process, the giant armadillo first attacks termite mounds and then burrows into them to hunt and eat termites. According to this, in each GAA iteration, the position of the population members is updated in two stages:

– exploration based on modeling the movement of giant armadillos towards termite mounds;

– exploitation based on simulating the behavior of giant armadillos that burrow into termite mounds to feed on termites.

Step 5. Preliminary assessment of the GAA search area. The diet of GAA is diverse, they feed on termites, carrion, insects and plants. Therefore, it is advisable to sort the quality of food.

Step 6. Classification of food sources for GAA.

Locations with the best food source (minimum fitness) are considered termites (FS_{ht}), locations from the next three food sources have dead animal carcasses (FS_{at}) and the rest are considered normal plant food (FS_{nt}):

$$FS_{ht}=FS(\text{sorte\_index}(1)), \quad (5)$$

$$FS_{at}(1:3)=\mathrm{FS}(\text{sorte\_index}(2:4)), \quad (6)$$

$$FS_{nt}(1:NP\text{-}4)=\mathrm{FS}(\text{sorte\_index}(5:NP)). \quad (7)$$

Step 7. Sorting the best GAA individuals. The selection of the best individuals is carried out using an advanced genetic algorithm proposed in [23]. While searching for food, the strongest GAA with the largest sizes directs another GAA in the group to search for food. This search behavior of the GAA leads to different scanning areas of the search space, which improves the exploration ability of the GAA in global search.

Step. 8. Attack on termite mounds by GAA.

At this stage of the GAA, the position of population members in the problem-solving space is updated based on simulating the attack of a giant armadillo on termite mounds during hunting. Modeling this attack process leads to significant changes in the position of the giant armadillo and, as a result, increases the exploration power of the algorithm in the global search for solutions [24–26].

In the GAA, for each population member that represents a giant armadillo, the location of other population members that have a better objective function value is considered a termite mound. The set of potential termite mounds for each population member is determined using equation (8):

$$TM_i = \{X_k : F_k < F_i \text{ and } k \neq i\}, \tag{8}$$

where $i = 1, 2, ..., N$ and $k \in \{1, 2, ..., N\}$, TM_i is the set of potential locations of termite mounds for the r-th giant armadillo, X_k is the population member with a better objective function value than the i-th giant armadillo, F_k is the value of its objective function.

A giant armadillo randomly selects one of the potential termite mounds and attacks it. Based on simulating the movement of giant armadillos towards termite mounds, a new position for each population member is calculated using equation (9). This new position then replaces the previous position of the corresponding member if it improves the value of the objective function according to equation (10):

$$x_{i,j}^{P1} = x_{i,j} + r_{i,j} \cdot \left(STM_{i,j} - I_{i,j} \cdot x_{i,j}\right), \tag{9}$$

$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} \leq F_i, \\ X_i, \text{else,} \end{cases} \tag{10}$$

where STM_i is the selected termite mound for the i-th giant armadillo of the GAA, $STM_{i,j}$ is its j-th size. X_i^{P1} is a new position calculated for the i-th giant armadillo based on the attack phase of the proposed GAA, $x_{i,j}^{P1}$ is the j-th dimension of the termite mound chosen for attack, F_i^{P1} is the value of the objective function of the termite mound, $r_{i,j}$ is random numbers from the interval [0, 1], $I_{i,j}$ is the numbers that are randomly selected as 1 or 2.

Step 9. Digging termite mounds by GAA.

In the second stage of the GAA, the position of the population members in the problem-solving space is updated based on a simulation of a giant armadillo burrowing in termite mounds to feed on termites. Modeling this digging process of a giant armadillo to hunt and eat termites leads to small changes in the position of the giant armadillo and, as a result, increases the exploitation power of the algorithm in local search management.

In the GAA project, based on modeling the ability of a giant armadillo to dig termite mounds, the new position is calculated for each population member using equation (11). Then, if the value of the objective function improves, this new position replaces the previous position of the corresponding member according to equation (12):

$$x_{i,j}^{P2} = x_{i,j} + \left(1 - 2r_{i,j}\right) \cdot \frac{ub_j - lb_j}{t}, \tag{11}$$

$$X_i = \begin{cases} X_i^{P2}, F_i^{P2} \leq F_i, \\ X_i, \text{else,} \end{cases} \tag{12}$$

where X_i^{P2} is the new position calculated for the i-th giant armadillo based on the digging phase of the proposed GAA, $x_{i,j}^{P2}$ is its j-th size, F_i^{P2} is the value of the objective function, $r_{i,j}$ is random numbers from the interval [0, 1], t is the number of iterations.

Step 10. Updating GAA positions. The process of updating the GAA position is mathematically modeled based on the feeding mechanism under the leadership of the most vital member of the group, using (13), (14). While selecting the updated GAA positions, the noise degree of data taken into account using the corresponding correction factors is additionally considered. In this process, a new position for GAA is first generated according to equation (13). This new position replaces the previous position if it improves the value of the objective function; this concept is modeled in equation (14):

$$x_{i,j}^{P_1} = x_{i,j} + rand_{i,j} \cdot \left(SW_j - I_{i,j} \cdot x_{i,j}\right), \tag{13}$$

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i, \\ X_i, \text{else,} \end{cases} \tag{14}$$

where $X_i^{P_1}$ is the new generated position for the i-th GAA, $x_{i,j}^{P_1}$ is the j-th size of the GAA; $F_i^{P_1}$ is the value of the objective function, $rand_{i,j}$ is random numbers from the interval [0, 1], SW is the best decision-making candidate, which is considered the strongest GAA; $I_{i,j}$ are integers randomly selected between 1 and 2.

$I_{i,j}$ is used to increase the exploration power of the algorithm, so if it is chosen as 1, it produces more significant and wider changes in the GAA position compared to 0.5, which is the normal state of this displacement. These conditions help to improve the global search of the algorithm in order to avoid local optima and identify the original optimal region in the problem-solving space.

Step 11. Checking for the presence of a GAA predator. At this stage of the GAA, the presence of predators is checked. If there are predators, go to Step 12. If there are no predators, go to Step 11.

Step 12. Escape and fight against GAA predators. Giant armadillos are constantly attacked by cougars, coyotes, wolves and dogs. In many countries, they are the object of hunting for meat (considered a delicacy) and shell used for products (musical instruments, decorative baskets, etc.). They are persecuted by herdsmen, as armadillo burrows often cause mutilations and broken legs of livestock. The strategy of escaping and fighting these predators leads to a change in the GAA position near the position where they are located. Simulating this natural GAA behavior improves the exploitation power of GAA in local search in the problem-solving space around potential solutions. Since this process occurs near the position of each GAA, the GAA plan assumes that this range of GAA position change occurs in a corresponding zone centered on the GAA with a certain radius. In the initial iterations of the algorithm, priority is given to a global search to identify the optimal region in the search space, and the radius of this environment is considered variable. First, the highest value is set and then it becomes smaller during iterations of the algorithm. For this reason, local lower/upper bounds were used in this stage of the GAA to create a variable radius with the iteration of the algorithm. To model this phenomenon in GAA, a neighborhood around each GAA is assumed, which first randomly generates a new position in this neighborhood using equations (15) and (16). Then, if the value of the objective function improves, this new position replaces the previous position according to equation (17):

$$x_{i,j}^{P_3} = x_{i,j} + \left(lb_{local,j}^{t} + \left(ub_{local,j}^{t} - rand \cdot lb_{local,j}^{t}\right)\right), \tag{15}$$

$$Local\ bounds: \begin{cases} lb_{local,j}^{t} = \dfrac{lb_j}{t}, \\ ub_{local,j}^{t} = \dfrac{ub_j}{t}, \end{cases} \tag{16}$$

$$X_i = \begin{cases} X_i^{P_3}, \ F_i^{P_3} < F_i; \\ X_i, \text{else}, \end{cases} \qquad (17)$$

where $X_i^{P_3}$ is the new generated position of the i-th GAA, $x_{i,j}^{P_3}$ is the j-th size of the GAA, $F_i^{P_3}$ is the value of the objective function, t is the iterative circuit, lb_j and ub_j are the lower and upper bounds of the j-th variable. $lb_{local,j}^t$ and $ub_{local,j}^t$ are the local lower and local upper bounds admissible for the j-th variable, respectively, to simulate a local search in the neighborhood of candidate solutions.

Step 13. Checking the stop criterion. The algorithm terminates if the maximum number of iterations is completed. Otherwise, the behavior of generating new places and checking conditions is repeated.

Step 14. Training GAA knowledge bases.

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

Step 15. Determining the amount of necessary computing resources of the intelligent decision support system.

In order to prevent looping of calculations on Steps 1–14 of this method and increase the efficiency of calculations, the system load is additionally determined. When the specified 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 [27–30].

End of the algorithm.

5. 2. Example of using the proposed method in the analysis of the operational group of troops (forces)

A method of increasing the efficiency of decision-making in organizational and technical systems is proposed. Initial data for assessing the state of the operational situation using the method:

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

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

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

The efficiency of the improved GAA is compared with the algorithms given in Tables 1–3. The comparison was made with unimodal and multimodal functions. Each function is calculated for ten independent runs to better compare the results of different algorithms.

As can be seen from Tables 1–3, the increase in decision-making efficiency is achieved at the level of 14–19 % due to the use of additional procedures.

Table 1

Efficiency of optimization algorithms in determining the composition of a brigade tactical group

Name of the algorithm	T_s	Optimal variables		L	Optimal cost
		T_h	R		
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
Proposed method	0.7794994	0.385819	40.386517	200	5,909.3749
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	0.3858127	40.320627	199.96442	5,890.2105
Genetic algorithm	1.5622593	0.4813024	47.695987	124.64823	10,807.366
Cat swarm optimization algorithm	1.1300127	1.1576349	44.110061	190.7876	11,984,417
Invasive weed optimization algorithm	1.55006	0.6231249	63.139483	49.78495	9,998.6395
Firefly algorithm	1.406417	0.7832762	58.253368	73.964478	10,920,286

Table 2

Statistical results in determining the composition of an operational group of troops (forces)

Name of the algorithm	Average	Best	Worst	Standard	Median	Rank
Walrus optimization algorithm	5,882.8955	5,882.8955	5,882.8955	1.87E-12	5,882.8955	1
Particle swarm optimization algorithm	5,891.226	5,882.9013	5,965.0365	22.218932	5,882.9017	3
Flying squirrel search optimization algorithm	6,219.5386	5,882.9077	7,046.3206	352.35848	6,047.6955	5
Artificial bee colony algorithm	12,409,586	7,759.8234	19,991,769	3,127.065	11,403.338	9
Ant colony optimization algorithm	5,882.9013	5,882.9013	5,882.9013	3.68E-06	5,882.9013	2
Proposed method	6,271.132	5,909.3749	6,948.3792	333.1584	6,143.6153	6
Monkey search algorithm	7,998.6372	6,270.8621	12,805,388	1,681.8974	7,579.6333	8
Bat algorithm	6,518.1019	6,003.8497	7,050.4059	320.31898	6,572.19	7
Locust swarm optimization algorithm	6,012.3675	5,890.2105	6,670.9945	239.38549	5,898.5494	4
Genetic algorithm	28,273,334	10,807.366	60,311.64	13,795.65	24,975,491	12
Cat swarm optimization algorithm	20,643,589	11,984,417	32,105,445	6711.6675	19,830,394	10
Invasive weed optimization algorithm	29,687,575	9998.6395	50,712.307	12,915,318	32,709,339	13
Firefly algorithm	25,427,766	10,920,286	45,530,922	10,828,815	22,551,255	11

Table 3

Efficiency of optimization algorithms in determining the composition of an operational-strategic group of troops (forces)

Name of the algorithm	h	Optimal variables		b	Optimal cost
		l	t		
Walrus optimization algorithm	0.2057296	3.4704887	9.0366239	0.2057296	1.7246798
Particle swarm optimization algorithm	0.2057296	3.4704888	9.0366238	0.2057296	1.7248523
Flying squirrel search optimization algorithm	0.205056	3.4850976	9.0365299	0.2057339	1.7257923
Artificial bee colony algorithm	0.1977725	3.5270192	9.8188942	0.2163579	1.9455461
Ant colony optimization algorithm	0.2057296	3.4704887	9.0366239	0.2057296	1.7248523
Proposed method	0.2043787	3.4924081	9.0609	0.2061055	1.7327713
Monkey search algorithm	0.2127738	3.3465331	8.9813136	0.2191754	1.8098061
Bat algorithm	0.2059617	3.465488	9.0437236	0.2060167	1.7279454
Locust swarm optimization algorithm	0.2056085	3.4732685	9.0362859	0.2057905	1.7254435
Genetic algorithm	0.3021777	4.3080233	7.0649912	0.3989007	2.86852
Cat swarm optimization algorithm	0.2833168	2.8111202	7.6140935	0.2957385	2.0415263
Invasive weed optimization algorithm	0.3526171	3.4301508	7.5466754	0.5299732	3.7483578
Firefly algorithm	0.2220901	6.5032092	7.9154768	0.2925869	2.6371953

It can be noted that the improved GAA is able to converge to the true value for most unimodal functions with the highest convergence rate and accuracy, while the convergence results of the particle swarm optimization algorithm are far from satisfactory.

6. Discussion of the results of developing a method of increasing the efficiency of decision-making

The advantages of the proposed method are as follows:

– when initially setting GAA, when searching for them, the type of uncertainty is taken into account (Step 2), compared to [9, 14, 21];

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

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

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

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

– taking into account the presence of a predator, which allows you to avoid local optima (Steps 9, 10), compared to [12, 13, 15–18];

– taking into account the degree of distortion (unreliability) of a priori information while determining the food location (Step 8), compared to [12, 13, 15–20];

– accelerated selection of individuals in the swarm due to the use of an advanced genetic algorithm (Step 7), compared to [9, 12, 13–18];

– the universality of solving the problem of analyzing the state of GAA objects due to the hierarchical nature of their description (Steps 1–15), compared to [9, 12, 13–18];

– the possibility of quick search for solutions due to the simultaneous search for a solution by several GAA (Steps 1–15, Tables 1–3);

– the adequacy of the obtained results (Steps 1–15), compared to [9–22, 31];

– the ability to avoid the local extremum problem (Steps 1–15);

– the possibility of deep learning of GAA knowledge bases (Step 14), compared to [9–22, 31];

– 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 15), compared to [9–22, 31].

The disadvantages of the proposed method include:

– the loss of informativeness while assessing the state of organizational and technical systems due to the construction of the membership function;

– lower accuracy of assessment by a single parameter for evaluating organizational and technical systems;

– 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:

– to assess the state of organizational and technical systems;

– to determine effective measures to improve management efficiency;

– to increase the speed of assessing the state of heterogeneous organizational and technical systems;

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

The limitations of the study are the need for an initial database on the state of organizational and technical systems, 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.

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, 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. The defined algorithm provides the following opportunities:

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

– to implement adaptive strategies for finding food sources;
– to take into account the presence of a predator while choosing food sources;
– to take into account the available computing resources of the system for analyzing the state of organizational and technical systems;
– to change the search area of individual GAA;
– to change the GAA velocity;
– to take into account the search priority of GAA;
– to carry out the initial setting of GAA individuals, taking into account the type of uncertainty;
– to carry out accurate training of GAA individuals;
– to determine the best GAA individuals using an advanced genetic algorithm;
– to conduct a local and global search taking into account the noise degree of data on the state of organizational and technical systems;
– 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, 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 organizational and technical systems due to the hierarchical nature of description of organizational and technical systems;
– to check the adequacy of the obtained results;
– to avoid the problem of local extremum.

Due to this, it increases the effectiveness of assessing the state of the organizational and technical system.

2. An example of using the proposed method in assessing and forecasting the state of the operational situation of a group of troops (forces) is given. The specified example showed an increase in the efficiency of data processing at the level of 14–19 % due to the use of additional advanced procedures of adding correction factors for uncertainty and noise of data, selection and training of GAA.

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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