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DEVELOPMENT OF A SOLUTION SEARCH METHOD USING AN IMPROVED LOCUST SWARM ALGORITHM

Vitalii Tyurin
PhD, Associate Professor, Chief Researcher
The Scientific and Methodological Center of Scientific, Scientific and Technical Activities Organization
The National Defence University of Ukraine
Povitroflotskyi ave., 28, Kyiv, Ukraine, 03049

Robert Bieliakov
PhD, Assosiate Professor*

Elena Odarushchenko
PhD, Associate Professor
Department of Information Systems and Technologies
Poltava State Agrarian University
Skovorody str., 1/3, Poltava, Ukraine, 36003

Volodymyr Yashchenok
PhD, Associate Professor, Head of Department
Department of Design and Durability of Aircraft and Engines
Ivan Kozhedub Kharkiv National Air Force University
Sumska str., 77/79, Kharkiv, Ukraine, 61023

Olena Shaposhnikova
PhD, Associate Professor
Department of Computer Systems
Kharkiv National Automobile and Highway University
Yaroslava Mudroho str., 25, Kharkiv, Ukraine, 61002

Anna Lyashenko
Corresponing author
Researcher
Scientific Center*
E-mail: Anutka-2-0-0-8@ukr.net

Oleksandr Stanovskyi
Doctor of Technical Sciences, Professor
Department of Integrated Management Technologies
Odessa Polytechnic National University
Shevchenka ave., 1, Odessa, Ukraine, 65044

Borys Melnyk
PhD, Head
Scientific-Research Department**

Sviatoslav Sus
PhD, Researcher
Scientific-Research Department**

Mykola Dvorskyi
Researcher
Research Department
Scientific-Research Institute of Military Intelligence
Yuriy Illenka str., 81, Kyiv, Ukraine, 04050

*Military Institute of Telecommunications and Information Technologies named after Heroes of Kruty
Kyivska str., 45/1, Kyiv, Ukraine, 01011

**Central Scientifically-Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine
Povitroflotskyi ave., 28, Kyiv, Ukraine, 03049

The object of the research is decision support systems. The subject of the research is the decision-making process in management problems using the locust swarm algorithm and evolving artificial neural networks.

A solution search method using an improved locust swarm algorithm is proposed. The research is based on the locust swarm algorithm for finding a solution regarding the state of an object. For training locust agents (LA), evolving artificial neural networks are used. The method has the following sequence of steps:

– input of initial data;

– processing of initial data taking into account the degree of uncertainty;

– initial setting of LA in the search area;

– determination of the initial speed of the LA movement;

– a search vector is generated taking into account the degree of uncertainty;

– calculation of the change in the value of the LA fitness function;

– training of LA knowledge bases.

The originality of the proposed method lies in the arrangement of LA taking into account the uncertainty of the initial data, improved procedures of global and local search taking into account the degree of noise of data about the state of the analysis object. Also, the originality of the research is avoiding the concentration of LA on the current best positions, reducing the probability of premature convergence of the algorithm and maintaining a balance between the convergence rate of the algorithm and diversification. The peculiarity of the proposed method is the use of an improved procedure for LA training. The training procedure consists in learning the parameters and architecture of individual elements and the architecture of the artificial neural network as a whole

Keywords: swarm intelligence, decision support systems, hierarchical systems, locust swarm algorithm

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1. Introduction

Researchers study and adapt models of collective behavior of many species living in social groups (swarm, colony, flock) as frameworks for solving complex optimization problems. In artificial intelligence, the direction that models the collective behavior of decentralized, self-organizing systems in the form of an optimization algorithm is referred to as swarm intelligence [1].

Swarm intelligence has a number of advantages, such as scalability, fault tolerance, adaptability, speed, modularity, autonomy and parallelism. The swarm system can effectively adapt to internal and external changes.

Well-known nature-inspired swarm intelligence algorithms are:

– particle swarm optimization algorithms (PSO – Particle Swarm Optimization);

– ant (ACO – ant colony optimization) and bee (ABC – Artificial Bee Colony) colonies;

– bats (BA – Bat Algorithm), fireflies (FA – Firefly Algorithm), butterflies flying to the light (MFO – Moth Flame Optimization), chemotaxis of bacteria (BFO – Bacterial Foraging Optimization), etc. [2, 3].

However, they have certain disadvantages, such as premature convergence, the difficulty of overcoming local optima while searching for a global optimum. During the execution of the algorithm, the population of solutions quickly loses its diversity or, on the contrary, a slow convergence is observed. Finding a balance between the algorithm's convergence rate and the diversification of the solution search space is an open research problem that is important to ensure the accuracy and performance of optimization algorithms.

In particular, insect colonies offer a large set of metaphors for designing balanced metaheuristic optimization algorithms. Such cooperative entities are complex systems consisting of agents with different cooperative tasks and specialized behavior patterns depending on their type. Meanwhile, most swarm bioheuristic algorithms use search agents with the same properties and behavior patterns. In such conditions, the operators of these algorithms lose their attractiveness, do not allow improving the diversity of the population and expanding the search space for optimal solutions. Therefore, the inclusion of operators simulating the individual behavioral characteristics of population agents in the algorithm will contribute to the emergence of computing mechanisms that improve the balance between the convergence rate of the algorithm and the diversification of the search space [4].

The swarm algorithm and differential evolution algorithm are the most popular bioheuristic algorithms for solving complex optimization problems. However, they have serious drawbacks related to premature convergence and difficulties in overcoming local optima [5]. In particular, in the swarm algorithm, problems are associated with operators that change the location of swarm agents and update the position of each swarm agent at the next iteration, which causes them to move in the direction of the best individual.

In the differential evolution algorithm, a new solution is selected for further search only if it improves the previous solution. As a result, the entire population concentrates around the best solution or randomly diverges in the search process. This contributes to the violation of the balance between the convergence rate of the algorithm and the diversification of the search space. Meanwhile, cooperative swarm behavior toward simple agents in the population ensures their survival using limited local information and simple behavioral rules.

Locusts are a representative example of insects that can combine swarming and individual behavior. These are different patterns of behavior. Individual behavior implies that the locust avoids contact and, as a result, the swarm is distributed throughout the search space. Swarm behavior involves the concentration of locusts around individuals that managed to find a food source [6–8].

Given the above, an urgent scientific task is to develop a solution search method using an improved locust swarm algorithm, which would increase the efficiency of decisions made to manage 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 shortcomings of this approach include the lack of consideration of the type of uncertainty about the state of the analysis object.

The work [10] disclosed the essence of cognitive modeling and scenario planning. A system of complementary principles of building and implementing scenarios is proposed, different approaches to building scenarios are highlighted, the procedure for modeling scenarios based on fuzzy cognitive maps is described. The approach proposed by the authors does not take into account the type of uncertainty about the state of the analysis object and the noise of the initial data.

The work [11] carried out an analysis of the main approaches to cognitive modeling. Cognitive analysis allows you: to investigate problems with fuzzy factors and relationships; 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. 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 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 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 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: analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The scope of their application is defined. It is shown that the analytic hierarchy process works well under the condition of complete initial information, but due to the need for experts to compare alternatives and choose evaluation criteria, it has a high share of subjectivity. For forecasting problems under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

The work [20] developed a method of structural and objective analysis of the development of weakly structured systems. An approach to the study of conflict situations caused by contradictions in the interests of subjects that affect the development of the studied system and methods of solving poorly structured problems based on the formation of scenarios for the development of the situation. At the same time, the problem is defined as the non-compliance of the existing state of the system with the required one, which is set by the management entity. The disadvantages of the proposed method include the problem of the local optimum and the inability to conduct a parallel search.

The work [21] presents a cognitive approach to simulation modeling of complex systems. The advantages of the specified approach, which allows you to describe the hierarchical components of the system, are shown. The shortcomings of the proposed approach include the lack of consideration of the computing resources of the system.

The work [22] indicated that the most popular evolutionary bio-inspired algorithms are the so-called «swarm» procedures (Particle Swarm Optimization – PSO). Among them, there are optimization algorithms based on cat swarms (Cat Swarm Optimization – CSO), which are very promising both in terms of speed and ease of implementation. These algorithms have proven their effectiveness in solving a number of rather complex problems and have already undergone a number of modifications. Among the modifications, procedures based on harmonic search, fractional derivatives, adaptation of search parameters and, finally, «crazy cats» can be noted. At the same time, these procedures are not without some drawbacks that worsen the properties of the global extremum search process.

The work [23] investigates the locust swarm algorithm. Just like other metaheuristic algorithms, this algorithm belongs to evolutionary ones and is able to solve a number of optimization problems, including nonlinearity, non-differentiability, high dimensionality of the search space with a high convergence rate. Another advantage of the locust swarm algorithm is that it is regulated by a small number of parameters, making it quite easy to implement.

The basic locust swarm algorithm is subject to the following rules:

1. Input of initial data.
2. Initial setting of LA in the search area.
3. Generation of the LA search vector.
4. Calculation of the change in the value of the LA fitness function.

The analysis of the works [9–23] 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;
– premature convergence of algorithms;
– an imbalance between the algorithm convergence rate and diversification;
– 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.

For this purpose, it is proposed to develop a solution search method using an improved locust swarm algorithm.

3. The aim and objectives of the study

The aim of the study is to develop a solution search method using an improved locust swarm algorithm. This will allow increasing the efficiency of assessment and multidimensional forecasting with a given reliability and developing subsequent management decisions. This will make it possible to develop software for intelligent decision support systems.

To achieve the aim, the following objectives were set:

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

4. Materials and methods

The problem that is solved in the study is to increase the efficiency of decision-making in management problems while ensuring the given reliability, regardless of the hierarchy of the object. The object of research is decision support systems. The subject of research is the decision-making process in management problems using the locust swarm algorithm and evolving artificial neural networks.

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

Simulation of the proposed method was carried out in the MathCad 14 software environment (USA). The problem to be 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.

An 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 in accordance with current regulations.

The research is based on the locust swarm algorithm – for finding a solution regarding the state of an object. For LA training, evolving artificial neural networks are used.

5. Development of a solution search method using an improved locust swarm algorithm

5. 1. Algorithm for implementing the solution search method using the improved locust swarm algorithm

The proposed algorithm is an improved locust swarm algorithm and consists of the following sequence of steps:

Step 1. Input of initial data. At this stage, available initial data on the object to be analyzed are entered. The existing model of the analysis object is also initialized. At this stage, the decision matrix D is filled: each column is filled with a subset ω_i.

Step 2. Processing of initial data taking into account the degree of uncertainty.

At this stage, the type of uncertainty about the object to be analyzed is taken into account and the basic state model of the analyzed object is initialized [2, 19, 21–28]. At the same time, the degree of uncertainty can be: full awareness; partial uncertainty and total uncertainty. This is done using correction factors.

Step 3. Initial setting of the LA in the search area.

We describe the change in the position of an individual locust with individual behavior. Let x_i^k be the current position of the i-th LA in a swarm of N individuals. Then a new position x_i^{k+1} of the LA is calculated by the following formula:

$$x_i^{k+1} = x_i^k + \Delta x_i, \tag{1}$$

where Δx_i is the change in the position of the i-th LA on the (k+1)-th iteration due to interaction with other LA of the swarm. Two LAs with individual behavior do not tend to get closer if there is a small distance between them and, on the contrary, they get closer, maintaining the cohesion of the swarm, if there is a significant distance between them [29–33]. The force of attraction/repulsion of LA is defined as the difference:

$$s(r) = kar \cdot e^{-\frac{r}{\lim}} - e^{-r}, \tag{2}$$

where r is the distance between a pair of LA, kar is the coefficient of attraction/repulsion of LA, lim is the permissible value of the distance between LA. If $kar\langle 1$ and $\lim\rangle 1$, this means that there is a small distance between LA and repulsion is stronger than attraction. Then the force of influence of the j-th locust on the i-th locust is determined as follows:

$$s_{ij} = s(r_{ij}) \cdot d_{ij}, \tag{3}$$

where $r_{ij} = |x_j - x_i|$ is the distance between the j-th and i-th LA of the swarm, $d_{ij} = (x_j - x_i)/r_{ij}$ is a unit vector. Then the total attraction/repulsion force of the swarm for the i-th locust is defined as the superposition of all paired interactions [34–36]:

$$S_i = \sum_{j=1, j\neq 1}^{N} s_{ij}. \tag{4}$$

The change in the position of the i-th locust Δx_i corresponds to (4):

$$\Delta x_i = S_i. \tag{5}$$

In contrast to individual behavior in swarm behavior, the LA rapidly concentrates around individuals that have found food sources. In order to simulate equal behavior, we introduced a food index $f_i\left(f_i \in [0,1]\right)$ for each LA x_i. Then, N individuals of the population are ranked according to a decrease of this index, and then b individuals ($b << N$) with the highest food indicators are selected among them. Around each of b individuals in the radius R_c, a subset of locusts are randomly concentrated.

We assume that the entire search space is a plantation where LA interact with each other. Each solution in the search space represents the position of the LA on the plantation and is characterized by the value of the fitness function reflecting the level of the food index. The algorithm implements patterns of individual and swarm behavior, which are controlled by a set of operators that simulate these behavioral patterns.

The population $L^k(\{l_1^k, l_2^k, ..., l_N^k\})$ of N LA individuals evolves from the initial position (k=0) to a given number of generations (k=gen). Every locust $l_i^k(i = 1...N)$ is an n-dimensional vector $\{l_{i1}^k, l_{i2}^k, ..., l_{in}^k\}$, where each element corresponds to a variable solution of the optimization problem. The set of variable solutions makes up a valid search space:

$$S = \left\{ l^k \in R^n \mid lb_d \le l^k \le ub_d \right\}, \tag{6}$$

where lb_d and ub_d correspond to the lower and upper bounds of dimension d, respectively. The food index level associated with each locust is estimated by the function $f_i\left(l_i^k\right)$.

In the *SIBL* algorithm, at each iteration of the evolution process, two behavior operators are used: ***A*** – individual and ***B*** – swarm. Operator ***A*** is used to diversify the solution search space, and operator ***B*** – to refine the solution in a certain area of the space. Let us consider each of the operators in more detail.

Operator ***A***, implementing the pattern of individual behavior of the LA, changes the current position l_i^k of the i-th LA (i=1...N) with a speed v_i by the value Δl_i^k: $p_i = l_i^k + \Delta l_i^k$ taking into account the value of the fitness function and the position of dominant LA of the swarm.

Step 4. Determination of the initial speed of the LA movement.

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

$$v_i = (v_1, v_2 ... v_S),\ v_i = v_0. \tag{7}$$

Step 5. Generation of a search vector for each LA taking into account the degree of uncertainty:

$$\omega_i = \left((\omega_{i1} \times \eta_{i1}), (\omega_{i2} \times \eta_{i2}), \ldots, (\omega_{in} \times \eta_{in}) \right). \tag{8}$$

To start the motion process, a vector of the LA motion direction is generated:

$$\Delta\omega_i = (\Delta\omega_{i1}, \Delta\omega_{i2}, \ldots, \Delta\omega_{in}), \tag{9}$$

$$\Delta\omega_{ij} = \begin{cases} a, & \text{if } t = rand(0,1) > 1/2, \\ -a, & \text{if } t \le 1/2, \end{cases} \tag{10}$$

where $j=1, 2, \ldots, n$, $a(a>0)$ is the step length selected depending on the studied area.

The force of attraction/repulsion between the j-th and i-th individuals is calculated as follows:

$$s_{ij}^m = \rho(l_i^k, l_j^k) \cdot s(r_{ij}) \cdot d_{ij} + rand(1,-1), \tag{11}$$

where $s(r_{ij})$ is determined accordingly by (1); $d_{ij} = (l_j^k - l_i^k)/r_{ij}$ is a unit vector directed from l_i^k to l_j^k; rand $(1, -1)$ is a random number from the interval $(-1, 1)$; $\rho(l_i^k, l_j^k)$ is the dominance function between the j-th and i-th LA. To determine ρ, all LA of the population $L^k(\{l_1^k, l_2^k, \ldots, l_N^k\})$ are ranked in decreasing order of their fitness functions. The best LA is assigned a rank of 0, the worst individual receives a rank of N–1. Thus, the function $\rho(l_i^k, l_j^k)$ is defined as follows:

$$\rho(l_i^k, l_j^k) = \begin{cases} e^{-(5 \cdot rank(l_i^k)/N)}, & \text{if } rank(l_i^k) < rank(l_j^k), \\ e^{-(5 \cdot rank(l_j^k)/N)}, & \text{if } rank(l_i^k) > rank(l_j^k), \end{cases} \tag{12}$$

where the $rank(\alpha)$ function indicates the rank of an individual. According to (12), the function ρ acquires values from the interval (0, 1), and the value 1 is reached when one of the individuals is the best element of the population, and a value close to 0, when both individuals have low values of the fitness function.

Finally, the total force of attraction/repulsion acting on the i-th individual is calculated as the superposition of all paired interactions:

$$S_i^m = \sum_{j=1, j\ne 1}^{N} s_{ij}^m. \tag{13}$$

Step 6. Calculation of the change in the value of the LA fitness function.

After calculating the new positions $P(\{p_1, p_2, \ldots, p_N\})$ of LA of the population L^k, it is necessary to change the values of the fitness functions $F(\{f_1, f_2, \ldots, f_N\})$. This allows only those changes that guarantee improvement of the search results. In other words, if $f_i(p_i) > f_i(l_i^k)$, then the new position p_i is taken, otherwise the position l_i^k is preserved:

$$f_i = \begin{cases} p_i, & \text{if } f(p_i) > f(l_i^k), \\ l_i^k, & \text{otherwise.} \end{cases} \tag{14}$$

Operator $\boldsymbol{B}$, which implements the swarm behavior pattern of the LA, is aimed at refining the solution in a certain area of the search space. To perform it, the fitness functions of LA are first sorted in descending order. The sorting results are stored in the set $B(\{b_1, b_2, \ldots, b_n\})$. Among them, g best LA with the highest value of the fitness function are distinguished. They form a subset $\boldsymbol{E}$ of the most promising solutions. A subspace with a radius C_j is created around each individual with $f \in E$, which is determined as follows:

$$e_d = \frac{\sum_{q=1}^{n} (ub_q - lb_q)}{n} \cdot \beta, \tag{15}$$

where ub_d and lb_d are the upper and lower limits in the q-th dimension, n is the dimension of the variables of the optimization problem, $\beta \in \{0,1\}$ is the parameter of the algorithm. The boundaries of the subspace C_j are modeled as follows:

$$uss_j^q = b_{j,q} + e_d, \; lss_j^q = b_{j,q} - e_d, \tag{16}$$

where uss_j^q and lss_j^q are the upper and lower limits in the q-th dimension of the subspace C_j, respectively. Within this subspace, h ($h < 4$) new LA are randomly generated, among which the individual with the best value of the fitness function is selected.

Step 7. Training of LA 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 LA.

The end of the algorithm.

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

A solution search method using an improved locust swarm algorithm is proposed.

Simulation of the solution search processing method was carried out according to steps 1–7. The simulation of the proposed method was performed in the MathCad 14 software environment (USA). The problem to be solved during the simulation was to assess the elements of the operational situation of a group of troops (forces).

Initial data for assessing the state of the operational situation using the improved method:

– the number of sources of information about the state of the monitoring object – 3 (radio monitoring tools, remote earth sensing tools and unmanned aerial vehicles). To simplify the simulation, 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. Such parameters include: affiliation, type of organizational and staff formation, priority, minimum width along the front, maximum width along the front. The number of personnel, minimum depth along the flank, maximum depth along the flank, the number of samples of weapons and military equipment (WME), the number of types of WME samples and the number of communication means), the type of operational structure are also taken into account;

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

During the simulation, the following settings of the improved locust algorithm were used: kar=0.75; N=50, gen=1,000. The results were averaged over 30 independent runs.

During initialization ($k=0$), an initial population $L^0(\{l_1^0, l_2^0, \ldots, l_N^0\})$ is formed. The values $(\{l_{i1}^0, l_{i2}^0, \ldots, l_{in}^0\})$ of each individual dimension d are distributed randomly and uniformly between the predefined lower initial limit of the parameter lb_d and the upper initial limit of the parameter ub_d:

$$l_{ij}^0 = lb_d + rand \cdot (ub_d - lb_d),$$

where $i=1 \ldots N$, $d=1 \ldots n$. In the process of iterative execution of the algorithm, the individual operator $\boldsymbol{A}$ and the swarm operator $\boldsymbol{B}$ are executed until the number of iterations $k=gen$ is reached.

To test the performance of the improved algorithm, a set of three multidimensional test functions was used: Rosenbrock function $f_1(x)$, Sphere function $f_2(x)$, and Ackley function $f_3(x)$. The description of the test functions is presented in Table 1. In Table 1, n is the dimension of the function, I^n is the range of variation of variables x_i, x^* is the optimal solution, $f_i(x^*)$ is the minimum value of the function.

Table 1

Set of test functions

Test function $f_i(x)$	$x_i \in I^n$	n	Minimum
$f_1(x)=\sum_{i=1}^{n-1}\left[100\left(x_{i+1}-x_i^2\right)\times\left(x_i-1\right)^2\right]$	$[-5, 10]^n$	50	$f_1(x^*)=0$, $x^*=(1\ldots1)$
$f_2(x)=\sum_{i=1}^{n} x_i^2$	$[-100, 100]^n$	50	$f_2(x^*)=0$, $x^*=(0\ldots0)$
$f_3(x)=-20\exp\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}x_i^2}\right)-$ $-\exp\left(\sqrt{\frac{1}{n}\sum_{i=1}^{n}\cos(2\pi x_i)}\right)+20$	$[-32, 32]^n$	50	$F_3(x^*)=0$, $x^*=(0\ldots0)$

The Rosenbrock function $f_1(x)$ has a large, slowly decreasing plateau. The global minimum of the function lies within a parabolic highly elongated surface. The sphere function $f_2(x)$ is unimodal, unlike the Ackley function $f_3(x)$, which is multimodal.

6. Discussion of the results of developing a solution search method using an improved locust swarm algorithm

The comparison was based on the following indicators: average best solution, median best solution and standard deviation from the best solution. The averaged results corresponding to 30 individual runs are given in Table 2.

Table 2

Comparative evaluation of the proposed algorithm with known ones

Test function $f_i(x)$	Particle swarm algorithm [10]	Differential evolution algorithm [12]	Canonical locust swarm algorithm [23]	Improved locust swarm algorithm
$f_1(x)$	$2.77\cdot10^{-02}$	$2.27\cdot10^{-02}$	$5.47\cdot10^{-04}$	$5.02\cdot10^{-04}$
	$2.66\cdot10^{-02}$	$2.23\cdot10^{-02}$	$4.87\cdot10^{-04}$	$4.1\cdot10^{-04}$
	$5.86\cdot10^{-03}$	$5.03\cdot10^{-03}$	$1.33\cdot10^{-05}$	$1.11\cdot10^{-05}$
$f_2(x)$	$8.55\cdot10^{-03}$	$6.93\cdot10^{-03}$	$9.23\cdot10^{-06}$	$8.82\cdot10^{-06}$
	$3.15\cdot10^{-02}$	$5.53\cdot10^{-05}$	$7.95\cdot10^{-06}$	$7.02\cdot10^{-06}$
	$1.65\cdot10^{-03}$	$1.02\cdot10^{-05}$	$1.17\cdot10^{-06}$	$0.95\cdot10^{-06}$
$f_3(x)$	$3.55\cdot10^{-02}$	$7.02\cdot10^{-04}$	$4.22\cdot10^{-05}$	$3.9\cdot10^{-05}$
	$4.83\cdot10^{-02}$	$7.20\cdot10^{-04}$	$2.65\cdot10^{-05}$	$2.2\cdot10^{-05}$
	$1.2\cdot10^{-03}$	$2.22\cdot10^{-04}$	$3.71\cdot10^{-06}$	$3.1\cdot10^{-06}$

Each cell of Table 2 shows the average, median solution and standard deviation from the best solution, respectively. According to Table 2, the improved locust swarm algorithm provides a gain of 25–28 % compared to the canonical algorithm. The level of significance is 6 % at $T<0.05$ (sums of Wilcoxon ranks for independent samples).

The advantages of the proposed method are as follows:

– avoids the concentration of LA on the current best positions (Step 3) compared to [6, 9];

– reduces the probability of premature convergence of the algorithm (expressions (2)–(6)) compared to [22, 23];

– maintains a balance between the convergence rate of the algorithm and diversification (expressions (1)–(16)) compared to [18, 19];

– the type of uncertainty (Step 2) is taken into account while setting up LA compared to [7–12];

– universality of solving the problem of analyzing the state of LA objects due to the hierarchical nature of their description (Steps 1–7) compared to [9–13];

– the possibility of quick search for solutions due to the simultaneous search for a solution by several individuals (Steps 1–7, Tables 1, 2) compared to [15–18];

– the adequacy of the results obtained (Steps 1–7) compared to [15–19];

– the ability to avoid the local extremum problem (Steps 1–7) compared to [11–18];

– the possibility of deep learning of LA knowledge bases (Step 7) compared to [11–18].

The disadvantages of the proposed method include:

– loss of informativeness while assessing the state of the analysis object due to the construction of the membership function;

– lower accuracy of assessment by a single parameter for assessing the state of the analysis object;

– loss of credibility of the obtained solutions while searching for a solution in several directions at the same time;

– lower assessment accuracy compared to other assessment methods.

This method will allow you:

– to assess the state of a heterogeneous object of analysis;

– to determine effective measures to improve management efficiency;

– to increase the speed of assessing the state of a heterogeneous object of analysis;

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

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

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

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

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

7. Conclusions

1. The algorithm for implementing the method is defined, characterized by the use of additional improved procedures, namely:

– avoiding the concentration of LA in the current best positions;

– reducing the probability of premature convergence of the algorithm;

– maintaining a balance between the convergence rate of the algorithm and diversification;

– taking into account the type of uncertainty and noise of data;

– taking into account the available computing resources of the system for analyzing the state of the analysis object;

– taking into account the priority of LA search;

– carrying out the initial setting of LA individuals, taking into account the type of uncertainty;

– carrying out accurate training of LA individuals;

– conducting a local and global search taking into account the degree of noise of data on the state of the analysis object;

– conducting training of knowledge bases 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;

– using as a universal tool for solving the problem of analyzing the state of analysis objects due to the hierarchical description of analysis objects;

– checking the adequacy of the obtained results;

– avoiding the problem of local extremum.

2. An example of using the proposed method is given on 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 25–28 % due to the use of additional improved procedures of adding correction factors for uncertainty and noise of data and LA training.

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 work has associated data in the data repository.

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