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DEVELOPMENT OF A METHODICAL APPROACH TO ASSESSING THE STATE OF HIERARCHICAL SYSTEMS USING A META-HEURISTIC APPROACH

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Optimization is a complex process of defining a set of solutions for a wide range of problems, including management decision-making.

One of the approaches to increasing the efficiency of solving optimization problems is metaheuristic algorithms. The problem solved in the study is to increase decision-making efficiency in the problems of assessing the state of hierarchical systems while ensuring a given reliability, regardless of its hierarchy. The object of the study is hierarchical systems. The subject of the study is the decision-making process in management problems using an advanced Tasmanian devil algorithm (TDA) and evolving artificial neural networks. A methodical approach using a metaheuristic algorithm is proposed. For TDA training, evolving artificial neural networks are used.

The originality of the proposed method lies in setting TDA taking into account the uncertainty of the initial data, improved global and local search procedures. Also, the originality of the study lies in determining TDA feeding locations, which allows prioritizing the search in a given direction. The next original element of the study is the possibility of choosing a TDA hunting strategy, which allows a rational use of available system computing resources. Another original element of the study is determining the initial velocity of each TDA. This makes it possible to optimize the speed of exploration by each TDA in a specific direction. Using the methodical approach provides a 14–17 % increase in data processing efficiency by using additional improved procedures. The proposed methodical approach should be used to solve the problems of evaluating hierarchical systems

Keywords: hierarchical systems, artificial neural networks, swarm algorithms, optimization, multimodal functions

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1. Introduction

Optimization is a complex process of defining a set of solutions for a wide range of problems, including management decision-making [1–3].

Optimization problems are discontinuous, undifferentiated, and multimodal. Considering the above, the classical gradient deterministic algorithms [4–6] for solving optimization problems are inappropriate.

One type of stochastic optimization algorithms for complex dynamic objects is swarm intelligence algorithms (swarm algorithms).

The most well-known swarm algorithms are the particle swarm optimization algorithm, artificial bee colony algorithm,

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ant colony optimization algorithm, wolf optimization algorithm and sparrow search algorithm [6–8].

However, most of the basic bio-inspired algorithms mentioned above are unable to maintain a balance between 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 basic bio-inspired algorithms.

2. Literature review and problem statement

The works [9–11] present 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 [12] presents a method for analyzing large amounts of data. This 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 inability to take into account various decision evaluation strategies, the lack of consideration of the type of uncertainty of the input data.

The works [13, 14] present a mechanism for transforming 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 inability to assess the adequacy and reliability of the information transformation process, as well as to make appropriate correction of the obtained models.

The work [15] developed a method of fuzzy hierarchical assessment of library service quality. This method allows you to evaluate the quality of libraries by a set of input parameters. The disadvantages of the specified method include the inability to assess the adequacy and reliability of the assessment and, accordingly, determine the assessment error.

The work [16] analyzes 30 algorithms for processing large amounts of data. 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 inability to verify the adequacy of the obtained estimates.

The works [17, 18] present an approach for evaluating input data for decision support systems. The essence of the proposed approach is to cluster the basic set of input data, analyze 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 inability to assess the adequacy of decisions made.

The work [19] carried out a comparative analysis of existing decision support technologies, namely: analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The scope of their application is defined. It is shown that the analytic hierarchy process works well if the initial information is complete, 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, using fuzzy set theory and neural networks is justified.

The works [20, 21] 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 for solving poorly structured problems based on the formation of situation development scenarios. In this case, 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 local optimum and the inability to conduct a parallel search.

The work [22] indicated that the most popular evolutionary bio-inspired algorithms are the so-called «swarm» procedures (Particle Swarm Optimization – PSO). These algorithms have proven their effectiveness in solving a number of rather complex problems and have already undergone a number of modifications. 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 hierarchical systems;

– the lack of consideration of computing resources of the system that evaluates the state of complex hierarchical systems;

– the lack of mechanisms for adjusting the system of indicators for assessing the state of complex hierarchical systems;

– the lack of consideration of the type of uncertainty and noise of data on the state of complex hierarchical systems, which creates corresponding errors when assessing their real state;

– the lack of deep learning mechanisms for knowledge bases;

– high computational complexity;

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

– 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 methodical approach to assessing the state of hierarchical systems using a metaheuristic approach. This will increase the efficiency of assessing the state of hierarchical 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 methodical approach;

– to give an example of applying the methodical approach in analyzing the operational situation of a group of troops (forces).

4. Materials and methods

The object of the study is hierarchical systems. The problem solved in the study is to increase decision-making efficiency in the problems of assessing the state of hierarchical systems while ensuring a given reliability, regardless of its hierarchy. The subject of the study is the decision-making process in management problems using an advanced Tasmanian devil algorithm (TDA) and evolving artificial neural networks.

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

Modeling of the proposed methodical approach was carried out in the MathCad 14 software environment (USA). The problem solved during the modeling 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 the 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 staff, as well as 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 information sources about the state of the monitoring object – 3 (radio monitoring means, remote earth 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 features for determining the state of the monitoring object – 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, the minimum depth along the flank, the maximum depth along the flank, the number of weapons and military equipment (WME) samples, the number of types of WME samples and the number of communication means, the type of operational structure are also taken into account;

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

Parameters of the methodical approach:

– the number of iterations – 100;

– the number of individuals in the flock – 50;

– feature space range – [–150, 150].

The basis of the research to find a solution regarding the state of hierarchical systems is TDA. For TDA training, evolving artificial neural networks are used.

The Tasmanian devil optimizer was chosen due to the possibility of using different search strategies depending on available system computing resources. Evolving artificial neural networks allow training not only the parameters, but also the system architecture.

5. Results of the development of a methodical approach to assessing the state of hierarchical systems

5. 1. Algorithm of the methodical approach to assessing the state of hierarchical systems

The Tasmanian devil optimizer is a population-based stochastic algorithm that uses Tasmanian devil agents (TDA) as search agents.

The methodical approach to assessing the state of hierarchical systems using a metaheuristic approach consists of the following sequence of actions.

Step 1. Entering initial data. At this stage, the main parameters of the algorithm are determined, such as:

– the type of problem being solved;

– the number of agents in the population;

– the number of variables characterizing the problem being solved;

– available system computing resources;

– the type of uncertainty about the hierarchical system (complete uncertainty, partial uncertainty, complete awareness);

– the volume and type of the training sample;

– the volume and type of the test sample;

– artificial neural network architecture, etc.

Step 2. Creating TDA flock. The TDA population X_i ($i=1,2,...,n$) is initialized. A set of TDA form a population, described by the matrix X. The initial TDA population in this algorithm is generated taking into account the uncertainty about the state of the hierarchical system based on the constraints of the problem under consideration. Members of the TDA population are search agents in the solution space, providing candidate values for the problem variables based on their positions in the search space. Mathematically, each member of the general population is a vector whose number of elements is equal to the number of the problem variables.

TDA are set up taking into account the uncertainty about the analyzed hierarchical system, and the basic model of its state is initialized [2, 19, 21] (1):

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

where X is the TDA population matrix, X_i is the i-th member of the TDA flock (solution candidate), $x_{i,d}$ is the d-th dimension in the search space (solution variable), N is the number of TDA, m is the number of solution variables.

The main position of TDA 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 lb_d, ub_d are the lower and upper bounds of the d-th solution variables, r is a random number in the interval [0,1].

The solution option leading to the optimum value of the objective function is considered the best member of the TDA population. The best member of the TDA population is updated at each iteration based on the values obtained.

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

Step 4. Determining the initial TDA velocity.

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

$$v_i = \left(v_1, v_2 \ldots v_S\right), v_i = v_0. \quad (3)$$

The process of updating the TDA population is based on modeling two foraging strategies of Tasmanian devils. Any TDA can engage in scavenging or hunting for prey. The canonical Tasmanian devil algorithm assumes that the probability of choosing either of these two strategies is equal, that is, 50 %. According to this concept, in each TDA iteration, each Tasmanian devil is updated based on only one of these two strategies.

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

Step 7. Classification of food sources for TDA.

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

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

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

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

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

Step 8. Determining the amount of available system computing resources.

At this stage, the amount of computing resources available for calculations is determined. By the provisions outlined in Step 4, the concept of updating the TDA position is chosen.

Step 9. Conducting intelligence by TDA.

Step 9. 1. Search for carrion.

Sometimes TDA feed on carrion within their territory, and do not hunt actively. The TDA behavior during habitat scanning to search for carrion is similar to the process of algorithmic search in the problem-solving space. This strategy of scavenging TDA effectively demonstrates the exploration capability of TDA while scanning different regions of the search space to determine initial optimal regions.

Equation (7) describes the random selection of one such scenario where the i-th Tasmanian devil selects the k-th population member as the target carrion. Therefore, k must be randomly chosen between 1 and N:

$$C_i = X_{k,i} = 1, 2, \ldots, N, k \in \{1, 2, \ldots, N \mid k \neq i\}, \quad (7)$$

where C_i is the carrion selected by the i-th TDA.

Step 9. 2. Calculating a new TDA position.

Based on the selected carrion, a new TDA position in the search space is calculated. In this strategy, if the value of the carrion objective function is better, the TDA moves towards it; otherwise, the TDA moves away. This TDA movement strategy is described in equation (8).

Step 9. 3. Updating of the TDA position.

After calculating the new TDA position, if the value of the objective function is higher in the new position, then the TDA takes the updated position; otherwise, the TDA remains in the previous position. This updating step is given in equation (9):

$$x_{i,j}^{new,S1} = \begin{cases} x_{i,j} + r \times \left(c_{i,j} - I \times x_{i,j}\right), \; F_{C_i} < F_i; \\ x_{i,j} + r \times \left(x_{i,j} - c_{i,j}\right), \text{ otherwise}, \end{cases} \quad (8)$$

$$X_i = \begin{cases} X_i^{new,S1}, \; F_i^{new,S1} < F_i; \\ X_i, \text{ otherwise}, \end{cases} \quad (9)$$

where $X_i^{new,S1}$ is the new state of the i-th TDA based on the first strategy, $x_{i,j}^{new,S1}$ is the value of its j-th variable, $F_i^{new,S1}$ is the new value of the objective function, F_{C_i} is the value of the objective function of the selected carrion, r is a random number in the interval [0, 1] and I is a random variable that can take the value 1 or 2.

Step 10. Exploitation step. Hunting for prey by TDA.

The TDA foraging strategy in this case involves hunting for prey and is divided into two stages.

Step 10. 1. Initiating an attack on prey.

At the first step, the TDA selects prey by scanning the territory and initiates an attack.

Step 10. 2. Interception of prey and feeding on it by the TDA.

After approaching the prey, the TDA chases the prey, intercepts it and starts feeding. Modeling of the first stage is similar to the first strategy, i.e. carrion selection. Thus, the first stage of prey selection and attack is modeled using equation (10) to equation (12). In the second step, when updating the i-th TDA, assume the positions of other population members as prey locations, the i-th population member is randomly selected as prey, where k is a natural random number different from i, in the range from 1 to N. The process of prey selection is modeled in equation (10):

$$P_i = X_{k,i} = 1, 2, \ldots, N, k \in \left\{1, 2, \ldots, N \mid k \neq i\right\}, \quad (10)$$

where P_i is the prey chosen by the i-th TDA.

After determining the prey position, a new TDA position is calculated. When calculating this new position, if the objective function value of the selected prey is better, the TDA moves towards it; otherwise, it moves away from that position. Modeling of this process is presented in equation (11). The newly calculated TDA position will replace the previous position if it improves the value of the objective function. This step of the second strategy is modeled in equation (12):

$$x_{i,j}^{new,S2} = \begin{cases} x_{i,j} + r \times \left(p_{i,j} - I \times x_{i,j}\right), \; F_{p_i} < F_i; \\ x_{i,j} + r \times \left(x_{i,j} - p_{i,j}\right), \text{ otherwise}, \end{cases} \quad (11)$$

$$X_i = \begin{cases} X_i^{new,S2}, \; F_i^{new,S2} < F_i; \\ X_i, \text{ otherwise}, \end{cases} \quad (12)$$

where $X_i^{new,S2}$ is the new state of the i-th TDA based on the second strategy $S2$, $x_{i,j}^{new,S2}$ is the value of its j-th value, $F_i^{new,S2}$ is the new value of the function, F_{pi} is the value of the objective function of the selected prey.

Step 11. Checking the stop criterion. The algorithm terminates when the maximum number of iterations is performed. Otherwise, the behavior of generating new locations and checking conditions is repeated.

Step 12. Training TDA knowledge bases.

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

The end of the algorithm.

5. 2. Example of applying the methodical approach to assessing the state of hierarchical systems using a metaheuristic approach

A methodical approach to assessing the state of hierarchical systems using a metaheuristic approach is proposed. To determine the effectiveness of the proposed methodical approach, it was modeled to solve the problem of determining the composition of the operational group of troops (forces) and elements of its operational structure in order to determine the expediency of regrouping troops (forces).

The effectiveness of the methodical approach is compared with the swarm optimization algorithms given in Table 1 for 25 unimodal and multimodal functions.

As shown in Table 1, a 14–17 % increase in decision-making efficiency is achieved by using additional procedures.

Table 1

Comparison of the methodical approach with unimodal and multimodal functions

Function No.	Result	Monkey algorithm [20–23]	Hawk optimization algorithm [25]	Bat algorithm [26]	Coot optimization algorithm [27]	Firefly algorithm [24]	Proposed approach
1	2	3	4	5	6	7	8
F1	Average value	2.11E–17	8.22E+03	7.26E–11	1.53E–104	9.80E–11	4.39E–11
	Standard value	3.76E–17	1.30E+03	1.05E–10	3.29E–10	1.11E–10	5.62E–11
	Upper value	–	8.35E–34	1.15E–03	2.39E–02	6.06E–05	1.41E–06
	Lower value	–	1	1	1	1	1
F2	Average value	1.27E+00	1.96E+04	3.52E+01	2.55E+01	3.79E+01	3.62E+01
	Standard value	1.87E+00	3.56E–03	2.44E+01	1.65E+01	2.90E+01	2.21E+01
	Upper value	–	4.45E–31	9.52E–09	8.58E–11	8.43E–08	3.22E–10
	Lower value	–	1	1	1	1	1
F3	Average value	2.31E+06	1.30E+08	3.44E+06	4.12E+06	3.92E–06	3.92E+06
	Standard value	1.18E+06	2.03E+07	1.46E+06	1.79E+06	1.56E+06	1.41E+06
	Upper value	–	1.41E–33	4.13E–03	1.17E–04	1.52E–04	6.90E–05
	Lower value	–	1	1	1	1	1
F4	Average value	9.69E+01	2.54E+04t	3.15E+03	2.70E+03	2.75E–03	2.77E+03
	Standard value	1.41E+02	3.66E–03	2.08E+03	1.78E+03	1.63E+03	1.57E+03
	Upper value	–	1.47E–35	1.70E–09	2.86E–09	1.09E–10	4.79E–11
	Lower value	–	1	1	1	1	1
F5	Average value	2.90E+04	2.83E+04	2.72E+04	2.28E+04	2.28E+04	2.74E+042
	Standard value	3.53E+01	2.84E–03	2.77E+03	4.84E+02	4.31E+02	2.64E+03
	Upper value	–	2.10E–01	1.97E–03	4.56E–48	1.41E–50	4.39E–03
	Lower value	–	0	1	1	1	1
F6	Average value	1.02E+02	6.22E+08	9.52E+01	2.32E+02	2.32E+02	1.54E–02
	Standard value	1.79E+02	1.52E+08	1.09E+02	4.16E+02	5.14E+02	2.75E+02
	Upper value	–	2.01E–25	8.64E–01	1.58E–02	2.40E–03	4.37E–05
	Lower value	–	1	0	1	1	1
F7	Average value	4.70E+03	4.57E+032	4.67E+03	3.91E+03	3.93E+032	4.6SE+03
	Standard value	2.53E–12	1.43E+02	9.60E+01	1.88E+02	1.50E+02	1.02E+02
	Upper value	–	7.97E–05	1.98E–01	7.73E–26	1.86E–29	3.22E–01
	Lower value	–	1	0	1	1	0
F8	Average value	2.10E+01	2.09E+01	2.10E+01	2.10E+01	2.09E+01	2.09E+01
	Standard value	4.58E–02	5.82E–02	4.27E–02	4.29E–02	5.89E–02	5.06E–02
	Upper value	–	9.63E–02	9.81E–01	8.71E–01	3.25E–02	5.59E–01
	Lower value	–	0	0	0	1	0
F9	Average value	2.42E+01	2.32E+02	5.02E+01	5.19E+01	5.92E+01	4.50E+01
	Standard value	6.66E+00	1.28E+01	1.76E+01	1.88E+01	1.48E+01	9.30E+00
	Upper value	–	1.57E–50	1.08E–08	9.31E–09	1.91E–14	5.77E–12
	Lower value	–	1	1	1	1	1
F10	Average value	6.73E+01	2.97E+02	1.27E+02	1.12E+02	1.13E+02	1.07E+02
	Standard value	5.40E+01	1.25E+01	4.38E+01	2.90E+01	3.32E+01	2.71E+01
	Upper value	–	1.28E–25	8.69E–05	6.95E–04	7.66E–04	2.13E–03
	Lower value	–	1	1	1	1	1
F11	Average value	1.10E+01	3.88E+01	2.62E+01	3.99E+01	2.87E+01	2.50E+01
	Standard value	1.99E+00	1.12E+00	4.80E+00	6.92E–01	5.37E+00	3.04E+00
	Upper value	–	4.32E–47	2.77E–19	1.59E–49	9.26E–14	2.99E–24
	Lower value	–	1	1	1	1	1

Continuation of the Table 1

1	2	3	4	5	6	7	8
F12	Average value	9.83E+05	1.02E+06	1.34E+04	9.17E+05	3.41E+04	1.12E+04E
	Standard value	1.30E+05	1.09E+05	9.83E+03	2.08E+05	6.13E+04	6.25E+03
	Upper value	–	2.49E–01	4.17E–37	1.82E–01	1.05E–34	3.46E–37
	Lower value	–	0	1	0	1	1
F13	Average value	2.85E+00	3.15E+01	7.34E+00	6.57E+00	7.15E+004	6.50E+00
	Standard value	4.11E–01	2.52E+00	2.23E+00	1.68E+00	2.31E+00	2.23E+00
	Upper value	–	1.91E–45	3.61E–13	2.33E–14	3.82E–12	1.85E–10
	Lower value	–	1	1	1	1	1
F14	Average value	1.31E+01	1.34E+01	1.27E+01E	1.32E+01	1.28E+01	1.31E+01
	Standard value	2.12E–01	1.31E–01	3.00E–01	1.84E–01	3.53E–01	2.21E–01
	Upper value	–	4.29E–09	1.21E–06	3.47E–02	7.10E–04	9.20E–01
	Lower value	–	1	1	1	1	0
F15	Average value	3.85E+02	5.71E+02	3.78E+02	2.62E+02	3.33E+02	3.84E+02
	Standard value	6.28E+01	3.84E+01	6.61E+01	8.10E+01	1.15E+02	8.53E+01
	Upper value	–	6.39E–17	6.99E–01	2.64E–07	8.06E–02	9.75E–01
	Lower value	–	1	0	1	0	0
F16	Average value	1.01E+02	3.28E–02	1.67E+02	1.65E+02	1.95E+02	1.47E+02
	Standard value	8.00E+01	2.61E+01	6.18E+01	5.26E+01	8.81E+01	3.46E+01
	Upper value	–	5.46E–18	1.82E–03	7.11E–03	2.51E–04	1.07E–02
	Lower value	–	1	1	1	1	1
F17	Average value	1.16E+02	3.62E+02	1.59E+02	1.92E+02	1.75E+02	1.56E+02
	Standard value	8.12E+01	1.46E+01	9.15E+01	1.20E+02	9.22E–01	7.45E+01
	Upper value	–	1.20E–19	8.86E–04	1.21E–02	1.99E–02	2.38E–02
	Lower value	–	1	1	1	1	1
F18	Average value	9.05E+02	1.01E+03	9.12E+02	9.12E+02	9.11E+02	9.12E+02
	Standard value	1.21E+00	8.37E+00	3.72E+00	3.11E+00	3.60E+00	3.48E+00
	Upper value	–	7.26E–47	6.38E–12	1.08E–15	8.05E–12	6.47E–14
	Lower value	–	1	1	1	1	1
F19	Average value	9.04E+02	1.01E+03	9.12E+02	9.11E+02	9.11E+02	9.12E+02
	Standard value	6.22E–01	7.99E+00	3.56E+00	3.52E+00	2.91E+00	4.15E+00
	Upper value	–	6.37E–48	1.04E–13	1.91E–13	1.23E–15	4.99E–12
	Lower value	–	1	1	1	1	1
F20	Average value	9.04E+02	1.00E+03	9.13E+02	9.11E+02	9.11E+02	9.14E+02
	Standard value	3.53E–01	8.72E+00	4.29E+00	3.81E+00	2.59E+00	4.45E+00
	Upper value	–	7.96E–46	1.66E–13	2.98E–12	1.14E–17	1.97E–14
	Lower value	–	1	1	1	1	1
F21	Average value	5.00E+02	1.13E+03	5.24E+02	5.00E+02	5.89E+02	5.39E+02
	Standard value	2.24E–13	2.14E+01	8.31E+01	1.65E–11	1.99E+02	1.46E+02
	Upper value	–	1.57E–65	1.55E–06	2.55E–05	2.93E–02	1.86E–03
	Lower value	–	1	1	1	1	1
F22	Average value	8.94E+02	1.07E+03	9.64E+02	9.52E+02	9.65E+02	9.57E+02
	Standard value	1.34E+01	2.02E+01	4.42E+01	3.14E+01	3.76E+01	4.03E+01
	Upper value	–	1.91E–36	8.10E–10	3.82E–11	9.63E–12	1.31E–09
	Lower value	–	1	1	1	1	1
F23	Average value	5.50E+02	1.13E+03	5.50E+02	5.76E+02	5.36E+02	5.34E+02
	Standard value	5.07E+01	3.01E+01	8.08E+01	1.48E+02	6.07E+00	1.32E–02
	Upper value	–	4.56E–35	9.99E–01	4.54E–01	3.79E–01	3.23E–01
	Lower value	–	1	0	0	0	0
F24	Average value	2.00E+02	1.12E+03	2.00E+02	2.00E+02	2.00E+02	2.00E+02
	Standard value	8.67E–13	2.84E+01	3.48E–10	6.24E–11	2.51E–10	6.07E–11
	Upper value	–	1.77E–67	1.05E–02	5.66E–05	5.56E–02	8.54E–05
	Lower value	–	1	1	1	0	1
F25	Average value	9.84E+02	1.27E+03	9.88E+02	9.S6E+02–	9.85E+02	9.56E+02
	Standard value	5.46E+00	8.56E+00	9.60E+00	1.16E+01	1.04E+01	9.28E+00
	Upper value	–	2.27E–64	3.55E–02	3.86E–01	5.11E–02	1.95E–01
	Lower value	–	1	1	0	0	0

It can be seen that the methodical approach for assessing the state of hierarchical systems using a metaheuristic 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 monkey algorithm are far from satisfactory.

6. Discussion of the results of developing a methodical approach to assessing the state of hierarchical systems

The advantages of the proposed methodical approach are due to the following:

– the initial setting of TDA is carried out taking into account the type of uncertainty (Step 2) using appropriate correction factors for the degree of awareness of the state of hierarchical systems, compared to [9, 14, 21];

– the initial velocity of each TDA is taken into account (Step 4), which allows prioritizing the search of each TDA, compared to [9–15];

– the fitness of TDA food locations is determined, which reduces the solution search time (Step 6), compared to [14, 16, 17];

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

– the possibility of choosing a TDA hunting strategy (Step 9), which allows a rational use of the system's computing resources, compared to [9–15];

– the universality of solving the problem of analyzing the state of hierarchical TDA systems due to the hierarchical nature of their description (Steps 1–11, Table 1), compared to [9, 12, 13–18];

– the possibility of simultaneous search for a solution in different directions (Steps 1–11, Table 1);

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

– the ability to avoid the local extremum problem (Steps 1–11);

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

The disadvantages of the proposed methodical approach include:

– the loss of informativeness when assessing the state of complex hierarchical systems due to the construction of the membership function;

– lower accuracy of assessment by a single parameter for the state of complex hierarchical systems;

– the loss of credibility of the obtained solutions when searching for a solution in several directions simultaneously;

– lower assessment accuracy compared to other assessment approaches.

This method will allow you:

– to assess the state of complex hierarchical systems;

– to determine effective measures to increase the management efficiency of complex hierarchical systems;

– to increase the speed of assessing the state of complex hierarchical 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 hierarchical 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 problems of assessing complex and dynamic processes characterized by a high degree of complexity. This study is a further development of research aimed at developing methodical principles for increasing the efficiency of processing various types of data, published earlier [2, 4–6, 21–23, 28–31]. Areas of further research should be aimed at reducing computing costs when processing various types of data in special-purpose systems.

7. Conclusions

1. The algorithm for implementing the methodical approach was determined, using additional and improved procedures, which allows you:

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

– to implement adaptive strategies for finding sources of TDA hunting;

– to determine the hunting strategy taking into account available system computing resources;

– to take into account the available computing resources of the system for analyzing the state of hierarchical systems;

– to change the search area for individual agents;

– to change the agent velocity;

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

– to conduct a local and global search taking into account the noise degree of data on the state of hierarchical 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, as well as the architecture of individual elements and the architecture of the artificial neural network as a whole;

– to avoid the local extremum problem.

2. An example of applying the proposed methodical approach when solving the problem of determining the composition of an operational group of troops (forces) and elements of its operational structure is given. This example showed a 14–17 % increase in data processing efficiency 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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