The object of research is decision making processes in decision making support systems. The subject of the research is a method of decision making in management tasks using the walrus flock algorithm (WA), an advanced genetic algorithm and evolving artificial neural networks.

A method of finding solutions using an improved walrus flock algorithm is proposed. The research is based on the walrus flock algorithm for finding a solution to the object's condition. Evolving artificial neural networks are used to train walrus agents and an advanced genetic algorithm is used to select the best walrus agents. The method has the following sequence of actions:

– input of initial data;

– WA numbering in the flock;

– determination of the initial speed of WA;

– display of WA along the search plane;

– preliminary assessment of the WA search area;

– classification of food sources for WA;

– sorting of the best WA individuals;

– an update of WA positions;

– WA migration;

– checking the presence of a predator;

– checking the stop criterion;

– escape and struggle with predators;

– checking the stop criterion;

– training of WA knowledge bases;

– determination of the amount of necessary computing resources, intelligent decision making support system.

The originality of the proposed method lies in the placement of WA taking into account the uncertainty of the initial data, improved procedures of global and local edge taking into account the degree of noise of data on the state of organizational and technical systems. The use of the method makes it possible to increase the efficiency of data processing at the level 13–16 % due to the use of additional improved procedures. The proposed method should be used to solve problems of evaluating complex and dynamic processes

Keywords: organizational and technical systems, decision making support systems, complex processes, optimization tasks

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

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1. Introduction

The effectiveness of the functioning of any information system depends on the effectiveness of solving optimization tasks [1–5]. In work [1], the general trends in the development of automated systems of military control, integrated systems of communication and data transmission are considered. The key problem of these systems, which

ensures the advantage of any system over another, is the decision making time, which is provided by the complexity of the optimization algorithms. Optimization methods used for processing various types of data are proposed in works [2–5]. These works [2–5] consider the dependence of the sequence of solving optimization tasks on the decision making time.

Deterministic and stochastic approaches are used to solve the optimization problem. In order to choose the appropriate optimization approach for solving the optimization task, the user needs a complete information about the optimization task. However, as practical experience shows, in most cases this information is missing or partially available and to some extent unreliable. Therefore, for the accurate solution of scientific and applied optimization problems (tasks), both a priori uncertainty and distortion (noisiness) of information about the analysis object (optimization task) should be taken into account [6–8].

Each deterministic and stochastic approach to solving optimization problems has different advantages and in general, cannot be called universal [9–11].

As one of the most widely used stochastic approaches are metaheuristic algorithms using stochastic operators, concepts of trial and error, and stochastic search.

The possibilities of exploration and research of the already occupied space allow metaheuristic algorithms to obtain better quasi-optimal solutions. The exploration function refers to the ability to search globally in different regions of space to discover the best optimal regions, as opposed to the ability to search locally around available solutions and promising regions to converge to the global optimum. One of these approaches is the walrus swarm algorithm, which is based on modeling the behavior of walruses in nature [12–14].

The use of metaheuristic algorithms for finding solutions regarding the state of objects allows to realize [14–16]:

– an analysis of the stability of the state of organizational and technical systems in the process of combat application (exploitation);

– an analysis of the direct, aggregated and mediated interaction of systemic and external factors on the quality of the functioning of organizational and technical systems;

– an assessment of the reach of target situations of management of organizational and technical systems;

– scenario analysis with various destructive effects on the organizational and technical system;

– the forecast of changes in the state of organizational and technical systems under the influence of destabilizing factors during their combat use (exploitation);

– modeling and analysis of the dynamics of changes in the state of interdependent parameters of organizational and technical systems.

At the same time, the use of the above-mentioned algorithms in the canonical form does not allow to obtain an operational assessment of the object state with a given reliability [17–19]. The above mentioned determines the search for new (improvement of existing) approaches to the assessment of the state of objects by combining already known swarm algorithms with their further improvement.

Taking into account the above, an urgent scientific task is the development of a method for increasing the efficiency of decision making in organizational and technical systems, which would allow to increase the efficiency of decisions made regarding the management of the parameters of the control object 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 lack of consideration of the type of uncertainty about the analysis object state should be attributed to the shortcomings of this approach.

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 allow to take into account the type of uncertainty about the analysis object state and does not take into account 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 unclear factors and relationships; to take into account changes in the external environment and use objectively formed trends in the development of the situation in one's interests. 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 taking into account 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 the appropriate correction of the obtained models.

The work [14] developed an analytical web-platform for the research of geographical and temporal distribution of incidents. 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 should be attributed to the fact 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 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 has been established 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. Among the disadvantages of these methods should be attributed 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 making support systems. The essence of the

proposed approach consists in the clustering of the basic set of input data, their analysis, 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 the decisions made.

The work [18] presents an approach to data processing from various sources of information. This approach allows 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 making support technologies, namely: the method of analyzing hierarchies, neural networks, the theory of fuzzy sets, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The spheres of their application are defined. It is shown that the method of analyzing hierarchies 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 conditions of risk and uncertainty, the use of the theory of fuzzy sets 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 research 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 state of the system with the required one, which is set by the management entity. 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 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 optimization algorithms based on cat swarms (Cat Swarm Optimization – CSO), which are very promising both from the point of view of speed and ease of implementation. These algorithms have proven their effectiveness in solving a number of rather complex tasks 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.

The work [23] proposed a new optimization algorithm based on a flock of walruses. The walrus flock optimization algorithm (WA) is based on modeling the behavior of walruses in nature. A pack of walruses is characterized by feeding procedures during migration, escape and fighting predators.

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

An analysis of works [9–23] showed that the common shortcomings of the above-mentioned researches 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;
– a failure to take into account the type of uncertainty and noise of data on the analysis object state, which creates corresponding errors while assessing its real state;
– the lack of deep learning mechanisms of knowledge bases;
– a high computational complexity;
– the lack of consideration of computing (hardware) resources available in the system;
– the lack of search priority in a certain direction.

The problem that needs to be solved in the research is to increase the efficiency of solving the tasks of analyzing the state of organizational and technical systems while ensuring the given reliability.

For this purpose, it is proposed to develop a method for increasing the efficiency of decision making in organizational and technical systems.

3. The aim and objectives of the study

The aim of the study is the development of methods for increasing the efficiency of decision making in organizational and technical systems. This will allow to increase the speed of assessment of the state of organizational and technical systems with a given reliability and the development of 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 the implementation of the method;
– to give an example of the application of the method in the analysis of the operational situation of a group of troops (forces).

4. Research materials and methods

Problem, which is solved in the research, is to increase the efficiency of decision making in management tasks while ensuring the given reliability, regardless of the hierarchy of the object. The object of research is the decision making processes in decision making support systems. The subject of the research is a method of decision making in management tasks using the walrus swarm algorithm (WA), an advanced genetic algorithm and evolving artificial neural networks. The improved genetic algorithm and the improved learning algorithm of evolving artificial neural networks have shown their effectiveness in the previous researches of the authors [2–6, 19–22].

Research hypothesis is an increase in the efficiency of decision making due to the improvement of the walrus flock algorithm.

A simulation of the work of the proposed method was carried out in the MathCad 14 software environment (USA). The assessment of elements of the operational situation of the group of troops (forces) was the task to be solved during the simulation. The hardware of the research process is AMD Ryzen 5.

The operational grouping of troops (forces) was considered as an object of assessment and management. An operational

grouping of troops (forces) formed on the basis of an operational command with a typical composition of forces and devices according to the wartime staff, and with a range of responsibility in accordance with current regulations.

The research is based on walrus flock algorithm – for finding a solution regarding the object state. Evolving artificial neural networks are used to train WA and an advanced genetic algorithm is used to select the best WA.

5. The development of methods 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 method is an improved algorithm of a flock of walruses and consists of the following sequence of steps:

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

The main parameters of WA are the maximum number of iterations $Iter_{max}$, the population size NP, the number of decision variables n, the probability of the presence of a predator Pdp, the scaling factor sf, the migration constant Gc and the upper and lower bounds for the decision variable FS_U and FS_L:

$$FS_{i,j} = FS_L + rand(\ ) * (FS_U - FS_L), \tag{1}$$

$$i = 1,\ 2,...,NP, j = 1,\ 2,...,n,$$

where $rand()$ is a uniformly distributed random number in the range [0, 1].

Step 2. Numbering of WA in the flock, i, $i \in [0, S]$. At this stage, each WA is assigned a serial number.

Step 3. Determination of the initial speed of WA.

The initial speed v_0 of each WA is determined by the following expression:

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

Step 4. Exposure of WA along the search plane.

At this stage, WA is set up taking into account the type of uncertainty about the organizational and technical system to be analyzed and the basic model of its state is initialized [2, 19, 21]:

$$X = \begin{bmatrix} X_1 \\ \cdot \\ \cdot \\ \cdot \\ X_i \\ \cdot \\ \cdot \\ \cdot \\ X_N \end{bmatrix}_{N \times m} = \begin{bmatrix} x_{1,1} & \cdot & \cdot & \cdot & x_{1,j} & \cdot & \cdot & \cdot & x_{1,m} \\ \cdot & & & & \cdot & & & & \cdot \\ \cdot & & & & \cdot & & & & \cdot \\ \cdot & & & & \cdot & & & & \cdot \\ x_{i,1} & \cdot & \cdot & \cdot & x_{i,j} & \cdot & \cdot & \cdot & x_{i,m} \\ \cdot & & & & \cdot & & & & \cdot \\ \cdot & & & & \cdot & & & & \cdot \\ \cdot & & & & \cdot & & & & \cdot \\ x_{N,1} & \cdot & \cdot & \cdot & x_{N,j} & \cdot & \cdot & \cdot & x_{N,m} \end{bmatrix}_{N \times m} . \tag{3}$$

At the same time, the degree of uncertainty can be: full awareness; partial uncertainty and total uncertainty. The above mentioned is carried out with the help of appropriate correction coefficients, which are set at the analysis stage.

Step 5. Preliminary assessment of the WA search area. WA have a varied diet, feeding on over sixty species of marine organisms such as sea cucumbers, shells, soft corals, tubeworms, shrimp and a variety of mollusks. Therefore, it is advisable to sort the quality of the food.

Step 6. Classification of food sources for WA.

Locations with the best food source (minimum suitability) are considered benthic bivalves (FS_{ht}), locations from the following three food sources have mollusks (FS_{at}) and the rest are considered common marine organisms (FS_{nt}):

$$FS_{ht} = FS(\text{sorte\_index}(1)), \tag{4}$$

$$FS_{at}(1:3) = FS(\text{sorte\_index}(2:4)), \tag{5}$$

$$FS_{nt}(1:NP-4) = FS(\text{sorte\_index}(5:NP)). \tag{6}$$

Step 7. Sorting of the best WA individuals. The selection of the best individuals is carried out using the improved genetic algorithm proposed in the work [24]. While foraging, the strongest WA with the tallest tusks guides the other WA in the group to search for food. The length of tusks in WA is similar to the quality of the objective function values of the decision candidates. Thus, the best solution option with the best value for the objective function is considered the strongest WA in the group. This search behavior of walruses leads to different scanning areas of the search space, which improves the exploratory ability of WA in global search [25–30].

Step 8. Update of WA positions. The process of updating the WA position is mathematically modeled on the basis of the feeding mechanism under the leadership of the most vital member of the group, using the works (7), (8), [30–33]. While choosing updated WA positions, the degree of noise in the data is additionally taken into account, which is taken into account with the help of the corresponding correction coefficients. In this process, a new position for the walrus is first generated according to the work (7). This new position replaces the previous position if it improves the value of the objective function; this concept is modeled in the work (8):

$$x_{i,j}^{P_1} = x_{i,j} + rand_{i,j} \cdot (SW_j - I_{i,j} \cdot x_{i,j}), \tag{7}$$

$$X_i = \begin{cases} X_i^{P_1}, F_i^{P_1} < F_i, \\ X_i, \text{else}, \end{cases} \tag{8}$$

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

$I_{i,j}$ is used to increase the exploratory power of the algorithm, so if it is chosen to be 2, it produces more significant and wider changes in WA position compared to 1, which is the normal state of this displacement. These conditions help to improve the global search of the algorithm to avoid local optima and discover the original optimal region in the problem solution space.

Step 9. WA migration. One of the natural behaviors of walruses is their migration to empty or rocky beaches due to warming air in late summer. This migration process is used in the WA to guide the WA in the search space to discover relevant regions in the search space. This mechanism of behavior is mathematically modeled using the works (9), (10). This simulation assumes that each WA migrates to a different walrus position (chosen randomly) in a different region of the search space. Therefore, the proposed new position is

first generated based on the work (9). Then according to the work (10), if this new position improves the value of the objective function, it replaces the previous position of WA:

$$x_{i,j}^{P_2} = \begin{cases} x_{i,j} + rand_{i,j} \cdot \left(x_{k,j} - I_{i,j} \cdot x_{i,j} \right), F_k < F_i; \\ x_{i,j} + rand_{i,j} \cdot \left(x_{i,j} - x_{k,j} \right), \text{else}, \end{cases} \quad (9)$$

$$X_i = \begin{cases} X_i^{P_2}, F_i^{P_2} < F_i; \\ X_i, \text{else}, \end{cases} \quad (10)$$

where $X_i^{P_2}$ is the new generated position of the i-th WA, $x_{i,j}^{P_2}$ is the j-th size of WA, $F_i^{P_2}$ is the value of the objective function X_k, $k \in \{1, 2, ..., N\}$ and $k \neq i$ is the location of the selected WA to migrate the i-th WA to it, $x_{k,j}$ is the j-th size of the WA and F_k is the value of the objective function of the WA.

Step 10. Checking the presence of a predator. At this stage, WA is checked for the presence of predators. If there are predators, go to Step 10. If there are no predators, go to Step 9.

Step 11. Escape and struggle with predators. Walruses are always attacked by polar bears and killer whales. The strategy of escaping and fighting these predators leads to a change in the position of the walruses near the position they are in. Simulating this natural behavior of walruses improves the power of using WA in local search in the problem-solving space around potential solutions. Since this process occurs near the position of each walrus, the WA plan assumes that this range of walrus position change occurs in a corresponding zone centered on the walrus 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, the radius of this environment is considered variable. First, the highest value is set and then it becomes smaller during the iterations of the algorithm. For this reason, local lower/upper bounds were used in this phase of WA to create a variable radius with iteration of the algorithm. To model this phenomenon in WA, a neighborhood around each WA is assumed, which first randomly generates a new position in this neighborhood using the works (11), (12). Then, if the value of the objective function improves, this new position replaces the previous position according to the work (13):

$$x_{i,j}^{P_3} = x_{i,j} + \left(lb_{local,j}^t + \left(ub_{local,j}^t - rand \cdot lb_{local,j}^t \right) \right), \quad (11)$$

$$\text{Local bounds:} \begin{cases} lb_{local,j}^t = \dfrac{lb_j}{t}, \\ ub_{local,j}^t = \dfrac{ub_j}{t}, \end{cases} \quad (12)$$

$$X_i = \begin{cases} X_i^{P_3}, F_i^{P_3} < F_i; \\ X_i, \text{else}, \end{cases} \quad (13)$$

where $X_i^{P_3}$ is the new generated position of the i-th WA, $x_{i,j}^{P_3}$ is the j-th size of WA, $F_i^{P_3}$ is the value of the objective function, t is the iterative circuit, lb_j and ub_j are the lower and upper limits of the j-th variable. $lb_{local,j}^t$ and $ub_{local,j}^t$ are 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 12. Checking the stop criterion. The algorithm terminates when the maximum number of iterations is completed. Otherwise, the behavior of generating new places and checking seasonal monitoring conditions is repeated.

Step 13. Training of WA knowledge bases.

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

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

For the purpose of prevention of looping of calculations on Steps 1–13 of this method and increasing the efficiency of calculations is additionally determined by the system load. When the defined 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 the work [34].

The end of the algorithm.

5. 2. An example of the application of the proposed method in the analysis of the operational grouping of troops (forces)

The method of increasing the efficiency of decision making in organizational and technical systems is proposed. In order to evaluate the effectiveness of the developed method, its comparative evaluation was carried out based on the results of research presented in works [3–6, 23, 24, 34].

Simulation of the solution search processing method was carried out in accordance with steps 1–14. Simulation of the work of the proposed method was carried out in the Math-Cad 14 software environment (USA). The assessment of the elements of the operational situation of the group of troops (forces) was the task that was solved during the simulation.

Initial data for assessing the state of the operational situation using the method using the walrus flock algorithm:

– the number of sources of information about the state of the monitoring object is 3 (radio monitoring tools, remote sensing of the earth 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 status of the monitoring object is determined – 12. Such parameters include: ownership, 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), the type of operational construction are also taken into account;

– the variants of organizational and personnel formations are company, battalion, brigade.

The effectiveness of the improved WA is compared with the following algorithms of natural optimization: white shark algorithm, tree seed algorithm. 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.

The parameters of the algorithms are given in the Table 1. Table 2 provides a comparative analysis of algorithms with well-known decision making efficiency criteria.

From the analysis of the Table 2 improved algorithm of a flock of walruses with the parameters given in Table 1, provides the best decision making efficiency.

As a result of the simulation, sets of input parameters were obtained that ensure the optimal operation of the algorithm under the given conditions (Table 3).

Table 1

The parameters of the algorithms that are selected for comparison

Algorithm	Parameters	Value
Algorithm of a flock of walruses	F_{min} and F_{max}	0.07, 0.75
	τ, ao, a_1, a_2	4.125, 6.25, 100, 0.0005
Algorithm of white sharks	Fixed vector	$P=0.5$
	Random vector	R is a vector of uniform random numbers in the range [0, 1]
	Degree of aggregation (FADs)	FADs$=0.2$
	Binary vector	$U=0$ or 1
Tree seed algorithm	P_{min} and P_{max}	1, 4
	c_1, c_2, c_3	A random value in a range [0, 1]
Multi-world optimization algorithm	wormhole probability (WEP)	Min(WEP)$=0.2$ and Max(WEP)$=1$
	Accuracy of calculation by iterations (p)	$p=6$
Gray wolf pack method	Convergence parameter (a)	a: linear change from 2 to 0
Method of learning with a teacher	T_F: teacher factor	$T_F=$round$[(1+rand)]$
	Random number	A random value in the range [0, 1]
Gravity method	G_0, R_{norm}, R_{power}	20, 100, 2, 1
The particle swarm method	Topology	Fully connected
	Cognitive and social constants	$(c_1, c_2)=(2, 2)$
	Inertia weight	Change from 0.9 to 0.1
	Speed limit	10 % of the size range
Genetic algorithm	Type	Real coded
	Selection	Roulette wheel (proportional)
	Crossover	Probability$=0.8$, $\alpha \in [-0.5, 1.5]$
	Mutation	Gaussian probability$=0.05$

Table 2

Comparative analysis of algorithms with well-known decision making efficiency criteria

The name of the algorithm	A better solution	Average value	A worse solution	Mean square deviation	Median value
Improved walrus pack algorithm	0.012672	0.012701	0.012706	0.001106	0.012700
Algorithm of white sharks	0.012722	0.012754	0.012766	0.007391	0.012744
Tree seed algorithm	0.012782	0.012799	0.01283	0.00567	0.012802
Method of learning with a teacher	0.012786	0.012812	0.012836	0.004191	0.012815
Multi-world optimization algorithm	0.013305	0.014951	0.018023	0.002293	0.013312
Gray wolf pack method	0.012926	0.014594	0.018	0.001636	0.014147
Gravity method	0.012983	0.01356	0.01434	0.000289	0.013488
The particle swarm method	0.013147	0.014162	0.016398	0.002092	0.013119
Genetic algorithm	0.012885	0.013188	0.015352	0.000378	0.013069

Table 3

Results of the WA algorithm for test functions

Function	The dimensionality of the function	Number of WA	Number of iterations	Result	Average time, sec.
De Jong (global optimum: 0)	2	4	10000	0	0
	5	14		0	0.1
	10	28		0.005	3.11
	30	30		0.007	30,42
Rastrigin (global optimum: 0)	2	6	10000	0	0
	5	64		0	18,22
	10	50		0.03	62.5
	30	50		0.92	528.4
Hryvnoka (global optimum: 0)	2	6	10000	0	0
	5	16		0.002	0.17
	10	30		0.004	4.72
	30	43		0.024	89.32
Ackley (global optimum: 0)	2	6	10000	0	0
	5	24		0.001	0.15
	10	42		0.012	3.24
	30	50		0.021	66.73
Bukina (global optimum: 0)	2	8	10000	0	0
	5	20		0.002	2.08
	10	40		0.02	4.12
	30	50		0.89	70.4

Analyzing the results of the improved algorithm, shown in the Table 3, it can be seen that for functions with a small number of parameters, the algorithm demonstrates its greatest efficiency. However, when the dimension of multi-extremal functions with a complex landscape (such as the functions of Rastrygin, Grivonka, Bukin) increases, a small deviation from the global optimum occurs. This deviation can be smoothed out by increasing the number of iterations and agents that affect the duration of the method.

The Rosenbrock function should be noted separately: when the number of parameters increases to more than 10 WA shows a rather noticeable discrepancy from the optimal solution. To achieve the required accuracy requires a serious increase in time costs, which makes the method ineffective in this particular case.

As can be seen from the Tables 1–3 increasing the efficiency of decision making is achieved at the level of 13–16 % due to the use of additional procedures.

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

Based on the research conducted, it can be said that WA is more effective for working with functions with a small number of parameters. However, one of the ways to improve the accuracy of the solutions found for multiparameter multimodal functions is to modify or hybridize the method with other algorithms.

6. Discussion of the results of the development of the method for increasing the decision making efficiency

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

– at the initial presentation of WA, the type of uncertainty is taken into account during their search (Step 4), in comparison with works [9, 11];

– the initial speed of WA is taken into account (Step 2), in comparison with labor [23];

– additional determination of the suitability of the WA search location, which reduces the time to search for a solution (Step 5), compared to works [15, 23];

– universality of strategies for finding food places, which allows to classify the type of data to be processed (Steps 6, 7) in comparison with works [12, 13];

– there is a classification of food sources, which determines the priority of finding a solution (Step 6) in comparison with works [12, 15, 23];

– taking into account the presence of a predator, which allows to avoid local optima (Steps 10, 11) in comparison with labor [23];

– taking into account the degree of distortion (unreliability) of a priori information when determining the place of food (Step 8) in comparison with works [14–16];

– accelerated selection of individuals in the flock due to the use of an improved genetic algorithm (Step 7) in comparison with works [17, 23];

– the universality of solving the task of analyzing the state of WA objects due to the hierarchical nature of their description (Steps 1–14) in comparison with works [18, 20];

– the possibility of quick search for solutions due to the simultaneous search for a solution by several ABL (Steps 1–14, Tables 1, 2) in comparison with works [14, 21];

– the adequacy of the obtained results (Steps 1–14);

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

– the possibility of in-depth learning of ABL knowledge bases (Step 14) in comparison with works [9–23].

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 function of belonging;

– lower accuracy of assessment on a single parameter of assessment of 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 assessment of the state of heterogeneous organizational and technical systems;

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

The limitations of the research are the need to have an initial database on the state of organizational and technical systems, the need to take into account the time delay in collecting and proving 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 research is a further development of researches aimed at developing method principles for increasing the efficiency of processing various types of data, which were published earlier [2, 4–6, 23].

The directions 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 the implementation of the method has been determined, thanks to additional and improved procedures, which allows:

– to take into account the type of uncertainty and noisy data by adding correction coefficients;

– to implement adaptive strategies for finding food sources;

– to take into account the presence of a predator when choosing food sources;

– to take into account the available computing resources of the state analysis system of organizational and technical systems;

– to change the search area by individual WA;

– to change the WA speed;

– to take into account the priority of WA search;

– to conduct an initial exhibition of WA individuals taking into account the type of uncertainty;

– to carry out accurate training of WA individuals;

– to determine the best WA individuals using a genetic algorithm;

– to conduct a local and global search taking into account the degree of noise 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 task of analyzing the state of organizational and technical systems due to the hierarchical nature of the description of organizational and technical systems;

– to check the adequacy of the obtained results;

– to avoid the problem of local extremum.

2. An example of the use of the proposed method was conducted using the example of assessing and forecasting the state of the operational situation of a group of troops (forces). The specified example showed an increase in the efficiency of data processing at the level of 13–16 % due to the use of additional improved procedures of adding correction coefficients for uncertainty and noisy data, WA selection and WA training.

Conflict of interest

The authors declare that they have no conflict of interest in relation to this research, including financial, personal, authorship or any other, that could affect the research and its results presented in this article.

Financing

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The availability of data

The work has associated data in the data repository.

The use of artificial intelligence

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

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