UDC 004.81
DOI: 10.15587/1729-4061.2020.292574

DEVELOPMENT OF A SOLUTION SEARCH METHOD USING AN ADVANCED FLYING SQUIRREL ALGORITHM

Oleg Sova
Correspondin author
Doctor of Technical Science, Professor, Deputy Head of Scientific Center
Scientific Center for Building Integrity and Preventing Corruption in the Security and Defense Sector*
E-mail: soy135@ukr.net

Oleksandr Zhuk
Doctor of Technical Sciences, Associate Professor, Head of Department
Department of Communication Technologies and Cyber Protection*

Oksana Petruchenko
PhD, Assosiate Professor, Senior Researcher
Research Department
Scientific-Research Institute of Military Intelligence
Yuriya Illienka str., 81, Kyiv, Ukraine, 04050

Yurii Artabaiev
PhD, Head of Department
Research Department of Combat Crews
Research Center for Trophy and Perspective Weapons and Military Equipment
Dehtiarivska str., 13/24, Kyiv, Ukraine, 04119

Oleksandr Trotsko
PhD, Associate Professor, Head of Department
Department of Automated Control Systems**

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

Ruslan Boiko
PhD, Senior Researcher, Head of Department
Center for Military and Strategic Studies*

Yevhenii Redziuk
PhD, Associate Professor
Department of Computer Information Technology**

Viacheslav Shmyhol
Senior Lecturer
Department of Combined Arms Disciplines**
Kyivska str., 45/1, Kyiv, Ukraine, 010011

Vira Velychko
Lecturer
Department of Automated Control Systems**

*The National University of Defense of Ukraine
Povitroflotskyi ave., 28, Kyiv, Ukraine, 03049
**Military Institute of Telecommunications and Information Technologies named after Heroes of Kruty
Moskovsky str., 45/1, Kyiv, Ukraine, 01011

The object of the study is decision support systems. The subject of the study is the decision-making process in management problems using the flying squirrel algorithm (FSA), an advanced genetic algorithm and evolving artificial neural networks.

A solution search method using an advanced FSA is proposed. The study is based on the FSA algorithm for finding a solution regarding the state of an object. Evolving artificial neural networks are used to train FSA, and an advanced genetic algorithm is used to select the best FSA. The method has the following sequence of actions. Input of initial data and setting agents on the search plane take place. After that, numbering FSA in the flock and setting the initial fitness function are carried out. Then, the quality of food in the FSA search area is determined, and the classification of trees (food sources) for FSA is carried out. The next step is the creation of new locations by FSA gliding, formation of the FSA action algorithm in the presence of a predator. After that, the FSA seasonal monitoring conditions are checked, the stop criterion is checked, and new FSA positions are generated taking into account the degree of data noise.

The originality of the proposed method lies in setting FSA taking into account the uncertainty of the initial data, advanced global and local search procedures taking into account the noise degree of data on the state of the analysis object. The method makes it possible to increase the efficiency of data processing at the level of 21–25 % due to the use of additional advanced procedures. The proposed method should be used to solve the problems of evaluating complex and dynamic processes in the interests of solving national security problems

Keywords: decision support systems, global optimization, complex processes, bio-inspired algorithms

Received date 22.09.2023
Accepted date 27.11.2023
Published date 29.12.2023

How to Cite: *Sova, O., Zhuk, O., Petruchenko, O., Artabaiev, Y., Trotsko, O., Shaposhnikova, O., Boiko, R., Redziuk, Y., Shmyhol, V., Velychko, V. (2023). Development of a solution search method using an advanced flying squirrel algorithm. Eastern-European Journal of Enterprise Technologies, 6 (4 (126)), 14–22. doi: https://doi.org/10.15587/1729-4061.2023.292574*

1. Introduction

Optimization is the process of determining the solution variables of a function in such a way that the function has its maximum or minimum value. Many real-life computational problems refer to optimization problems [1–3], in which solution variables are defined so that systems operate at their best optimal point. Usually, these problems are discontinuous, undifferentiated, multimodal, and thus classical gradient deterministic algorithms [4–6] are not applied.

To overcome the shortcomings of classical algorithms, a significant number of stochastic optimization algorithms known as metaheuristic algorithms [7–9] have been developed in recent decades.

Using metaheuristic algorithms to find solutions regarding the state of objects allows you to perform:

– analysis of the stability of the state of heterogeneous objects in the process of combat application (operation);

– analysis of the direct, aggregated and indirect mutual influence of systemic and external factors;

– assessment of the reach of target situations of object management;

– scenario analysis for various destructive effects;

– forecasting of changes in the state of heterogeneous objects under the influence of destabilizing factors during combat application (operation);

– modeling and analysis of the dynamics of changes in the state of interrelated parameters of heterogeneous objects.

At the same time, using the above swarm algorithms in the canonical form does not allow obtaining an operational assessment of the object state with a given reliability. This determines the search for new (improvement of existing) approaches to assessing and forecasting the state of objects by combining already known swarm algorithms with their further improvement.

Given the above, an urgent scientific task is to develop a solution search method using an advanced flying squirrel algorithm, which would increase the efficiency of decisions regarding the management of the control object parameters 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, and 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] analyzes the main approaches to cognitive modeling. Cognitive analysis allows you to: investigate problems with fuzzy factors and relationships; take into account changes in the external environment and use objectively formed trends in the development of the situation to your advantage. At the same time, the issue of describing complex and dynamic processes remains unexplored in this work.

The work [12] presents a method of analyzing large data sets. The specified method is focused on finding hidden information in large data sets. The method includes the operations of generating analytical baselines, reducing variables, detecting sparse features and specifying rules. The disadvantages of this method include the impossibility of taking into account different decision evaluation strategies, the lack of consideration of the type of uncertainty of the input data.

The work [13] presents a mechanism of transformation of information models of construction objects to their equivalent structural models. This mechanism is designed to automate the necessary conversion, modification and addition operations during such information exchange. The disadvantages of the 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 dashboards with statistically significant results by territory. The disadvantages of the specified analytical platform include the impossibility of assessing the adequacy and reliability of the information transformation process and high computational complexity. Also, one of the shortcomings of the mentioned research is that the search for a solution is not unidirectional.

The work [15] developed a method of fuzzy hierarchical assessment of library service quality. This method allows you to evaluate the quality of libraries by 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 to evaluating input data for decision support systems. The essence of the proposed approach consists in clustering the basic set of input data, analyzing them, after which the system is trained based on the analysis. The disadvantages of this approach are the gradual accumulation of assessment and training errors due to the impossibility of assessing the adequacy of decisions made.

The work [18] presents an approach to processing data from various sources of information. This approach allows you to process data from various sources. The disadvantages of this approach include the low accuracy of the obtained estimate and the impossibility of verifying the reliability of the obtained estimate.

The work [19] carried out a comparative analysis of existing decision support technologies, namely: analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are indicated. The scope of their application is defined. It is shown that the analytic hierarchy process works well provided complete initial information, but due to the need for experts to compare alternatives and choose evaluation criteria, it has a high share of subjectivity. For forecasting problems under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

The work [20] developed a method of structural and objective analysis of the development of weakly structured systems. An approach to the study of conflict situations caused by contradictions in the interests of subjects that affect the development of the studied system and methods of solving poorly structured problems based on the formation of scenarios for the development of the situation. At the same time, the problem is defined as the non-compliance of the existing system state with the required one, which is set by the management subject. 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 are shown, which allows you to describe the hierarchical components of the system. The shortcomings of the proposed approach include the lack of consideration of the computing resources of the system.

The work [22] indicated that the most popular evolutionary bio-inspired algorithms are the so-called «swarm» procedures (Particle Swarm Optimization – PSO). Among them, cat swarm optimization algorithms (CSO) 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 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.

In [23], FSA simulates the dynamic foraging behavior of the southern flying squirrel by gliding, an effective mechanism used by small mammals for long-distance travel in deciduous forests of Europe and Asia [17]. In warm weather, squirrels change their location by gliding from one tree to another in the forest and exploring food sources. They can easily find acorns to meet their daily energy needs. After that, they start searching for hickory nuts (the optimal food source), which are stored for the winter. In cold weather, they become less active and support their energy needs with hickory nut reserves. When warm weather arrives, flying squirrels become active again. The above process is repeated and continues throughout the life span of the squirrel, which serves as the basis of FSA.

The basic FSA consists of the following sequence of actions:
– initialization of algorithm parameters;
– classification of tree types;
– creation of new locations by gliding;
– verification of the seasonal monitoring condition;
– checking the algorithm stop criterion.

However, FSA still suffers from premature convergence and easily falls into the local optimal solution trap, especially while solving very complex problems. The convergence rate of FSA, like other swarm intelligence algorithms, depends on the balance between exploration and operation capabilities. In other words, excellent performance in solving optimization problems requires fine-tuning the exploration and operation problem. According to the no-free-lunch theorem [20], there is no single optimization algorithm capable of achieving the best performance for all problems, and FSA is no exception. Thus, there is still an opportunity to improve the accuracy and convergence rates of FSA.

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;
– 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 particular direction.

The problem that needs to be solved in the study is to increase the efficiency of solving the problems of analysis and multidimensional forecasting of the state of objects while ensuring a given reliability.

To this end, it is proposed to develop a solution search method using an advanced flying squirrel algorithm.

3. The aim and objectives of the study

The aim of the study is to develop a solution search method using an advanced flying squirrel algorithm. This will increase the efficiency of assessment and multidimensional forecasting with a given reliability and 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 implementing the method;
– to give an example of applying 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 a given reliability regardless of the object hierarchy. The object of the study is decision support systems. The subject of the study is the decision-making process in management problems using an advanced flying squirrel algorithm, an advanced genetic algorithm and evolving artificial neural networks.

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

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

The operational group of troops (forces) was considered as an object of assessment and management. The operational group of troops (forces) formed on the basis of an operational command with a standard composition of forces and means according to the wartime state and with a range of responsibilities in accordance with current regulations.

The research is based on the flying squirrel algorithm for finding a solution regarding the state of an object. Evolving artificial neural networks are used to train FSA, and an advanced genetic algorithm is used to select the best FSA.

5. Development of a solution search method using an advanced flying squirrel algorithm

5. 1. Algorithm for implementing the solution search method using the advanced flying squirrel algorithm

The proposed algorithm is an advanced flying squirrel algorithm and consists of the following sequence of steps.

Step 1. Input of initial data. At this stage, the available initial data on the object to be analyzed are entered.

The main parameters of FSA are the maximum number of iterations $Iter_{\max}$, the population size NP, the number of solution variables n, the probability of predator presence Pdp, the scaling factor *sf*, the gliding constant *Gc* and the upper and lower bounds for the solution variable FS_U and FS_L. These parameters are set at the beginning of the FSA procedure:

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

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

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

Step 2. Setting up agents on the search plane.

At this stage, FSA is set up taking into account the type of uncertainty about the object to be analyzed, and the basic object state model is initialized [2, 19, 21]. At the same time, the degree of uncertainty can be: full awareness; partial uncertainty and total uncertainty. This is done using appropriate correction factors, which are set at the analysis stage.

Step 3. Numbering FSA in the flock, i, $i \in [0, S]$.

Step 4. Setting the initial fitness function.

The fitness value $f=(f_1, f_2, ..., f_{NP})$ of an individual of the FSA location is calculated by substituting the value of the solution variables into the fitness function:

$$f_i = f_i\left(FS_{i,1}, FS_{i,2},\dots,FS_{i,n}\right),\ i = 1,2,\dots,NP. \tag{2}$$

Step 5. Determining the quality of food in the FSA search area.

The quality of food sources is determined by the fitness value of the FSA location sorted in ascending order:

$$[sorted\_f, sorte\_index] = sort(f). \tag{3}$$

Step 6. Classification of trees (food sources) for FSA.

After sorting the food sources in each FSA location, three types of trees are classified: hickory (food source – hickory nuts), oak (food source – acorns), and common tree.

The location of the best food source (i.e. minimum fitness) is considered a hickory nut tree (FS_{ht}), the following three food source locations must be nut trees (FS_{at}) and the rest are considered common trees (FS_{nt}):

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

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

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

Step 7. Creating new locations by FSA gliding. At the stage of creating new locations, three main scenarios are used. Consider each of them in detail.

Step 7. 1. Flying squirrels on acorn nut trees tend to move toward hickory nut trees. New food areas can be created as follows:

$$FS_{at}^{new} = \begin{cases} FS_{at}^{old} + d_g G_c\left(FS_{ht}^{old} - FS_{at}^{old}\right), \text{if } R_1 \ge P_{dp}, \\ \text{random location, otherwise,} \end{cases} \tag{7}$$

where d_g is the random gliding distance of the FSA, R_1 is a function that returns the value of a uniform distribution on the interval [0, 1], and G_c is the gliding constant of the FSA.

Step 7. 2. Some FSA that live in common trees can move to the walnut tree to meet their daily energy needs. New food areas of FSA can be created as follows:

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c\left(FS_{at}^{old} - FS_{nt}^{old}\right), \text{if } R_2 \ge P_{dp}, \\ \text{random location, otherwise,} \end{cases} \tag{8}$$

where R_2 is a function that returns the value from a uniform distribution on the interval [0, 1].

Step 7. 3. Some FSA on common trees can switch to hickory nuts if they have already met their daily energy needs. In this scenario, a new location of squirrels can be generated as follows:

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c\left(FS_{ht}^{old} - FS_{nt}^{old}\right), \text{if } R_3 \ge P_{dp}, \\ \text{random location, otherwise,} \end{cases} \tag{9}$$

where R_3 is a function that returns the value from a uniform distribution on the interval [0, 1].

In all scenarios, the gliding distance of the FSA d_g is considered to be between 9 and 20 m [32]. However, this value is quite large and can introduce large perturbations (7)–(9) and lead to unsatisfactory performance of the algorithm. To achieve the acceptable performance of the algorithm, a scale factor (*sf*) was introduced as a divisor of d_g and its value was chosen to be 18 [33].

Step 8. Checking for the presence of a predator. At this stage of the FSA, the presence of predators is checked. If there are predators, go to Step 9. If there are no predators, go to Step 10.

Step 9. FSA actions in the presence of a predator. When FSA create new locations, their natural behavior is affected by the presence of predators, and this is controlled by the probability of predator presence P_{dp}. At an early stage of the search, the FSA population is often far from the food source and its distribution area is large. Thus, it faces a great threat from predators. In the course of evolution, FSA locations are near the food source (optimal solution). In this case, the distribution area of the FSA population becomes smaller and less threat from predators is expected. Thus, to improve the FSA performance, the adaptive P_{dp}, which changes dynamically as a function of the iteration number, is adopted as follows:

$$P_{dp} = \left(P_{dp\max} - P_{dp\min}\right) \times \left(1 - Iter / Iter_{\max}\right)^{10} + P_{dp\min}, \tag{10}$$

where $P_{dp\max}$ and $P_{dp\min}$ are the maximum and minimum probability of predator presence, respectively.

Step 10. Checking the FSA seasonal monitoring condition.

The foraging behavior of FSA largely depends on seasonal fluctuations. Therefore, the condition of seasonal monitoring is introduced into the algorithm to prevent the algorithm from falling into local optimal solutions.

First, the seasonal constant S_c and its minimum value are calculated:

$$S_c^t = \sqrt{\sum_{k=1}^{n}\left(FS_{at,k}^t - FS_{ht,k}\right)^2},\ t = 1,2,3, \tag{11}$$

$$S_{c\min} = \frac{10E-6}{365^{Iter/(Iter_{\max})/2.5}}. \tag{12}$$

Then the seasonal monitoring condition is checked. Provided $S_c^t < S_{c\min}$, winter is over, and FSA that lose the ability to explore the forest will again randomly move their food source search locations:

$$FS_{nt}^{new} = FS_L + Levy(n) \times (FS_U - FS_L), \tag{13}$$

where:

$$Levy(x) = 0.01 \times \frac{r_a \times \sigma}{|r_b|^{1/\beta}}, \tag{14}$$

where r_a and r_b are two functions that return values from a uniform Levy distribution on the interval [0, 1], β is a constant (β=1.5 in this study), and σ is calculated as follows:

$$\sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{((\beta-1)/2)}} \right)^{1/\beta}, \tag{15}$$

where $\Gamma(x)=(x-1)!$.

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

Step 12. Generation of FSA positions taking into account the degree of data noise.

Provided R_1, R_2, $R_3 < P_{dp}$, FSA continue to glide to the next potential food locations, different individuals tend to have different judgments and their gliding directions and change procedures. Gliding occurs taking into account the degree of data noise, which is distributed from 0 to 1. In other words, the foraging behavior of FSA has the characteristics of randomness and fuzziness. These characteristics can be artificially described and integrated using a conventional cloud model. In the model, a conventional cloud generator model is used instead of uniformly distributed random functions to generate a new location for each flying squirrel. Thus, (7)–(9) are replaced by the following equations:

$$FS_{at}^{new} = \begin{cases} FS_{at}^{old} + d_g G_c \left(FS_{ht}^{old} - FS_{at}^{old} \right), \text{if } R_1 \geq P_{dp}, \\ Cx\left(FS_{at}^{old}, En, He \right), \text{otherwise}, \end{cases} \tag{16}$$

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c \left(FS_{at}^{old} - FS_{nt}^{old} \right), \text{if } R_2 \geq P_{dp}, \\ Cx\left(FS_{nt}^{old}, En, He \right), \text{otherwise}, \end{cases} \tag{17}$$

$$FS_{nt}^{new} = \begin{cases} FS_{nt}^{old} + d_g G_c \left(FS_{ht}^{old} - FS_{nt}^{old} \right), \text{if } R_3 \geq P_{dp}, \\ Cx\left(FS_{nt}^{old}, En, He \right), \text{otherwise}, \end{cases} \tag{18}$$

where *En* (entropy) represents the uncertainty measurement of a qualitative concept, and *He* (hyperentropy) is the uncertain degree of entropy *En* [32]. In particular, in (16)–(18), *En* stands for the search radius, and $He=0.1 \cdot En$ is used to represent search stability. In early iterations, a large *En* is required because the location of flying squirrels is often far from the optimal solution. Under the condition of finite generations, where the population location is close to the optimal solution, a smaller *En* is suitable for fine-tuning the solutions. Therefore, the search radius *En* changes dynamically with the iteration number:

$$En = En_{\max} \times \left(1 - Iter / Iter_{\max}\right)^{10} + P_{dp\min}, \tag{19}$$

where $En_{\max}=(FS_U-FS_L)/4$ is the maximum search radius.

Step 13. Accelerating the FSA feeding area search intensity.

In the basic FSA, all dimensions of one FSA individual are updated simultaneously. The main drawback of this process is the principle that different food areas are dependent, and changing one food area can have a negative impact on others, preventing them from finding optimal variables in their own areas.

To further enhance the intensive search for each foraging area, the following steps are performed for each iteration. The newly generated solution is produced:

$$FS_{best,j}^{new} = Cx\left(FS_{best,j}^{old}, En, He \right), \ j = 1, 2, \ldots, n. \tag{20}$$

Step 14. Training the FSA 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 FSA. The method is used to change the movement pattern of each FSA for more accurate analysis results in the future.

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

In order to prevent the looping of calculations on Steps 1–14 of this method and increase the efficiency of calculations, the system load is additionally determined. 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 [33].

The end of the algorithm.

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

A solution search method using the advanced flying squirrel algorithm is proposed. To evaluate the effectiveness of the developed method, its comparative evaluation was performed by the results of the research presented in [3–6, 23, 24, 33].

Simulation of the solution search processing method was carried out in accordance with Steps 1–15. Simulation of the proposed method in the MathCad 14 software environment (USA) was carried out. 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 flying squirrel method:

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

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

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

The efficiency of the advanced FSA is compared to the following natural optimization algorithms:

– basic FSA;

– fruit fly optimization algorithm;

– advanced fruit fly optimization algorithm;

– fruit fly optimization algorithm based on a cloud model.

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 results of the comparative analysis are shown in Table 1.

Table 1

Results of comparative analysis

Parameter	Advanced FSA	Basic FSA	Particle swarm algorithm	Fruit fly optimization algorithm based on the cloud model	Advanced fruit fly optimization algorithm	Fruit fly optimization algorithm
$Iter_{max}$	10,000	10,000	10,000	10,000	10,000	10,000
NP	50	50	50	50	50	50
G_c	1.9	1.91	–	–	–	–
sf	18	18	–	–	–	–
$P_{dp\max}$	0.12	–	–	–	–	–
$P_{dp\min}$	0.001	–	–	–	–	–
P_{dp}	–	0.15	–	–	–	–
C_1 and C_2	–	–	2.1	–	–	–
w	–	–	0.91	–	–	–
En_max	–	–	–	(UB–UL)/4	–	–
λ_{max}	–	–	–	–	(UB–UL)/2	–
λ_{min}	–	–	–	–	0.000014	–
$randValue$	–	–	–	–	–	1

The initial data for the comparative analysis of the effectiveness of the proposed FSA are set the same for all algorithms, for example, the size population NP=50; the maximum number of iterations $Iter_{max}$=10,000. The specific parameters of the algorithm are chosen in the same way. Table 1 summarizes both general and specific parameters for the advanced FSA and the other five algorithms. The error value defined as $(f(x)–F_{min})$ is written for the solution x, where $f(x)$ is the optimal fitness value of the function calculated by the algorithms, and F_{min} is the true minimum value of the function. The mean and standard deviation of the error values for all independent runs are calculated.

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 2).

Analyzing the results of the advanced algorithm shown in Table 2, it can be seen that the algorithm demonstrates the greatest efficiency for functions with a small number of parameters. However, when the dimension of multi-extremal functions with a complex landscape (such as the Rastrygin, Griewank, Bukin functions) 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, FSA shows a rather noticeable discrepancy from the optimal solution. Therefore, to achieve the required accuracy, a serious increase in time costs is required, which makes the method ineffective in this particular case.

It can be seen that the advanced FSA is able to converge to the true value for most unimodal functions with the fastest convergence rate and the highest accuracy. As the convergence results of the particle swarm algorithm and the fruit fly algorithm are far from satisfactory.

Based on the conducted research, it can be said that FSA 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.

As can be seen from Tables 1, 2, the specified example showed an increase in the efficiency of data processing at the level of 21–25 % due to the use of additional advanced procedures of adding correction factors for uncertainty and noise of data, selection and training of FSA.

Table 2

Results of the AIP algorithm for test functions

Function	Dimensionality of the function	Number of AIP	Number of iterations	Result	Average time, sec.
De Jong (global optimum: 0)	2	4	10,000	0	0
	5	14		0	0.1
	10	28		0.001	3.17
	30	30		0.007	30.42
Rastrigin (global optimum: 0)	2	6	10,000	0	0
	5	64		0	18.23
	10	50		0.03	62.5
	30	50		0.97	528.4
Griewank (global optimum: 0)	2	6	10,000	0	0
	5	16		0.002	0.17
	10	30		0.004	4.77
	30	43		0.028	89.38
Ackley (global optimum: 0)	2	6	10,000	0	0
	5	24		0.001	0.15
	10	42		0.013	3.24
	30	50		0.021	66.73
Bukina (global optimum: 0)	2	8	10,000	0	0
	5	20		0.002	2.08
	10	40		0.03	4.16
	30	50		0.85	70.4

6. Discussion of the results of developing a solution search method using the advanced flying squirrel algorithm

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

– in the initial setting of FSA, the type of uncertainty is taken into account while searching for them (Step 2), compared to [19–23];

– additional determination of the suitability of the FSA search location, which reduces the solution search time (Step 5), compared to [19–23];

– the universality of food area search strategies, which allows classifying the type of data to be processed (Steps 6, 7), compared to [19–23];

– taking into account the presence of a predator, which allows avoiding local optima (Steps 8, 9), compared to [19–23];

– the universality of solving the problem of analyzing the state of FSA objects due to the hierarchical nature of their description (Steps 1–15), compared to [9–23];

– the possibility of quick solution search due to the simultaneous search for a solution by several FSA (Steps 1–15, Table 1, Table 2), compared to [19–23];

– the adequacy of the obtained results (Steps 1–15);

– adaptive change of the search area by individual FSA (Step 13), compared to [19–23];

– the ability to avoid the local extremum problem (Steps 1–15), compared to [19–23];

– the possibility of deep learning of FSA knowledge bases (Step 15), compared to [9–23].

The disadvantages of the proposed method include:

– the 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 assessment parameter for the state of the analysis object;

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

– lower assessment accuracy compared to other assessment methods.

This method will allow you:

– to assess the state of a heterogeneous analysis object;

– to determine effective measures to improve management efficiency;

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

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

The limitations of the study are the need to have an initial database on the state of the analysis object, the need to take into account the delay time for collecting and reporting 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.

The specified algorithm is advisable to use while developing software in intelligent decision support systems and in automated control systems while analyzing the state of complex hierarchical objects.

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, 28].

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

7. Conclusions

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

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

– to implement adaptive food source search strategies;

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

– to take into account the available computing resources of the object state analysis system;

– to change the search area by individual FSA;

– to take into account the priority of FSA search;

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

– to carry out accurate training of FSA individuals;

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

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

– 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 be used as a universal tool to solve the problem of analyzing the state of analysis objects due to the hierarchical description of analysis objects;

– to check the adequacy of the obtained results;

– to avoid 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 21–25 % due to the use of additional advanced procedures of adding correction factors for uncertainty and noise of data, selection and training of FSA.

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.

Financing

The research was conducted without financial support.

Data availability

The work has associated data in the data repository.

Use of artificial intelligence

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

References

1. Bashkyrov, O. M., Kostyna, O. M., Shyshatskyi, A. V. (2015). Rozvytok intehrovanykh system zviazku ta peredachi danykh dlia potreb Zbroinykh Syl. Ozbroiennia ta viyskova tekhnika, 1, 35–39. Available at: http://nbuv.gov.ua/UJRN/ovt_2015_1_7
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskyi, R., Repilo, I. et al. (2020). Development of a method for training artificial neural networks for intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (2 (105)), 37–47. doi: https://doi.org/10.15587/1729-4061.2020.203301
3. Sova, O., Shyshatskyi, A., Salnikova, O., Zhuk, O., Trotsko, O., Hrokholskyi, Y. (2021). Development of a method for assessment and forecasting of the radio electronic environment. EUREKA: Physics and Engineering, 4, 30–40. doi: https://doi.org/10.21303/2461-4262.2021.001940
4. Pievtsov, H., Turinskyi, O., Zhyvotovskyi, R., Sova, O., Zvieriev, O., Lanetskii, B., Shyshatskyi, A. (2020). Development of an advanced method of finding solutions for neuro-fuzzy expert systems of analysis of the radioelectronic situation. EUREKA: Physics and Engineering, 4, 78–89. doi: https://doi.org/10.21303/2461-4262.2020.001353
5. Zuiev, P., Zhyvotovskyi, R., Zvieriev, O., Hatsenko, S., Kuprii, V., Nakonechnyi, O. et al. (2020). Development of complex methodology of processing heterogeneous data in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 4 (9 (106)), 14–23. doi: https://doi.org/10.15587/1729-4061.2020.208554
6. Shyshatskyi, A. (2020). Complex Methods of Processing Different Data in Intellectual Systems for Decision Support System. International Journal of Advanced Trends in Computer Science and Engineering, 9 (4), 5583–5590. doi: https://doi.org/10.30534/ijatcse/2020/206942020
7. Yeromina, N., Kurban, V., Mykus, S., Peredrii, O., Voloshchenko, O., Kosenko, V. et al. (2021). The Creation of the Database for Mobile Robots Navigation under the Conditions of Flexible Change of Flight Assignment. International Journal of Emerging Technology and Advanced Engineering, 11 (5), 37–44. doi: https://doi.org/10.46338/ijetae0521_05
8. Rotshteyn, A. P. (1999). Intellektual'nye tekhnologii identifikatsii: nechetkie mnozhestva, geneticheskie algoritmy, neyronnye seti. Vinnitsa: «UNIVERSUM», 320.
9. Ko, Y.-C., Fujita, H. (2019). An evidential analytics for buried information in big data samples: Case study of semiconductor manufacturing. Information Sciences, 486, 190–203. doi: https://doi.org/10.1016/j.ins.2019.01.079
10. Ramaji, I. J., Memari, A. M. (2018). Interpretation of structural analytical models from the coordination view in building information models. Automation in Construction, 90, 117–133. doi: https://doi.org/10.1016/j.autcon.2018.02.025
11. Pérez-González, C. J., Colebrook, M., Roda-García, J. L., Rosa-Remedios, C. B. (2019). Developing a data analytics platform to support decision making in emergency and security management. Expert Systems with Applications, 120, 167–184. doi: https://doi.org/10.1016/j.eswa.2018.11.023
12. Chen, H. (2018). Evaluation of Personalized Service Level for Library Information Management Based on Fuzzy Analytic Hierarchy Process. Procedia Computer Science, 131, 952–958. doi: https://doi.org/10.1016/j.procs.2018.04.233
13. Chan, H. K., Sun, X., Chung, S.-H. (2019). When should fuzzy analytic hierarchy process be used instead of analytic hierarchy process? Decision Support Systems, 125, 113114. doi: https://doi.org/10.1016/j.dss.2019.113114
14. Osman, A. M. S. (2019). A novel big data analytics framework for smart cities. Future Generation Computer Systems, 91, 620–633. doi: https://doi.org/10.1016/j.future.2018.06.046
15. Gödri, I., Kardos, C., Pfeiffer, A., Váncza, J. (2019). Data analytics-based decision support workflow for high-mix low-volume production systems. CIRP Annals, 68 (1), 471–474. doi: https://doi.org/10.1016/j.cirp.2019.04.001
16. Harding, J. L. (2013). Data quality in the integration and analysis of data from multiple sources: some research challenges. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, XL-2/W1, 59–63. doi: https://doi.org/10.5194/isprsarchives-xl-2-w1-59-2013
17. Kosko, B. (1986). Fuzzy cognitive maps. International Journal of Man-Machine Studies, 24 (1), 65–75. doi: https://doi.org/10.1016/s0020-7373(86)80040-2
18. Koval, M., Sova, O., Shyshatskyi, A., Artabaiev, Y., Garashchuk, N., Yivzhenko, Y. et al. (2022). Improving the method for increasing the efficiency of decision-making based on bio-inspired algorithms. Eastern-European Journal of Enterprise Technologies, 6 (4 (120)), 6–13. doi: https://doi.org/10.15587/1729-4061.2022.268621
19. Jain, M., Singh, V., Rani, A. (2019). A novel nature-inspired algorithm for optimization: Squirrel search algorithm. Swarm and Evolutionary Computation, 44, 148–175. doi: https://doi.org/10.1016/j.swevo.2018.02.013
20. Koshlan, A., Salnikova, O., Chekhovska, M., Zhyvotovskyi, R., Prokopenko, Y., Hurskyi, T. et al. (2019). Development of an algorithm for complex processing of geospatial data in the special-purpose geoinformation system in conditions of diversity and uncertainty of data. Eastern-European Journal of Enterprise Technologies, 5 (9 (101)), 35–45. doi: https://doi.org/10.15587/1729-4061.2019.180197
21. Mahdi, Q. A., Shyshatskyi, A., Prokopenko, Y., Ivakhnenko, T., Kupriyenko, D., Golian, V. et al. (2021). Development of estimation and forecasting method in intelligent decision support systems. Eastern-European Journal of Enterprise Technologies, 3 (9 (111)), 51–62. doi: https://doi.org/10.15587/1729-4061.2021.232718

22. Gorokhovatsky, V., Stiahlyk, N., Tsarevska, V. (2021). Combination method of accelerated metric data search in image classification problems. Advanced Information Systems, 5 (3), 5–12. doi: https://doi.org/10.20998/2522-9052.2021.3.01
23. Levashenko, V., Liashenko, O., Kuchuk, H. (2020). Building Decision Support Systems based on Fuzzy Data. Advanced Information Systems, 4 (4), 48–56. doi: https://doi.org/10.20998/2522-9052.2020.4.07
24. Meleshko, Y., Drieiev, O., Drieieva, H. (2020). Method of identification bot profiles based on neural networks in recommendation systems. Advanced Information Systems, 4 (2), 24–28. doi: https://doi.org/10.20998/2522-9052.2020.2.05
25. Kuchuk, N., Merlak, V., Skorodelov, V. (2020). A method of reducing access time to poorly structured data. Advanced Information Systems, 4 (1), 97–102. doi: https://doi.org/10.20998/2522-9052.2020.1.14
26. Shyshatskyi, A., Tiurnikov, M., Suhak, S., Bondar, O., Melnyk, A., Bokhno, T., Lyashenko, A. (2020). Method of assessment of the efficiency of the communication of operational troop grouping system. Advanced Information Systems, 4 (1), 107–112. doi: https://doi.org/10.20998/2522-9052.2020.1.16
27. Raskin, L., Sira, O. (2016). Method of solving fuzzy problems of mathematical programming. Eastern-European Journal of Enterprise Technologies, 5 (4 (83)), 23–28. doi: https://doi.org/10.15587/1729-4061.2016.81292
28. Lytvyn, V., Vysotska, V., Pukach, P., Brodyak, O., Ugryn, D. (2017). Development of a method for determining the keywords in the slavic language texts based on the technology of web mining. Eastern-European Journal of Enterprise Technologies, 2 (2 (86)), 14–23. doi: https://doi.org/10.15587/1729-4061.2017.98750
29. Stepanenko, A., Oliinyk, A., Deineha, L., Zaiko, T. (2018). Development of the method for decomposition of superpositions of unknown pulsed signals using the second-order adaptive spectral analysis. Eastern-European Journal of Enterprise Technologies, 2 (9 (92)), 48–54. doi: https://doi.org/10.15587/1729-4061.2018.126578
30. Gorbenko, I., Ponomar, V. (2017). Examining a possibility to use and the benefits of post-quantum algorithms dependent on the conditions of their application. Eastern-European Journal of Enterprise Technologies, 2 (9 (86)), 21–32. doi: https://doi.org/10.15587/1729-4061.2017.96321
31. Koval, M., Sova, O., Orlov, O., Shyshatskyi, A., Artabaiev, Y., Shknai, O. et al. (2022). Improvement of complex resource management of special-purpose communication systems. Eastern-European Journal of Enterprise Technologies, 5 (9 (119)), 34–44. doi: https://doi.org/10.15587/1729-4061.2022.266009
32. Wang, L., Shi, Y., Liu, S. (2015). An improved fruit fly optimization algorithm and its application to joint replenishment problems. Expert Systems with Applications, 42 (9), 4310–4323. doi: https://doi.org/10.1016/j.eswa.2015.01.048
33. Yuan, X., Dai, X., Zhao, J., He, Q. (2014). On a novel multi-swarm fruit fly optimization algorithm and its application. Applied Mathematics and Computation, 233, 260–271. doi: https://doi.org/10.1016/j.amc.2014.02.005