*The object of the study is heterogeneous data in organizational-technical systems. The subject of the study is the process of heterogeneous data processing. The problem of this study is enhancing the efficiency of heterogeneous data processing in organizational-technical systems while ensuring a predefined level of reliability, regardless of the volume of incoming data. A method for heterogeneous data processing in organizational-technical systems has been developed. The originality of the method lies in the use of additional improved procedures, which allow:*

*– achieving the placement of the initial population of agents in the combined algorithm swarm and their initial position in the search space, considering the uncertainty level of input data circulating in the organizational-technical system. This is achieved using correction coefficients;*

*– accounting for the initial velocity of each agent in the combined algorithm swarm, enabling search prioritization in the corresponding search space (across elements and components of the organizational-technical system);*

*– determining the feasibility of decisions in heterogeneous data processing, considering external factors, which reduces the solution search time;*

*– ability to calculate the required computational resources, determining the additional resources needed in case existing computational capacity is insufficient.*

*A practical implementation of the proposed method was tested on heterogeneous data processing in an operational military task force, demonstrating: a 14–20 % increase in decision-making efficiency due to the integration of additional procedures; a decision reliability level maintained at 0.9*

*Keywords: heterogeneous data, unimodal functions, multimodal functions, destabilizing factors, heterogeneous grouping*

UDC 004.81

DOI: 10.15587/1729-4061.2025.322629

# DEVELOPMENT OF HETEROGENEOUS DATA PROCESSING METHOD IN ORGANIZATIONAL AND TECHNICAL SYSTEMS

**Salman Rasheed Owaid**
PhD, Assosiate Professor
Department of Computer Engineering
Al Taff University College
Karrada str., 3, Karbala, Iraq, 31001

**Svitlana Kashkevich**
Senior Lecturer
Department of Intelligent Cybernetic Systems*

**Andrii Shyshatskyi**
*Corresponding author*
Doctor of Technical Sciences, Senior Researcher, Professor
Department of Intelligent Cybernetic Systems*
E-mail: ierikon13@gmail.com

**Hryhorii Radzivilov**
PhD, Professor, Deputy Head of the Institute for Research**

**Oleg Sova**
Doctor of Technical Sciences, Professor, Head of Center
Simulation Modeling Center
National University of Defense of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03049

**Artur Zarubenko**
PhD, Deputy Head of Department
Department of Telecommunication Systems and Networks**

**Andrii Veretnov**
PhD, Leading Researcher
Research Department
Central Scientifically-Research Institute of Armaments and Military Equipment of the Armed Forces of Ukraine
Povitrianykh Syl ave., 28, Kyiv, Ukraine, 03049

**Roman Lazuta**
Junior Researcher
Scientific and Organizational Department
Research Center
Institute of Special Communications and Information Protection
National Technical University of Ukraine "Igor Sikorsky Kyiv Polytechnic Institute"
Beresteiskyi str., 4, Kyiv, Ukraine, 03056

**Oleksii Noskov**
Adjunct
Scientific and Organizational Department**

**Anastasiia Voznytsia**
PhD Student*

*State University "Kyiv Aviation Institute"
Lubomyra Huzara ave., 1, Kyiv, Ukraine, 03058

**Military Institute of Telecommunications and Informatization named after Heroes of Kruty
Knyaziv Ostroz'kykh str., 45/1, Kyiv, Ukraine, 01011

*Received 03.12.2024*
*Received in revised form 16.01.2025*
*Accepted 07.02.2025*
*Published 24.02.2025*

***How to Cite:** Owaid, S. R., Kashkevich, S., Shyshatskyi, A., Radzivilov, H., Sova, O., Zarubenko, A., Veretnov, A., Lazuta, R., Noskov, O., Voznytsia, A. (2025). Development of heterogeneous data processing method in organizational and technical systems. Eastern-European Journal of Enterprise Technologies, 1 (4 (133)), 64–71. https://doi.org/10.15587/1729-4061.2025.322629*

## 1. Introduction

The issue of enhancing the efficiency of heterogeneous data processing in decision support systems (DSS) is highly relevant in modern information and automated systems of various functional purposes [1–3]. The experience of recent conflicts involving modern information and automated systems has shown that the use of existing heterogeneous data processing methods allows for the processing of only 5 to 10 % of the heterogeneous data circulating within them [3–5].

This limitation is due to the following factors:

– significant role of the human factor in processing heterogeneous data circulating in information and automated systems;

– large number of heterogeneous information sources included in automated and information systems;

– heterogeneous data processing is performed under uncertainty, causing delays in data processing;

– presence of a large amount of destabilizing data, which affects the efficiency of heterogeneous data processing;

– existence of structured and unstructured data in information and automated systems, all of which require processing.

Given the diversity of data types, the large number of destabilizing factors, and the varying dimensions of data descriptors, the need to process large volumes of heterogeneous data necessitates the search for new processing approaches. One such approach is the use of metaheuristic algorithms [5–8].

Using metaheuristic algorithms in their canonical form improves the efficiency of heterogeneous data processing; however, further enhancements cannot be achieved solely by limiting their application to canonical forms.

This necessitates the development of various strategies to improve the convergence speed and accuracy of fundamental metaheuristic algorithms in heterogeneous data processing. One approach to increasing the efficiency of heterogeneous data processing using metaheuristic algorithms is their further refinement through integration, comparison, and the development of new procedures for their combined application.

## 2. Literature review and problem statement

In [9], a cognitive modeling algorithm is presented, highlighting the main advantages of cognitive tools. However, a drawback of this approach is the lack of consideration for the type of uncertainty regarding the state of the analyzed object.

In [10], the essence of cognitive modeling and scenario planning is discussed. The study proposes a system of complementary principles for constructing and implementing scenarios, different scenario-building approaches, and a scenario modeling procedure based on fuzzy cognitive maps. However, the proposed approach fails to account for the type of uncertainty regarding the analyzed object's state and does not consider the noise in initial data.

In [11], an analysis of cognitive modeling approaches is conducted. Cognitive analysis allows for: examining problems with fuzzy factors and interconnections; considering changes in the external environment and using objectively formed development trends in decision-making. However, the study does not address the description of complex and dynamic processes.

In [12], a method for analyzing large data sets is presented, aimed at extracting hidden information from big data. The method includes generating analytical baselines, reducing variables, detecting sparse features, and formulating rules. A limitation of this method is the inability to consider different decision evaluation strategies and the lack of consideration for the type of uncertainty in input data.

In [13], a mechanism for transforming information models in construction projects into their equivalent structural models is presented. This mechanism is designed to automate operations related to transformation, modification, and data exchange. However, this approach does not allow for assessing the adequacy and reliability of the information transformation process, nor does it support correcting the generated models.

In [14], an analytical web platform is developed to analyze the geographic and temporal distribution of incidents. The platform contains multiple information panels displaying statistically significant results across different regions. However, limitations of this platform include the inability to evaluate the adequacy and reliability of information transformation processes, high computational complexity, and a lack of a unified approach to solution searching.

In [15], a fuzzy hierarchical method for evaluating library service quality is proposed. This method enables quality assessment based on multiple input parameters. However, it does not allow for evaluating the adequacy and reliability of assessments, making it difficult to determine evaluation errors.

In [16], an analysis of 30 big data processing algorithms is conducted, outlining their advantages and limitations. The study concludes that big data analysis should be layered, operate in real time, and support self-learning. However, the high computational complexity and lack of verification for obtained assessments remain major drawbacks.

In [17], a data assessment approach for decision support systems (DSS) is introduced. The method involves clustering input data, analyzing it, and using the results for system training. However, it suffers from gradual accumulation of evaluation errors and lacks a mechanism to verify the adequacy of decision-making results.

In [18], a data processing approach for multiple information sources is presented. While the approach enables data processing from various sources, it has low assessment accuracy and does not allow for verification of result reliability.

In [19], a comparative analysis of existing decision support technologies is conducted, covering hierarchy analysis, neural networks, fuzzy set theory, genetic algorithms, and neuro-fuzzy modeling. The study highlights the advantages and disadvantages of these approaches and their areas of application. It is shown that hierarchy analysis works well with complete initial data but introduces subjectivity due to expert comparisons of alternatives and evaluation criteria selection. For forecasting under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

In [20], a combination of multiple metaheuristic algorithm strategies is discussed. However, the approach has insufficient processing efficiency for heterogeneous data when using multiple metaheuristic algorithms simultaneously.

The analysis of studies [9–20] reveals the following common shortcomings:

– lack of a hierarchical indicator system for evaluating the heterogeneous data processing process;

– failure to account for computational resources in the data processing management system;

– absence of mechanisms for adjusting system indicators in heterogeneous data processing management;

– lack of deep learning mechanisms for knowledge bases;

– high computational complexity;

– no consideration of available (hardware) resources in DSS;

– no prioritization in searching for solutions in specific directions.

## 3. The aim and objectives of the study

The aim of this study is to develop a heterogeneous data processing method for organizational-technical systems. This will enhance the efficiency of heterogeneous data processing in such systems with a predefined level of reliability and facilitate the subsequent development of managerial decisions based on heterogeneous data processing. The results will enable the development (or improvement) of software for heterogeneous data processing in organizational-technical systems.

To achieve this aim, the following objectives were defined:

– define an algorithm for method implementation;

– provide an example of method application for heterogeneous data processing in organizational-technical systems.

## 4. Materials and methods

The object of the study is heterogeneous data in organizational-technical systems. The problem addressed in this study is the enhancement of heterogeneous data processing efficiency in organizational-technical systems, ensuring a predefined level of reliability regardless of the volume of input data.

The subject of the study is the heterogeneous data processing process, including:

– an improved combined algorithm, which enhances the efficiency of heterogeneous data processing through a competitive strategy among agents in the combined algorithm;

– evolving artificial neural networks, which enable deep learning of knowledge bases in multi-agent systems by training both parameters and architectures of artificial neural networks.

The use of a combined algorithm enables optimal solution searching based on a defined criterion across the entire search space, simultaneously exploring multiple directions. The use of evolving artificial neural networks allows for training not only parameters but also the architecture of the artificial neural network.

The research hypothesis is that it is possible to increase decision-making efficiency in heterogeneous data processing while ensuring a predefined level of reliability through the improved combined algorithm.

The performance modeling of the proposed method was conducted using Microsoft Visual Studio 2022 (USA), simulating the heterogeneous data processing process and solving the problem of determining the composition of a military task force. The hardware setup used for the research included an AMD Ryzen 5 processor.

Optimized Algorithm Parameters:

– number of iterations: 50;

– number of agents in the swarm: 25;

– feature space range: [–150, 150].

## 5. Development of a method for heterogeneous data processing in organizational-technical systems

### 5. 1. Algorithm for heterogeneous data processing in organizational-technical systems

The sequence of actions for processing heterogeneous data in organizational-technical systems is outlined below and consists of the following steps:

Action 1. Entering the initial data. The initial data are entered, including:

– the number and types of components within the organizational-technical system;

– the types of data circulating within the organizational-technical system;

– available computational resources, number of system elements, and their interconnections;

– technical characteristics of control and data transmission channels;

– information about the operating environment, etc.

Action 2. Initialization and formation of agent groups in the combined algorithm.

At this stage, initial random sets of solutions representing groups of agents in the combined algorithm are generated.

The mathematical representation of the agent groups from the set of possible agents within a given area is described as follows:

$$P_{i,j} = P_{i,j}^{\min} + \left(\lambda\left(P_{i,j}^{\max} - P_{i,j}^{\min}\right)\right)\gamma, \quad (1)$$

where $\lambda$ – a random number between 0 and 1, $P_{i,j}$ – $i$-th representation of the $j$-th group of agents in the combined algorithm. The agents in the combined algorithm swarm are arranged in ascending order of their objective function values $f(P_i)$, with the best solution ($P_i^{best}$) and the worst solution ($P_i^{worst}$), $\gamma$ – the data circulating in the organizational-technical system is determined. At this stage, the objective function for heterogeneous data processing $f(P)$, the population size ($m$) of the combined algorithm swarm, the number of variables ($n$), constraints on variable values ($LB$, $UB$) and the algorithm termination criterion ($FE'_{\max}$) are also determined.

Action 3. Numbering of agents in the combined algorithm swarm in the population, $i$, $i \in [0, S]$.

At this stage, each agent in the combined algorithm swarm in the population is assigned a sequential number.

Action 4. Determination of the initial velocity of agents in the combined algorithm swarm in the population.

The initial velocity $v_0$ of each agent in the population is determined using the following expression:

$$v_i = \left(v_1, v_2 \ldots v_S\right),\ v_i = v_0. \quad (2)$$

Action 5. Preliminary assessment of the search area by agents of the combined algorithm swarm. In this procedure, the search area is defined in natural language as the aura for each group in the combined algorithm swarm.

Action 6. Classification of food sources for agents of the combined algorithm swarm.

The following designations are used for classifying food sources for agents in the combined algorithm swarm: $FS_{ht}$ – location of the best food source, $FS_{at}$ – delicacy food, $FS_{nt}$ – other non-priority food sources:

$$FS_{ht}=FS(\text{sorte\_index}(1)), \quad (3)$$

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

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

Action 7. Execution of the cheetah swarm algorithm procedures.

Action 7. 1. Search behavior of cheetah agents.

This behavior represents a situation where a cheetah is searching for prey. Cheetahs use two methods for finding prey: waiting or actively exploring the surrounding territory. In this case, the environment represents the solution space for heterogeneous data processing. The search behavior of cheetah agents is proposed to be modeled using the following equation:

$$X_{i,j}^{t+1} = X_{i,j}^{t} + \hat{r}_{i,j}^{-1}\alpha_{i,j}^{t}, \quad (6)$$

where $X_{i,j}^{t}$ – current position of the cheetah agent group $i$ or individual cheetah agents $i$ ($i$=1,2…,$n$) in population $j$ or in the search space plane $j$ ($j$=1,2…,$d$), where $n$ – number of cheetah agents in the population, $d$ – dimensionality of the optimization problem. $X_{i,j}^{t+1}$ – next position of the cheetah agent, $t$ – hunting time of the cheetah agents, $T$ – maximum hunting time, $\hat{r}_{i,j}^{-1}$ – randomization parameter, $\alpha_{i,j}^{t}$ – step length for cheetah agent $i$ in population $j$. The randomization parameter $\hat{r}_{i,j}$ follows a standard normal distribution, while the step length $\alpha_{i,j}^{t} > 0$ is set to $0.001\times t/T$, since cheetahs are slow searchers.

Action 7. 2. Waiting strategy of cheetah agents.

The waiting strategy is formally described as follows:

$$X_{i,j}^{t+1} = X_{i,j}^{t}, \quad (7)$$

where $X_{i,j}^{t+1}$, $X_{i,j}^{t}$ – new position of the cheetah agent $i$ in population $j$, respectively. The proposed strategy introduces a special coordination approach in the optimization algorithm, where all agents in the group attack simultaneously. This approach significantly increases the probability of a successful hunt and reduces the risk of premature convergence toward food sources.

Action 7. 3. Active attack behavior of cheetah agents.

This procedure describes two key characteristics of the active hunting phase: speed and flexibility. It is important to note that cheetahs do not use group tactics during hunting, and all their attack strategies can be mathematically defined as follows:

$$X_{i,j}^{t+1} = X_{B,j}^{t} + \hat{r}_{i,j}\cdot\beta_{i,j}^{t}, \quad (8)$$

where $X_{B,j}^{t}$ – current position of the prey in the search space $j$; $\hat{r}_{i,j}$, $\beta_{i,j}^{t}$ – rotation and interaction factors associated with cheetah agent $i$ in the search space $j$, $\hat{r}_{i,j}$ – random value, described by a normal distribution $\left|\hat{r}_{i,j}\right|^{\exp\left(r_{i,j}/2\right)}\sin\left(2\pi r_{i,j}\right)$ and $r_{i,j}$ – a random number from a normal distribution.

Action 8. Execution of the particle swarm algorithm procedures.

Action 8. 1. Updating the velocity of particle swarm agents.

The velocity generation of particle swarm agents is calculated based on two parameters: global best particle $G_{best}$ and local best particle $L_{best}$. Velocities are updated using the following equation:

$$V_i^{t+1} = \omega V_i^t + c_1 r_{1i}^t\left(L_{best}^t - x_i^t\right) + c_2 r_{2i}^t\left(G_{best}^t - x_i^t\right), \quad (9)$$

where $V_i^{t+1}$ – velocity of the particle at iteration ($t$+1), $V_i^t$ – velocity of the particle at the previous iteration, $x_i^t$, $r_{1i}^t$, $r_{2i}^t$ – vectors $d$-dimensional random vectors uniformly distributed between 0 and 1, describing the position of particle $i$; $c_1$ and $c_2$ – learning coefficients, $\omega$ – inertia weight, usually set to 1.

Action 8. 2. Movement of particles in the search space.

The new position of the particles is generated using the following equation (10), where $x_i^{t+1}$ – new position of the particles, $x_i^t$ – previous position of the particles, $V_i^{t+1}$ – velocity of the particles, calculated using equation (9):

$$x_i^{t+1} = x_i^t + V_i^{t+1}. \quad (10)$$

Action 9. Combining the search strategies of both algorithms.

After the initial population is created, each agent receives a population size equal to half of the initial population, as defined in the study. The application of metaheuristic operators is simplified by sequentially applying the behavior of the cheetah swarm algorithm and the particle swarm algorithm, following their respective procedures.

The combination procedure of the two search strategies is modified as follows:

$$x_{i+1}^k = x_i^k\alpha + 1 - \alpha x_{best}^k M_i^k. \quad (11)$$

where $x_{i+1}^k$ – new position of the candidate solution $x_i^k$. Scaling coefficient $\alpha$ is set to 0.1, $x_{best}^k$ – best solution for iteration $k$; $M_i^k$ – modulation variable for the candidate from the agent swarm. Equation (8) defines the combined population of agents in the combined algorithm swarm, which exhibits the best performance.

Action 9. 1. Modulation of metaheuristic operators.

In this study, the modulation of the influence of each metaheuristic operator is determined not only by the traditional comparison with the best candidate solution but also by analyzing its elite behavior. This competition begins with defining the solution $x_c^k$ based on the obtained solution $x_i^k$. The obtained solution $x_c^k$ has only one restriction, $x_c^k$ it must be different from the best-known solution $x_i^k$.

Action 9. 2. Pairwise competition between agent groups in the combined algorithm.

The competition procedure among groups of individuals in the combined algorithm is described by equation (12):

$$\begin{aligned}&\text{if } f\left(x_i^k\right) < f\left(x_c^k\right) \text{ then } x_i^k = x_c^k \text{ and } M_i^k,\\ &\text{if } \left(x_i^k\right) > f\left(x_c^k\right) \text{ and } Pr > r \text{ then } x_i^k = G\left(x_c^k\right) \text{ and } M_i^k = M_c^k.\end{aligned} \quad (12)$$

Furthermore, the probability threshold is determined by the difference in performance between the obtained solution and the best solution, which varies over iterations. This probability threshold is calculated using equation (13):

$$Pr = \left|\frac{f\left(x_i^k\right) - f\left(x_c^k\right)}{BF}\right|, \quad (13)$$

where $Pr$ – probability threshold, $x_i^k$ – actual obtained solution, $x_c^k$ – reference solution, $BF$ – cost of the obtained solution. The new position $x_i^k$ is set by considering the Euclidean distance between $x_i^k$ and $x_c^k$. The position is updated using equation (14):

$$r\cdot dist - x_c^k, \quad (14)$$

where $r$ – a random number that is normally distributed, a $dist$ – Euclidean distance between $x_i^k$ and $x_c^k$. It is important to note that this procedure facilitates the exploration of new search regions in the solution space $x_i^k$. This approach prevents premature convergence and ensures an analysis of the algorithm's computational capabilities.

Action 10. Checking the stopping criterion for the combined algorithm swarm agents.

The algorithm terminates if the maximum number of iterations is reached. Otherwise, the generation of new locations and condition verification is repeated.

Action 11. Training the knowledge bases of the combined algorithm swarm agents.

It is proposed to use the method suggested in study [2] for the complete training of the knowledge bases of each agent in the combined algorithm swarm.

Action 12. Determination of the required computational resources for the intelligent decision support system.

To prevent infinite loops during the execution of Actions 1–11 and enhance the efficiency of heterogeneous data processing, an additional calculation of available hardware resources is conducted. For this purpose, study [23] is used.

End of the algorithm.

**5. 2. Example of applying the proposed method for heterogeneous data processing in organizational-technical systems**

The proposed method for heterogeneous data processing in organizational-technical systems was tested to evaluate its effectiveness. A simulation of its operation was conducted to solve the task of heterogeneous data processing under the initial conditions specified in Section 4, namely: optimized algorithm parameters:

– number of iterations: 50;

– number of agents in the swarm: 2;

– feature space range: [–150, 150].

The simulation was performed based on an operational military task force, formed according to wartime regulations under an operational command without additional reinforcements from higher command units.

The effectiveness of the proposed method for heterogeneous data processing in organizational-technical systems is evaluated using functions whose results are presented in Table 1.

Table 2 presents the results of the reliability assessment of decisions made using various optimization methods for heterogeneous data processing in organizational-technical systems.

From the analysis of Tables 1, 2, it can be concluded that the proposed method ensures the stable operation of the algorithm for both unimodal and multimodal test functions.

Table 1

Evaluation of the effectiveness of the proposed method for heterogeneous data processing based on the information processing efficiency criterion

| Function name | Metric | Canonical particle swarm algorithm [20] | Ant colony algorithm [8] | Black widow algorithm [18] | Gray Wolf algorithm [20] | Cheetah swarm algorithm [20] | Proposed method |
|---|---|---|---|---|---|---|---|
| U22-1 | Average value | 298.000 | 299.000 | 300.000 | 301.000 | 301.000 | 300.125 |
| | Standard value | 2.17566E-07 | 1.9445E-07 | 1.7387E-07 | 1.7311E-07 | 1.51122E-07 | 1.72158E-07 |
| B22-2 | Average value | 411 | 409.265772 | 407.7973158 | 406.265772 | 403.3986579 | 400.54 |
| | Standard value | 4.9899E-09 | 1.0114275 | 1.6219 | 1.01143 | 1.21642 | 1.379 |
| B22-3 | Average value | 600.008 | 600.07 | 600.03 | 600.012 | 600.03 | 600.05 |
| | Standard value | 0.0216328 | 0.18499 | 0.115607 | 0.0535 | 0.1470 | 0.1011 |
| B22-4 | Average value | 826.57 | 827.33 | 823.879 | 826.301 | 826.267 | 825.77 |
| | Standard value | 9.13818 | 8.364212 | 11.3087 | 8.186623 | 9.136108 | 10.05992 |
| B22-5 | Average value | 900.7439 | 900.9505 | 900.98 | 900.801 | 900.546 | 901.203 |
| | Standard value | 0.782 | 1.4246 | 1.2758 | 0.9034 | 0.636 | 1.5999 |
| B22-6 | Average value | 1888.525 | 1874.87 | 1876.3 | 1847.185 | 1888.927 | 1842.87 |
| | Standard value | 127.2561384 | 91.221851 | 69.000033 | 32.769804 | 140.693675 | 31.3210875 |
| H22-7 | Average value | 2027.479589 | 2030.7586 | 2029.5567 | 2032.2387 | 2028.17798 | 2029.12861 |
| | Standard value | 6.106897593 | 8.0271954 | 5.8134872 | 7.4464893 | 8.00396845 | 8.1977332 |
| H22-8 | Average value | 2223.108805 | 2223.5375 | 2222.0707 | 2223.1402 | 2220.88848 | 2220.69054 |
| | Standard value | 4.74965511 | 2.9634082 | 4.8952829 | 3.9956695 | 5.45165401 | 6.33735399 |
| H22-9 | Average value | 2510.93033 | 2510.931 | 2536.359 | 2498.217 | 2523.6447 | 2498.2161 |
| | Standard value | 65.9388011 | 65.938802 | 85.77898 | 48.385852 | 77.589977 | 48.3858518 |
| C22-10 | Average value | 2594.61591 | 2596.834 | 2585.257 | 2591.211 | 2605.3042 | 2619.3089 |
| | Standard value | 48.201329 | 49.7181 | 57.10341 | 56.36587 | 42.573952 | 34.10383 |
| C22-11 | Average value | 2695.9819 | 2685.588 | 2733.854 | 2710.622 | 2700.169 | 2715.333 |
| | Standard value | 116.365204 | 110.1476 | 146.3337 | 118.50988 | 113.79138 | 109.3009 |
| C22-12 | Average value | 2857.067086 | 2858.7438 | 2854.96 | 2861.4257 | 2859.408 | 2860.7198 |
| | Standard value | 9.364348 | 14.8897 | 5.5391044 | 17.962 | 15.0055 | 16.348 |

Table 2

Evaluation of the effectiveness of the proposed management method based on the information processing reliability criterion

| Function Name | Metric | Canonical particle swarm algorithm [20] | Ant colony algorithm [8] | Black widow algorithm [18] | Gray Wolf algorithm [20] | Cheetah swarm algorithm [20] | Proposed method |
|---|---|---|---|---|---|---|---|
| U22-1 | Average value | 0.67 | 0.74 | 0.68 | 0.69 | 0.81 | 0.91 |
| | Standard value | 0.71 | 0.73 | 0.69 | 0.692 | 0.833 | 0.913 |
| B22-2 | Average value | 0.71 | 0.74 | 0.72 | 0.712 | 0.771 | 0.893 |
| | Standard value | 0.72 | 0.74 | 0.72 | 0.72 | 0.76 | 0.91 |
| B22-3 | Average value | 0.69 | 0.73 | 0.7 | 0.71 | 0.77 | 0.93 |
| | Standard value | 0.7 | 0.74 | 0.69 | 0.73 | 0.78 | 0.91 |
| B22-4 | Average value | 0.68 | 0.75 | 0.71 | 0.721 | 0.78 | 0.94 |
| | Standard value | 0.61 | 0.73 | 0.68 | 0.73 | 0.794 | 0.923 |
| B22-5 | Average value | 0.61 | 0.72 | 0.641 | 0.73 | 0.8 | 0.91 |
| | Standard value | 0.62 | 0.73 | 0.644 | 0.744 | 0.882 | 0.923 |
| B22-6 | Average value | 0.65 | 0.74 | 0.661 | 0.773 | 0.854 | 0.932 |
| | Standard value | 0.67 | 0.76 | 0.664 | 0.782 | 0.833 | 0.921 |
| H22-7 | Average value | 0.68 | 0.73 | 0.68 | 0.75 | 0.81 | 0.92 |
| | Standard value | 0.69 | 0.72 | 0.69 | 0.74 | 0.83 | 0.92 |
| H22-8 | Average value | 0.69 | 0.75 | 0.69 | 0.75 | 0.84 | 0.93 |
| | Standard value | 0.66 | 0.75 | 0.67 | 0.77 | 0.81 | 0.91 |
| H22-9 | Average value | 0.64 | 0.76 | 0.66 | 0.69 | 0.83 | 0.91 |
| | Standard value | 0.71 | 0.73 | 0.71 | 0.71 | 0.841 | 0.932 |
| C22-10 | Average value | 0.7 | 0.72 | 0.7 | 0.72 | 0.83 | 0.942 |
| | Standard value | 0.69 | 0.72 | 0.7 | 0.73 | 0.83 | 0.915 |
| C22-11 | Average value | 0.68 | 0.73 | 0.69 | 0.71 | 0.82 | 0.915 |
| | Standard value | 0.68 | 0.73 | 0.68 | 0.74 | 0.91 | 0.915 |
| C22-12 | Average value | 0.64 | 0.74 | 0.65 | 0.75 | 0.82 | 0.915 |
| | Standard value | 0.63 | 0.75 | 0.66 | 0.76 | 0.83 | 0.915 |

As seen in Tables 1, 2, the decision-making efficiency is improved by 14–20 % due to the implementation of additional procedures, while maintaining a decision reliability level of 0.9.

## 6. Discussion of the results of the heterogeneous data processing method in organizational-technical systems

The advantages of the proposed method are as follows:

– the initial population of agents in the combined algorithm swarm and their initial positions in the search space are determined considering the uncertainty level of the input data circulating in the organizational-technical system by using correction coefficients, compared to studies [9, 14, 20]. This reduces the time required for initial configuration of the heterogeneous data processing subsystem during primary setup;

– the initial velocity of each agent in the combined algorithm swarm is taken into account, allowing for search prioritization in the corresponding search space (across elements and components of the organizational-technical system), compared to studies [9, 13, 15];

– the feasibility of decisions in heterogeneous data processing is determined considering external factors, which reduces the solution search time (Action 5), compared to studies [14, 16, 17];

– the universal strategy for food source search by agents enables classification of conditions and factors affecting heterogeneous data processing (Action 6), compared to studies [14, 16, 17]. This helps determine the most suitable processing options based on a defined optimization criterion;

– ability to explore solution spaces for functions described by non-standard functions through the step selection procedure of cheetah agents in the combined algorithm swarm (Action 7), compared to studies [9, 12, 14];

– replacement of unfit search agents by updating the population of agents in the combined algorithm swarm (Actions 8–10), compared to studies [9, 12, 13, 16];

– capability to compare the efficiency of heterogeneous data processing through the modulation of metaheuristic operators (Action 9. 1), compared to study [20];

– simultaneous solution search in multiple directions (Actions 1–12, Tables 1, 2);

– deep learning capabilities for the knowledge bases of agents in the combined algorithm swarm (Action 10), compared to studies [14, 15, 20];

– ability to calculate the required computational resources, determining the necessary additional resources if existing computational capacity is insufficient (Action 12), compared to studies [9, 13, 17, 20].

*Disadvantages of the proposed method*. The proposed method has the following limitations:

– loss of informativeness during heterogeneous data processing due to the membership function construction;

– lower accuracy in assessing individual parameters for evaluating the state of heterogeneous data processing;

– loss of decision reliability when searching for solutions in multiple directions simultaneously;

– lower evaluation accuracy compared to other heterogeneous data processing methods.

The proposed method will enable:

– optimization of heterogeneous data processing efficiency based on a defined optimization criterion;

– identification of effective measures to enhance heterogeneous data processing efficiency;

– increase in processing speed while maintaining the predefined reliability of decision-making;

– reduction in computational resource usage for decision support systems.

The limitations of the study include the requirement for information on the degree of uncertainty of the data circulating within organizational-technical systems, as well as the need to account for delays in data collection and transmission from the components of these systems.

The proposed method is most suitable for solving heterogeneous data processing tasks that are characterized by a high level of complexity.

## 7. Conclusions

1. The algorithm for method implementation has been defined, incorporating additional and improved procedures, which enable:

– establishing the initial population of agents in the combined algorithm swarm and their initial positions in the search space, considering the uncertainty level of the input data circulating in the organizational-technical system. This is achieved by applying correction coefficients, reducing the time required for initial configuration of the heterogeneous data processing subsystem during primary setup;

– considering the initial velocity of each agent in the combined algorithm swarm, allowing prioritization of the search within the corresponding search space (across elements and components of the organizational-technical system);

– determining the feasibility of decisions during heterogeneous data processing, taking into account external factors, which reduces solution search time;

– classifying conditions and factors influencing the heterogeneous data processing process, utilizing the universal food source search strategy of combined algorithm swarm agents. This enables identifying the most optimal solutions based on a defined optimization criterion;

– exploring solution spaces for functions described by non-standard functions, achieved by applying the step selection procedure of cheetah agents in the combined algorithm swarm;

– replacing unfit search agents by updating the population of combined algorithm swarm agents;

– conducting a comparative evaluation of heterogeneous data processing efficiency using the modulation procedure of metaheuristic operators;

– enabling simultaneous solution search in multiple directions;

– providing deep learning capabilities for the knowledge bases of combined algorithm swarm agents;

– determining the required computational resources, estimating additional resource needs in cases where available computing resources are insufficient.

2. An example of the proposed method's application for heterogeneous data processing within an operational military task force was conducted, demonstrating an increase in decision-making efficiency by 14–20 % due to the use of additional procedures, while ensuring a decision reliability level of 0.9.

**Conflict of interest**

The authors declare that they have no conflicts of interest related to this study, including financial, personal, authorship-related, or any other conflicts that could influence the research and its presented results.

**Financing**

This study was conducted without financial support.

**Data availability**

The manuscript includes associated data stored in a data repository.

**Use of artificial intelligence**

The authors confirm that no artificial intelligence technologies were used in the creation of this study.

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. 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., 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. 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. 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/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. https://doi.org/10.46338/ijetae0521_05
8. Shyshatskyi, A., Stasiuk, T., Odarushchenko, E., Berezanska, K., Demianenko, H. (2023). Method of assessing the state of hierarchical objects based on bio-inspired algorithms. Advanced Information Systems, 7 (3), 44–48. https://doi.org/10.20998/2522-9052.2023.3.06
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
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., Stonel, H. M. (2008). Characteristics and Energetics of Great Egret and Snowy Egret Foraging Flights. Waterbirds, 541. https://doi.org/10.1675/1524-4695-31.4.541
20. Litvinenko, O., Kashkevich, S., Shyshatskyi, A., Dmytriieva, O., Neronov, S., Plekhova, G. et al.; Shyshatskyi, A. (Ed.) (2024). Information and control systems: modelling and optimizations. Kharkiv: TECHNOLOGY CENTER PC, 180. https://doi.org/10.15587/978-617-8360-04-7