

*The object of the study is decision support systems.*

*The problem of increasing decision-making efficiency in conditions of uncertainty and a set of different parameters was solved using a bio-inspired algorithm.*

*The subject of the study is the decision-making process in management problems using the heron flock algorithm, the improved genetic algorithm and evolving artificial neural networks.*

*A solution search method using the improved heron flock algorithm is proposed. The study is based on the heron flock algorithm to find a solution regarding the object state. Evolving artificial neural networks are used to train the heron flock algorithm, and an advanced genetic algorithm is used to select the best individuals of the heron flock. The method has the following sequence of actions:*

- input of initial data;*
- setting agents on the search plane;*
- numbering heron agents in the flock;*
- setting the initial velocity of heron agents;*
- waiting strategy for heron agents;*
- aggressive strategy;*
- checking the discriminatory condition;*
- selection of the best individuals from the heron flock;*
- ranking and sorting the obtained solutions;*
- training heron knowledge bases;*
- determining the amount of necessary computing resources of the intelligent decision support system.*

*The originality of the proposed method consists in setting heron agents taking into account the uncertainty of the initial data, the noise degree of data about the analysis object state. The method makes it possible to reduce the time for decision-making at the level of 22–26 % due to the use of additional improved procedures. The proposed method should be used to solve the problems of evaluating complex and dynamic processes in the interest of solving national security problems*

*Keywords: unimodal functions, decision-making efficiency, optimization problems, hierarchical objects*

UDC 004.81

DOI: 10.15587/1729-4061.2024.300261

# DEVELOPMENT OF A SOLUTION SEARCH METHOD USING ARTIFICIAL INTELLIGENCE

**Qasim Abbood Mahdi**

PhD, Head of Department  
Department of Computer Technologies Engineering  
Al-Taff University College  
Karrada str., 3, Karbala, Iraq, 31001

**Andrii Shyshatskyi**

Corresponding author  
PhD, Senior Researcher, Associate Professor  
Department of Computerized Management Systems  
National Aviation University  
Lubomyra Huzara ave., 1, Kyiv, Ukraine, 03058  
E-mail: ierikon13@gmail.com

**Vitalina Babenko**

Doctor of Economic Sciences, Professor, Head of Department\*

**Robert Bieliakov**

PhD, Associate Professor  
Scientific and Organizational Department  
Military Institute of Telecommunications and Information Technologies named after Heroes of Kruty  
Kyivska str., 45/1, Kyiv, Ukraine, 01011

**Elena Odarushchenko**

PhD, Associate Professor\*\*\*

**Nadiia Protas**

PhD, Associate Professor\*\*\*

**Tetiana Stasiuk**

Lecturer  
Cyclic Commission of General Education Disciplines  
Sergeant Military College  
Military Institute of Telecommunications and Information Technologies named after Heroes of Kruty  
Zinkivska str., 44, Poltava, Ukraine, 36000

**Yurii Rukavyshnikov**

PhD, Associate Professor  
Department of Construction and Road-Building Machinery\*\*

**Ivan Miziak**

Postgraduate Student\*

**Oleh Lantrat**

Postgraduate Student\*

\*Department of Computer Systems\*\*

\*\*Kharkiv National Automobile and Highway University  
Yaroslava Mudroho str., 25, Kharkiv, Ukraine, 61002

\*\*\*Department of Information Systems and Technologies  
Poltava State Agrarian University  
Skovorody str., 1/3, Poltava, Ukraine, 36003

Received date 15.01.2024

Accepted date 22.03.2024

Published date 30.04.2024

**How to Cite:** Mahdi, Q. A., Shyshatskyi, A., Babenko, V., Bieliakov, R., Odarushchenko, E., Protas, N., Stasiuk, T., Rukavyshnikov, Y., Miziak, I., Lantrat, O. (2024). Development of a solution search method using artificial intelligence. Eastern-European Journal of Enterprise Technologies, 2 (4 (128)), 38–47. <https://doi.org/10.15587/1729-4061.2024.300261>

## 1. Introduction

The theory of artificial intelligence has taken an important place in solving optimization problems in the search

for solutions in various fields of human activity. Such components of artificial intelligence theory are metaheuristic algorithms, evolutionary algorithms, bio-inspired algorithms and physics-inspired algorithms [1–3].

Due to the global optimal and gradient-free solution, metaheuristic algorithms are widely used to solve problems of finding solutions regarding the state of complex hierarchical systems and then make appropriate decisions.

Metaheuristic algorithms imitate natural phenomena by modeling the behavior of animals and other microorganisms. These algorithms are generally inspired by three concepts: species evolution, biological behavior and physical principles [4–6].

Evolutionary algorithms generate different solution spaces for optimization problems by simulating the diversity of species evolution, cross-mutation and survival of the fittest individuals [7–9].

Physics-inspired optimization algorithms apply physical principles as a way to achieve an optimal solution.

Bio-inspired algorithms imitate the behavior of living organisms, such as predation, search for migration, growth and aggregation pathways in order to solve numerical optimization problems [10–13].

Metaheuristic algorithms have achieved excellent performance results in various subject areas of human activity. However, there is no close to ideal optimization method that can solve all optimization problems. In other words, if an optimization algorithm is suitable for one class of optimization problem, it may not be suitable for another. Alternatively, the search efficiency of an optimization algorithm is inversely related to its computational complexity and a certain amount of computational cost to increase search efficiency. An obvious advantage of metaheuristic algorithms, in addition to solving large-scale problems, is taking into account the experience of solving the problem by previous agents. One such metaheuristic algorithm is the heron flock algorithm.

Given the above, an urgent scientific task is to develop a solution search method using an improved heron flock algorithm, which would increase the efficiency (reduce the time) of decisions on managing 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 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; 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, detect-

ing 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 appropriate correction of the obtained models.

The work [14] developed an analytical web platform to study the geographical and temporal distribution of incidents. The web platform contains several information panels with statistically significant results by territory. The disadvantages of the specified analytical platform include the impossibility of assessing the adequacy and reliability of the information transformation process and high computational complexity. Also, one of the shortcomings of the mentioned research is that the search for a solution is not unidirectional.

The work [15] developed a method of fuzzy hierarchical assessment of library service quality. The specified method allows you to evaluate the quality of libraries based on a set of input parameters. The disadvantages of the specified method include the impossibility of assessing the adequacy and reliability of the assessment and, accordingly, determining the assessment error.

The work [16] carried out an analysis of 30 algorithms for processing large data sets. Their advantages and disadvantages are shown. It was found that the analysis of large data sets should be carried out in layers, take place in real time and have the opportunity for self-learning. The disadvantages of these methods include their high computational complexity and the impossibility of checking the adequacy of the obtained estimates.

The work [17] presents an approach for evaluating input data for decision support systems. The essence of the proposed approach consists in clustering the basic set of input data, analyzing them, after which the system is trained based on the analysis. The disadvantages of this approach are the gradual accumulation of assessment and training errors due to the 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 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, 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 cat swarm optimization algorithms (CSO), which are very promising both in terms of speed and ease of implementation. These algorithms have proven their effectiveness in solving a number of rather complex problems and have already undergone a number of modifications. Among the modifications, procedures based on harmonic search, fractional derivatives, adaptation of search parameters and, finally, «crazy cats» can be noted. At the same time, these procedures are not without some drawbacks that worsen the properties of the global extremum search process. One such algorithm is the heron flock algorithm.

An analysis of the works [9–22] showed that the common shortcomings of the above studies are:

- the lack of possibility of forming a hierarchical system of indicators;
- the lack of consideration of computing resources of the system;
- the lack of mechanisms for adjusting the system of indicators during the assessment;
- the lack of consideration of the type of uncertainty and noise of data on the state of the analysis object, which creates corresponding errors while assessing its real state;
- the lack of deep learning mechanisms for knowledge bases;
- high computational complexity;
- the lack of search priority in a certain direction.

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

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

### 3. The aim and objectives of the study

The aim of the study is to develop a solution search method using an improved heron flock algorithm. This will increase the efficiency of assessment and multidimensional forecasting with a given reliability and development of subsequent management decisions.

To achieve the aim, the following objectives were set:

- to develop an algorithm for its solution search method using the improved heron flock algorithm;
- to give an example of using the method in analyzing the operational situation of a group of troops (forces).

### 4. Materials and methods

The object of the study is decision support systems. The subject of the study is the decision-making process in management problems using an improved heron flock algorithm, an improved genetic algorithm and evolving artificial neural networks.

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

Simulation of the proposed method was carried out in the MathCad 14 software environment (USA). The problem solved during the simulation was to assess the elements of the operational situation of a group of troops (forces). The hardware of the research process is AMD Ryzen 5.

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

The research is based on the heron flock algorithm for finding a solution regarding the object state. Evolving artificial neural networks are used to train heron agents (HA), and an advanced genetic algorithm is used to select the best HA.

### 5. Results of developing a solution search method using the improved heron flock algorithm

#### 5.1. Development of a solution search algorithm, metrics and criteria using a metaheuristic approach

Heron is a collective term for four bird species. Herons are usually seen in pairs or small groups, but large flocks of dozens or hundreds can also be seen. Due to the high energy consumption in flight, the solution (prey) usually requires careful trajectory checking to ensure that it can gain more energy through the location of the food than what would be spent in flight. Herons use two strategies: sit and wait, the more stressful (aggressive) strategy. These strategies are characterized by different degrees of energy consumption and amounts of food that can be captured.

The proposed algorithm is an improved heron flock algorithm and consists of the following sequence of actions (Fig. 1):

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

Step 2. Setting heron agents (HA) on the search plane.

At this stage, HA are set taking into account the type of uncertainty about the object to be analyzed and the basic model of the object's state is initialized [2, 19, 21]. In this case, the degree of uncertainty can be: full awareness; partial uncertainty and total uncertainty:

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

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

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

Here  $X$  is the population matrix,  $X_i$  is the  $i$ -th member (solution candidate),  $x_{i,d}$  is the  $d$ -th dimension in the search space (solution variable),  $N$  is the number of HA,  $m$  is the number of solution variables,  $r$  is a random number in the interval  $[0,1]$ ,  $lb_d$  and  $ub_d$  are the lower and upper bounds of the  $d$  solution variables, respectively.

This is done using appropriate correction factors, which are set at the analysis stage.

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

Each HA is assigned a number that searches for food sources. A food source refers to a solution to the optimization problem.

Step 4. Setting the initial HA velocity.

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

$$v_i = (v_1, v_2 \dots v_s), v_i = v_0. \quad (3)$$

The initial velocity of each HA is determined in direct proportion to the distance that must be flown.

Step 5. Selection of the best individuals from the HA flock.

At this stage, the best HA in the flock are selected using an improved genetic algorithm proposed by the authors according to [23] by size indicators, mutation rate and attractiveness coefficient (geometric dimensions of the bird).

Step 5. 1. Input of initial data:  $s(x^{(k)})$  is non-normalized interval partial criteria of alternatives;  $s_{\min}$  and  $s_{\max}$  are the values of the minimum and maximum alternatives;  $kol$  is the number of iterations;  $d$  is the crossing-over position;  $q$  is the mutation position;  $w_j$  is the interval coefficient of the relative importance of the  $j$ -th partial criterion of alternatives and the determination of the initial population size  $P=2p$ .

Step 5. 2. Determining necessary optimization conditions:

Step 5. 3. Formation of the initial population – parent individuals (four options of the state vectors of the analysis object for each  $k$ -th alternative of the object state) using a random number generator:

$$s_1^P(x^{(1)}) = (s_1^{P(1)}, s_2^{P(1)}, s_3^{P(1)}, s_4^{P(1)}),$$

$$s_2^P(x^{(2)}) = (s_1^{P(2)}, s_2^{P(2)}, s_3^{P(2)}, s_4^{P(2)}),$$

$$s_3^P(x^{(3)}) = (s_1^{P(3)}, s_2^{P(3)}, s_3^{P(3)}, s_4^{P(3)}),$$

$$s_4^P(x^{(4)}) = (s_1^{P(4)}, s_2^{P(4)}, s_3^{P(4)}, s_4^{P(4)}).$$

Formation of the initial population in which chromosomes are encoded as 8-bit sets of values. This type of chromosome allows you to leave genes arranged sequentially after applying the mutation operator. Preserving the continuous arrangement of genes enables the genetic crossover operator to copy continuous sections of the working memory of the parent chromosomes to the daughter chromosome, which allows faster crossing [10].

Step 5. 4. Calculation of the resource intensity of the obtained values and checking the conditions for not exceeding  $res_{add}$  for each individual in the initial population:

$$res_i = f(U_{eff}), \quad (4)$$

where  $U_{eff}$  are key efficiency indicators.

Step 5. 5. Calculation of the membership function of the level of target achievement  $\Lambda_{ij}^{targ}$ , which consists in implementing an iterative procedure for calculating target indicators based on the developed fuzzy cognitive model:

$$\Lambda_{ij}^{targ} = f(U_{eff}), j = \overline{1, k}. \quad (5)$$

Step 5. 6. Calculation of the algorithm stop parameter based on the minimum deviation of the target achievement level with respect to the required value:

$$\Delta\Lambda_{ij}^{targ} = \Lambda_{ij}^{targ} - \Lambda_{i \text{ required value}}^{targ}, \quad (6)$$

$$\Delta\Lambda = \min_i \min_j \Delta\Lambda_{ij}^{targ}.$$

Step 5. 7. Adding the vector  $s_k^p(x^{(k)})$  in the population.

Step 5. 8. Carrying out a single-point crossover operation for the obtained options of vectors of the  $k$ -th alternative  $s^P(x^{(k)})$  (crossover point  $d < 4$ ). Selection of individuals and formation of pairs for crossing according to their fitness function. The proposed selection procedure is implemented using the optimization algorithm parameter adaptation mechanism described in [1].

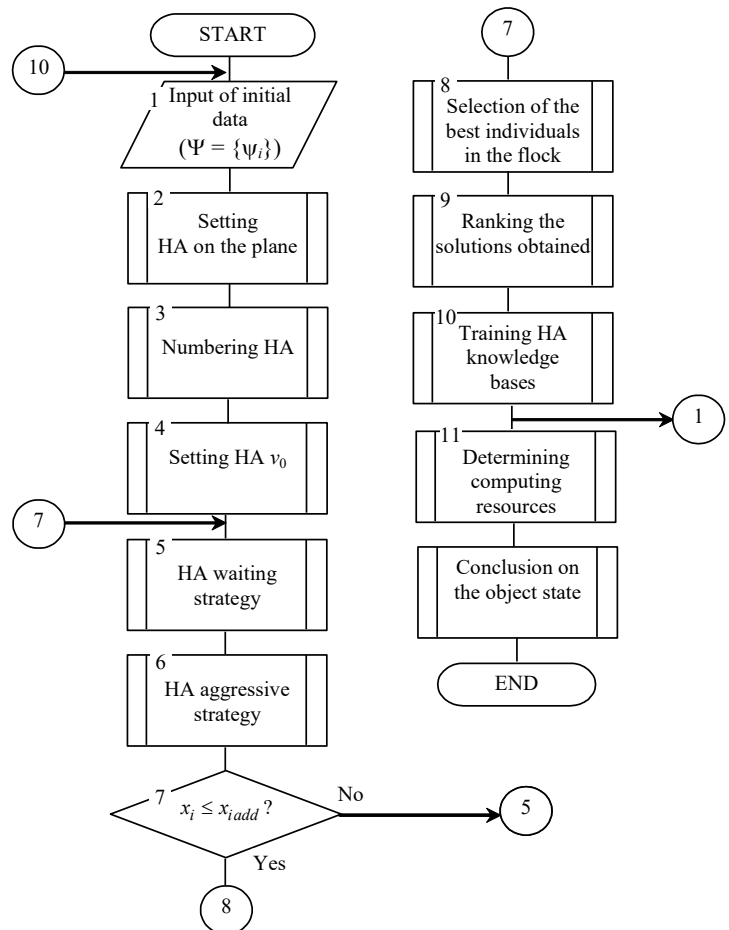


Fig. 1. Algorithm for implementing the solution search method



This adaptation mechanism is based on a compromise between the rate of convergence and the quality of the obtained locally optimal solution, its essence boils down to the fact that the probability of selecting individuals flexibly changes depending on the search background [11].

To this end, the normal probability distribution law of selection is used. The mathematical expectation is taken equal to the value of the fitness function of the best population chromosome for a given generation. If the best chromosome changes in the next generation, then the variance takes the maximum value, thereby expanding the search range. If a better chromosome is found within several generations, then the variance decreases, in the simplest case, in proportion to the number of generations:

$$D = D_{\max} - \beta \times g, \tag{7}$$

where  $D_{\max}$  is the maximum value of variance;  $\beta$  is the coefficient that determines the convergence rate of the algorithm;  $g$  is the number of «unsuccessful» generations.

The mathematical expectation of the distribution function is equal to the value of the  $F_{\max}$  function. The random variable  $X_i$  is continuous, unlike the discrete values  $F_k, k=1,2,\dots,M$  and it is necessary to choose such value  $F_k$  of the fitness function, the distance from which to  $F_{\max}$  would be closest to the distance from  $X_i$  to  $F_{\max}$ :

$$k = \arg \min \| |F_{\max} - X| - |F_{\max} - X| \|. \tag{8}$$

In this case, this value will be  $F_j$ .

In subsequent selection cycles, it is necessary to take into account the value of the fitness function corresponding to individuals already selected in previous cycles. This will ensure the diversity of the population composition.

The described mechanism forms prerequisites for elite selection, preserves the best of the found population chromosomes and is used in three cases [24–28]:

- before the crossing-over stage to select the crossed individuals;
- before the mutation stage to select mutating individuals;
- after applying all GA operators to select the most suitable individuals in the next generation.

As a result of the crossing-over operation, 12 offspring individuals are obtained:

$$\begin{aligned} s_1^P(x^{(1)}) &= (s_1^{P(1)}, s_d^{P(1)}, s_{d+1}^{P(2)}, s_4^{P(2)}), \\ s_2^P(x^{(2)}) &= (s_1^{P(2)}, s_d^{P(2)}, s_{d+1}^{P(1)}, s_4^{P(1)}), \\ s_3^P(x^{(1)}) &= (s_1^{P(1)}, s_d^{P(1)}, s_{d+1}^{P(3)}, s_4^{P(3)}), \\ s_4^P(x^{(3)}) &= (s_1^{P(3)}, s_d^{P(3)}, s_{d+1}^{P(1)}, s_4^{P(1)}), \\ s_5^P(x^{(1)}) &= (s_1^{P(1)}, s_d^{P(1)}, s_{d+1}^{P(4)}, s_4^{P(4)}), \\ s_6^P(x^{(4)}) &= (s_1^{P(4)}, s_d^{P(4)}, s_{d+1}^{P(1)}, s_4^{P(1)}), \\ s_7^P(x^{(2)}) &= (s_1^{P(2)}, s_d^{P(2)}, s_{d+1}^{P(3)}, s_4^{P(3)}), \\ s_8^P(x^{(3)}) &= (s_1^{P(3)}, s_d^{P(3)}, s_{d+1}^{P(2)}, s_4^{P(2)}), \\ s_9^P(x^{(2)}) &= (s_1^{P(2)}, s_d^{P(2)}, s_{d+1}^{P(4)}, s_4^{P(4)}), \\ s_{10}^P(x^{(4)}) &= (s_1^{P(4)}, s_d^{P(4)}, s_{d+1}^{P(2)}, s_4^{P(2)}), \\ s_{11}^P(x^{(3)}) &= (s_1^{P(3)}, s_d^{P(3)}, s_{d+1}^{P(4)}, s_4^{P(4)}), \\ s_{12}^P(x^{(4)}) &= (s_1^{P(4)}, s_d^{P(4)}, s_{d+1}^{P(3)}, s_4^{P(3)}). \end{aligned} \tag{9}$$

The crossing-over operator (crossover, crossing) allows you to create offspring chromosomes based on crossing the parents' chromosomes. Single-point crossover consists in cutting the parents' chromosomes at a randomly chosen common point of the cut (break) and exchanging the right parts («tails» of chromosomes).

Step 5.9. Adding the vector  $s_h^P(x^{(k)}), h=1,\dots,12$  to the population.

Step 5.10. Carrying out the operation of single-point mutation of the obtained 12 offspring individuals (mutation rate  $q=12$ ). With the arrival of an offspring individual by mutation, a new offspring individual with mutated genes  $\bar{s}_i^M(x^{(1)}) = (s_1^M, s_q^M, \bar{s}_{q+1}^M, s_4^M)$  emerges. Similarly, this operation is performed for other offspring individuals. The mutation operator allows you to randomly make changes to individuals, which later acquire new properties. Single-point mutation consists in randomly selecting a gene that exchanges its value with an adjacent gene.

Step 5.11. Implementation of normalization of partial criteria  $p_j^{norm}(x^{(k)})$ , including the expected cost of alternatives for each  $k$ -th alternative of evaluating the object state according to the formula:

$$\begin{aligned} c_j(x^{(k)}) &= [c_{j1}(x^{(k)}), c_{j2}(x^{(k)}), c_{j3}(x^{(k)}), c_{j4}(x^{(k)})], \\ p_j^{norm}(x^{(k)}) &= \left[ \frac{c_{j1}(x^{(k)})}{c_j^{\max}}, \frac{c_{j2}(x^{(k)})}{c_j^{\max}}, \frac{c_{j3}(x^{(k)})}{c_j^{\max}}, \frac{c_{j4}(x^{(k)})}{c_j^{\max}} \right], \\ c_j^{\max} &= \max_{1 \leq k \leq m} \{c_{j4}^{(k)}\}, \end{aligned} \tag{10}$$

where  $c_{j1}(x^{(k)}), c_{j4}(x^{(k)})$  are pessimistic and optimistic estimates of the interval boundaries,  $c_{j2}(x^{(k)}), c_{j3}(x^{(k)})$  are the interval of the most expected values. Calculation of interval coefficients  $w_j^{norm}$  of relative importance of partial criteria according to the formula:

$$w_j^{norm} = \frac{w_j}{\sum_{j=1}^n w_j}, j = \overline{1, n}, \tag{11}$$

where  $w_j$  is the interval coefficient of relative importance of the  $j$ -th part of the criterion, which can be represented as intervals, fuzzy triangular, trapezoidal numbers and polyhedral numbers.

Step 5.12. Selection of four individuals (four vectors) out of 12 possible with the largest values of the objective function, which will be parents for the next iteration (generation) or in the case of performing all iterations – the result of calculations.

Since the proposed problem considers four alternatives for estimating the state of an object, only four vectors of the expected state are selected. The selection of individuals is carried out by the ranking method, that is, individuals of the population are ranked according to the value of their fitness function (ranking is carried out in ascending order of values). Since estimates of generalized utility  $P(x^{(k)})$  are presented as trapezoidal fuzzy numbers, the Chiu-Park method is used to select an acceptable alternative for the object state.

Step 5.13. Saving the obtained results.

Step 5.14. Output of results (vectors of alternatives  $s(x^{(k)})$  and multicriteria estimation  $Cp(P(x^{(k)}))$  for each  $k$ -th alternative).

Step 5. 15. Selection of an acceptable alternative. An acceptable alternative is the one with the greatest generalized utility.

End of the algorithm.

Step 6. HA waiting strategy.

The observation equation is described from the assumption: assuming that the position of the  $i$ -th HA flock is described by the size of the search space  $x_i \in R^n$ ,  $n$ .

$A(*)$  is the probability of prey being present in its current location. Taking into account the multidimensionality of the search space, the current location (the place to which the HA moved) will be calculated using the Owen function  $T(h, a)$ , where  $h$  is the HA flight time;  $a$  is the distance covered by the HA per unit of time.

$\hat{y}$  is the attractiveness (priority of solution search in the specified search space) of the prey in the current location, which is defined by the following expression:

$$\hat{y}_i = A(x_i). \quad (12)$$

The method of estimating the value of the prey in the current location can be described as follows:

$$\hat{y}_i = \omega_i \cdot x_i. \quad (13)$$

The evaluation error  $e_i$  is described below:

$$e_i = \|\hat{y}_i - y_i\|^2 / 2. \quad (14)$$

Meanwhile,  $\hat{y}_i \in R^n$ , the practical gradient  $\omega_i$  can be obtained by taking the partial derivative of  $\omega_i$  for the error equation (4) and its direction  $\hat{d}_i$ :

$$\hat{g}_i = \frac{\partial \hat{e}_i}{\partial \omega_i} = \frac{\partial \|\hat{y}_i - y_i\|^2 / 2}{\partial \omega_i} = (\hat{y}_i - y_i) \cdot x_i, \quad (15)$$

$$\hat{d}_i = \hat{g}_i / |\hat{g}_i|.$$

HA refers to the best HA individual during hunting, based on its experience in assessing prey behavior and taking into account its own opinion.

While HA hunting, the correction of the direction of the best location of the flock elements  $d_{h,i} \in R^n$  and the correction of the direction of the best location of the entire flock  $d_{g,i} \in R^n$  are taken into account.

This is set taking into account the noise degree of information about the state of the analysis object, which is calculated by the following expressions:

$$d_{h,i} = \left( \frac{X_{ibest} - X_i}{|X_{ibest} - X_i|} \cdot \frac{f_{ibest} - f_i}{|X_{ibest} - X_i|} + d_{ibest} \right) \times \iota, \quad (16)$$

$$d_{g,i} = \left( \frac{X_{gbest} - X_i}{|X_{gbest} - X_i|} \cdot \frac{f_{gbest} - f_i}{|X_{gbest} - X_i|} + d_{gbest} \right) \times \iota, \quad (17)$$

where  $\iota$  is the coefficient that determines the noise degree of information about the research object. The coefficient of data noise is taken according to the reliability of the information before setting HA: reliable, probable, unlikely, doubtful, unreliable, without reliability assessment.

$best$  is the best solution for each variable from the entire set of values.

The integral gradient  $g_i \in R^n$  is described as follows  $r_h \in [0,0,5)$ ,  $r_g \in [0,0,5)$  taking into account expressions (1)–(17),

i.e. by determining the priority search directions taking into account the number of individuals in the flock and the size of the search space:

$$g_i = (1 - r_h - r_g) \cdot \hat{d}_i + r_h \cdot d_{h,i} + r_g \cdot d_{g,i}. \quad (18)$$

The adaptive weight update method [2] is used here,  $\beta_1$  is 0.99:

$$\begin{aligned} m_i &= \beta_1 \cdot m_i + (1 - \beta_1) \cdot g_i, \\ v_i &= \beta_1 \cdot v_i + (1 - \beta_1) \cdot g_i^2, \\ \omega_i &= \omega_i - m_i / \sqrt{v_i}. \end{aligned} \quad (19)$$

According to the HA assessment of the current situation, the next food search location  $x_{a,i}$  can be described as:

$$x_{a,i} = x_i + \exp(-t / (0.1 \cdot t_{\max})) \cdot 0.1 \cdot hop \cdot g_i, \quad (20)$$

$$y_{a,i} = f(x_{a,i}), \quad (21)$$

where  $t$  and  $t_{\max}$  are the current iteration time and maximum iteration time,  $hop$  is the gap between the lower and upper bounds of the solution space,  $y_{a,i}$  is the suitability of the food search location  $x_{a,i}$ , which is determined by the number of food sources per unit area.

Step 7. Aggressive strategy. HA tends to randomly search for prey, and its behavior is depicted below:

$$x_{b,i} = x_i + \tan(r_{b,1}) \cdot hop / (1 + t), \quad (22)$$

$$y_{b,i} = f(x_{b,i}), \quad (23)$$

where  $r_{b,i}$  is a random number in  $(-\pi/2, \pi/2)$ ,  $x_{b,i}$  is the expected next location of the HA;  $y_{b,i}$  is fitness.

HA prefers to aggressively pursue prey, so the encirclement mechanism is used as a method of updating its position:

$$\begin{aligned} D_h &= x_{ibest} - x_i, D_g = x_{gbest} - x_i, \\ X_{c,i} &= (1 - r_i - r_g) \cdot x_i + r_h \cdot D_h + r_g \cdot D_g, \end{aligned} \quad (24)$$

$$y_{b,i} = f(X_{b,i}),$$

$D_h$  is the gap matrix between the current location and the best position of this HA flock, while  $D_g$  is compared to the best location of all HA flocks;  $x_{c,i}$  is the expected location of HA;  $r_h$  and  $r_g$  are random numbers in  $[0,0,5]$ .

Step 8. Checking the discriminatory condition. After each member of the HA flock decides on its plan, taking into account the basic knowledge of the decision suitability criterion, the flock chooses the best option and performs joint actions according to the decision matrix of the  $i$ -th HA flock  $x_{s,i}$ :

$$x_{s,i} = [x_{a,i} x_{b,i} x_{c,i}], \quad (25)$$

$$y_{s,i} = [y_{a,i} y_{b,i} y_{c,i}], \quad (26)$$

$$C_i = \arg \min(y_{s,i}), \quad (27)$$

$$x_i = \begin{cases} x_{s,i|c_i} & \text{if } y_{s,i|c_i} \langle y_i \text{ or } r < 0.3, \\ x_i & \text{else.} \end{cases} \quad (28)$$

If the minimum value of  $y_{s,i}$  is better than the current fitness of  $y_i$ , the heron flock will make a choice. Or if the random number  $r \in (0, 1)$  is less than 0.15, it means that there is a 15 % probability that the worst case scenario will happen.

Step 9. Ranking and sorting the obtained solutions.

After recalculating the HA position, the mutation rate is added. The cost of HA is compared again, the best result is selected from the list of the best (in this case, out of 10). After each iteration, it is necessary to sort the best solutions and reduce the mutation rates.

Step 10. Training HA knowledge bases.

In this study, the learning method based on evolving artificial neural networks developed in [2] is used to train the knowledge bases of each HA. This is necessary to change the nature of movement of each HA, for more accurate analysis results in the future. The knowledge base is specified from the list of knowledge bases that are used for typical tasks: identifying weapons and military equipment, determining the type and number of similar objects in the area of interest, determining the organizational and staff structure of organizational and staff formations, etc. Neural networks are used to input, output, and update the necessary basic data. The work of this method is given in more detail in [2].

Step 11. Determining the amount of necessary computing resources of the intelligent decision support system.

In order to prevent looping of calculations on Steps 1–10 of the method, the necessary amount of resources that must be involved is determined. The maximum amount of computing resources is defined as the number of calculations per unit of time that the system can perform. Everything above must be involved.

When the specified threshold of computational complexity is exceeded, the amount of software and hardware resources that must be additionally involved is determined using the method proposed in [29].

End of the algorithm.

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

A solution search method using the improved heron flock algorithm is proposed. To assess the effectiveness of the developed method, its comparative evaluation was performed based on the results of research presented in [3–6, 29–31].

Simulation of the solution search processing method was carried out in accordance with Steps 1–11. Simulation of the proposed method was carried out in the MathCad 14 software environment (USA). The problem solved during the simulation was to assess the elements of the operational situation of a group of troops (forces).

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 means, earth remote sensing tools and unmanned aerial vehicles). To simplify the modeling, the same amount 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 devices, the type of operational structure are also taken into account;

- options of organizational and personnel formations – company, battalion, brigade.

The initial data for the comparative analysis of the effectiveness of the proposed HFA are set the same for all algorithms, for example, the population size  $NP=50$ ; the maximum number of iterations is 1,000.

Unimodal functions according to which the research was conducted are typical optimization functions. More detailed parameters of these functions are given in Table 1.

Analysis of tabular values given in Table 1 shows the same fitness of HA individuals for the proposed method for the main 7 unimodal functions.

Table 2 shows the results of a comparative evaluation of the efficiency of the algorithms by the criterion of efficiency of decision-making regarding the object state (the speed of determining the object state under reliability restrictions).

Table 1

Parameters of unimodal functions while solving an optimization problem

Type of unimodal function	Population size	Range of space solutions	$F_{min}$
$F_1(x) = \sum_{i=1}^n x_i^2$	50	[-150,150]	0
$F_2(x) = \sum_{i=1}^n  x_i  + \prod_{i=1}^n  x_i $	50	[-15,15]	0
$F_3(x) = \sum_{i=1}^n \left( \sum_{j=1}^i x_j \right)^2$	50	[-150,150]	0
$F_4(x) = \max_i \{  x_i , 1 \leq i \leq n \}$	50	[-150,150]	0
$F_5(x) = \sum_{i=1}^{n-1} \left[ 100(x_{i+1} - x_i^2)^2 + (x_i - 1)^2 \right]$	50	[-50,50]	0
$F_6(x) = \sum_{i=1}^n \left( [x_i + 0.5]^2 \right)$	50	[-150,150]	0
$F_7(x) = \sum_{i=1}^n ix_i^4 + random[0,1)$	50	[-1.5,1.5]	0

Table 2

Results of a comparative evaluation of the efficiency of the algorithms by the criterion of efficiency of decision-making regarding the object state

Name of the algorithm	Number of iterations	Reliability	Time, s
Walrus optimization algorithm	1,000	0.9	47,601
Particle swarm optimization algorithm			47,618
Flying squirrel search optimization algorithm			45,113
Artificial bee colony algorithm			46,009
Ant colony optimization algorithm			47,114
Proposed method			35,110
Monkey search algorithm			46,935
Bat swarm algorithm			44,770
Locust swarm optimization algorithm			49,155
Genetic algorithm			46,788
Cat swarm optimization algorithm			47,883
Firefly algorithm			46,152

Analysis of Tables 1, 2 allows us to conclude that the specified method can increase the efficiency of decision-making regarding the state of the analysis object by 22–25 %, depending on the type of function.

---

### 6. Discussion of the results of developing a solution search method using the improved heron flock algorithm

---

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

- when initially setting HA on the search plane, the type of uncertainty is taken into account (Step 2), in contrast to [9, 11];
- universality of application of the proposed method for analyzing the state of HA objects due to the hierarchical nature of their description (Steps 1–11), in contrast to [12, 13];
- simultaneous search for a solution on the plane by several HA (Steps 1–11, Tables 1, 2), in contrast to [13–20];
- convergence and adequacy of the results obtained (Steps 1–11), in contrast to [8, 17];
- the ability to avoid the local extremum problem (Steps 1–11), in contrast to [15–17];
- the possibility of deep learning of HA knowledge bases (Step 10), in contrast to [8–22, 30];

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 parameter for assessing 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 the heterogeneous analysis object;
- to determine effective measures to improve management efficiency;
- to increase the speed of assessing the state of the heterogeneous analysis object;
- 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 analysis object state, the need to take into account the delay time for collecting and communicating information from intelligence sources.

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

This study is a further development of research aimed at developing methodological principles for increasing the efficiency of processing various types of data, published earlier [2, 4–6, 30].

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

---

### 7. Conclusions

---

1. An algorithm for implementing the method was determined, due to additional and improved procedures, which allows you:

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

- to take into account the available computing resources of the object state analysis system;
- to take into account the search priority of HA;
- to carry out the initial setting of HA individuals taking into account the type of uncertainty;
- to carry out accurate training of HA individuals;
- to determine the best individuals of HA using a genetic algorithm;
- to conduct a local and global search taking into account the noise degree of data on the analysis object state;
- to conduct training of knowledge bases, which is carried out by training the synaptic weights of the artificial neural network, the type and parameters of the membership function, the architecture of individual elements and the architecture of the artificial neural network as a whole;
- to be used as a universal tool for solving the problem of analyzing the state of 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 in assessing and forecasting the state of the operational situation of a group of forces is given. The specified example showed an increase in the efficiency of data processing at the level of 22–26 % due to the use of additional improved procedures of adding correction factors for uncertainty and noise of data, HA selection and training.

---

### Conflict of interest

---

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

---

### Financing

---

The research was conducted without financial support.

---

### 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.

---

### Acknowledgments

---

The author team expresses gratitude for providing assistance in the preparation of the paper to:

- Shovkovska Nataliya – a teacher of the secondary school of grades I–III No. 2 in Svitlovodsk, Kirovohrad region;
- Doctor of Technical Sciences, professor Kuvshinov Oleksiy – deputy head of the educational and scientific institute of the National Defense University of Ukraine named after Ivan Chernyakhovsky;



– Doctor of Technical Sciences, professor Rotshtein Oleksandr – professor of the Mahon Lev Polytechnic Institute of Jerusalem;

– PhD, Associate Professor Bashkirov Oleksandr – leading researcher of the Central Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine.

---

### 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](http://nbuv.gov.ua/UJRN/ovt_2015_1_7)
2. Dudnyk, V., Sinenko, Y., Matsyk, M., Demchenko, Y., Zhyvotovskiy, 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. <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. <https://doi.org/10.21303/2461-4262.2021.001940>
4. Pievtsov, H., Turinskyi, O., Zhyvotovskiy, 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. <https://doi.org/10.21303/2461-4262.2020.001353>
5. Zuiev, P., Zhyvotovskiy, 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. <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. <https://doi.org/10.30534/ijatse/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. [https://doi.org/10.46338/ijetae0521\\_05](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. <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. <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. <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. <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. <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. <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. <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. <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. [https://doi.org/10.1016/s0020-7373\(86\)80040-2](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. <https://doi.org/10.15587/1729-4061.2022.268621>
19. Maccarone, A. D., Brzorad, J. N., Stone, H. M. (2008). Characteristics and Energetics of Great Egret and Snowy Egret Foraging Flights. *Waterbirds*, 31 (4), 541–549. <https://doi.org/10.1675/1524-4695-31.4.541>
20. Koshlan, A., Salnikova, O., Chekhovska, M., Zhyvotovskiy, 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. <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. <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. <https://doi.org/10.20998/2522-9052.2021.3.01>
23. Bezuhlyi, V., Oliynyk, V., Romanenko, I., Zhuk, O., Kuzavkov, V., Borysov, O. et al. (2021). Development of object state estimation method in intelligent decision support systems. *Eastern-European Journal of Enterprise Technologies*, 5 (3 (113)), 54–64. <https://doi.org/10.15587/1729-4061.2021.239854>
24. 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. <https://doi.org/10.20998/2522-9052.2020.1.16>
25. Raskin, L., Sira, O. (2016). Method of solving fuzzy problems of mathematical programming. *Eastern-European Journal of Enterprise Technologies*, 5 (4 (83)), 23–28. <https://doi.org/10.15587/1729-4061.2016.81292>
26. 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. <https://doi.org/10.15587/1729-4061.2017.98750>
27. Stepanenko, A., Oliinyk, A., Deineha, L., Zaiko, T. (2018). Development of the method for decomposition of superpositions of unknown pulsed signals using the secondorder adaptive spectral analysis. *Eastern-European Journal of Enterprise Technologies*, 2 (9 (92)), 48–54. <https://doi.org/10.15587/1729-4061.2018.126578>
28. Gorbenco, 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. <https://doi.org/10.15587/1729-4061.2017.96321>
29. 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. <https://doi.org/10.15587/1729-4061.2022.266009>
30. Levashenko, V., Liashenko, O., Kuchuk, H. (2020). Building Decision Support Systems based on Fuzzy Data. *Advanced Information Systems*, 4 (4), 48–56. <https://doi.org/10.20998/2522-9052.2020.4.07>
31. 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. <https://doi.org/10.20998/2522-9052.2020.2.05>