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DEVELOPMENT OF A METHOD FOR INCREASING THE EFFICIENCY OF PROCESSING DIFFERENT TYPES OF DATA IN ORGANIZATIONAL AND TECHNICAL SYSTEMS

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The object of the research is heterogeneous data circulating in organizational and technical systems. The subject of the research is the process of processing heterogeneous data. The problem addressed in the study is improving the responsiveness of heterogeneous data processing in organizational and technical systems while ensuring a specified level of reliability, regardless of the volume of data entering the system. The essence of the obtained results lies in the use of improved metaheuristic algorithms for processing heterogeneous data in combination with other approaches. The originality of the method lies in the use of additional improved procedures that allow for:

– accounting for the degree of influence of destabilizing factors affecting the processing of heterogeneous data in an organizational and technical system, which makes it possible to consider the elements of the system that provide the highest reliability in heterogeneous data processing;

– taking into account the initial speed of each agent in the swarm of the combined algorithm, which enables prioritization of the search in the corresponding search space (by elements and components of the organizational and technical system);

– optimizing the topology of heterogeneous data processing circulating in the organizational and technical system;

– considering the failed elements of the organizational and technical system that are unsuitable for heterogeneous data processing;

– taking into account the influence of destabilizing factors both during the initial placement of the agents in the swarm of the combined algorithm and during the processing of heterogeneous data circulating in the organizational and technical system;

– the ability to calculate the required number of computing resources that need to be engaged if the available computing resources are insufficient for performing calculations.

An example of the application of the proposed method in processing heterogeneous data within an operational grouping of troops (forces) demonstrated an improvement in decision-making responsiveness by 13–15 % due to the use of additional procedures and ensuring a decision reliability level of 0.9

Keywords: metaheuristic algorithms, unimodal functions, multimodal functions, destabilizing factors, heterogeneous grouping

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1. Introduction

The problem of improving the responsiveness of processing various types of data in decision support systems (DSS), which are integral components of information and automated systems with various functional purposes, is extremely acute [1, 2]. The experience of recent armed conflicts involving modern information and automated systems demonstrates that existing methods for processing different types of data enable the processing of only 5 to 10 % of the total volume of data circulating within them [3–5].

This is due to the following reasons:

– the significant role of the human factor in the process of processing various types of data circulating within information and automated systems;

– a large number of heterogeneous sources of information that are part of automated and information systems;

– the processing of various types of data is carried out under conditions of uncertainty, which causes delays in their processing;

– the presence of numerous destabilizing factors that affect the responsiveness of processing various types of data;

– the existence of both structured and unstructured data in information and automated systems, which are subject to processing, among others.

Considering the heterogeneity, the large number of destabilizing factors, the differing dimensionalities of the indicators that describe them, and the need to process large volumes of diverse data, there is a pressing need to seek new approaches to data processing. One such approach is the use of metaheuristic algorithms [5–8].

The use of metaheuristic algorithms in their canonical form allows for improved responsiveness in processing various types of data. However, further improvement in the responsiveness of processing cannot be achieved solely through the use of their canonical forms.

This necessitates the implementation of various strategies to enhance the convergence speed and accuracy of core metaheuristic algorithms when processing diverse types of data. One approach to increasing the responsiveness of 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], an algorithm for cognitive modeling is presented. The main advantages of cognitive tools are identified. 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 revealed. A system of complementary principles for constructing and implementing scenarios is proposed, various approaches to scenario construction are highlighted, and a procedure for scenario modeling based on fuzzy cognitive maps is described. The approach proposed by the authors does not account for the type of uncertainty about the state of the analyzed object and does not consider noise in the initial data.

In [11], an analysis of the main approaches to cognitive modeling is conducted. Cognitive analysis enables the exploration of problems with fuzzy factors and interrelations, the consideration of changes in the external environment, and the use of objectively formed trends in the development of a situation to one's advantage. However, the issue of describing complex and dynamic processes remains unexplored in the cited work.

In [12], a method for analyzing large datasets is presented. The method focuses on uncovering hidden information within large volumes of data. It includes operations such as generating analytical baselines, reducing variables, identifying sparse features, and formulating rules. The shortcomings of this method include the inability to consider different decision evaluation strategies and the lack of accounting for the type of uncertainty in the input data.

In [13], a mechanism for transforming information models of construction objects into their equivalent structural models is presented. This mechanism is intended to automate the necessary operations for transformation, modification, and augmentation during such information exchange. The disadvantages of this approach include the inability to assess the adequacy and reliability of the information transformation process and to perform appropriate corrections to the resulting models.

In [14], the development of an analytical web platform for studying the geographical and temporal distribution of incidents is conducted. The web platform includes several dashboards with statistically significant results by region. Drawbacks of this analytical platform include the inability to assess the adequacy and reliability of the information transformation process, as well as high computational complexity. Another shortcoming is the lack of unidirectional search for a solution.

In [15], the development of a method for fuzzy hierarchical evaluation of library service quality is carried out. This method allows for evaluating library quality based on multiple input parameters. Its shortcomings include the inability to assess the adequacy and reliability of the evaluation and, consequently, to determine the margin of error.

In [16], an analysis of 30 algorithms for processing large datasets is conducted. Their advantages and disadvantages are identified. It is established that the analysis of large data arrays should be layered, performed in real-time, and include self-learning capabilities. The disadvantages of these methods include high computational complexity and the inability to verify the adequacy of the obtained evaluations.

In [17], an approach to input data evaluation for decision support systems is presented. The essence of the proposed approach lies in clustering the basic set of input data, followed by analysis and system training based on the analysis. The drawbacks of this approach include the gradual accumulation of evaluation and training errors due to the inability to assess the adequacy of the decisions made.

In [18], an approach to data processing from various sources is presented. This approach allows for the processing of data from multiple sources. However, it suffers from low accuracy of the resulting evaluation and the inability to verify the reliability of the obtained results.

In [19], a comparative analysis of existing decision support technologies is conducted, specifically: analytic hierarchy process, neural networks, fuzzy set theory, genetic algorithms, and neuro-fuzzy modeling. The advantages and disadvantages of these approaches are outlined, and their application areas are defined. It is shown that the analytic hierarchy process performs well under conditions of complete initial information but is highly subjective due to the need for expert comparison of alternatives and selection of evaluation criteria. For forecasting tasks under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

In [20], the use of combinations of various metaheuristic algorithm strategies is mentioned. However, this approach is limited by insufficient responsiveness in processing heterogeneous data when multiple metaheuristic algorithms are used jointly.

The analysis of works [9–20] reveals that the common shortcomings of the aforementioned studies are:

– the absence of a hierarchical system of indicators for evaluating the heterogeneous data processing procedure;

– the lack of consideration for the computing resources of the system managing the heterogeneous data processing;

– the absence of mechanisms for adjusting the system of indicators governing the heterogeneous data processing;

– the lack of deep learning mechanisms for knowledge bases;

– high computational complexity;

– the absence of consideration for computing (hardware) resources available in DSS;

– the lack of prioritization in the search direction.

3. The aim and objectives of the study

The aim of the study is to develop a method for improving the responsiveness of heterogeneous data processing in organizational and technical systems. This will enhance the responsiveness of heterogeneous data processing in such systems while ensuring a specified level of reliability and facilitating subsequent management decisions based on the processed data. This, in turn, will enable the development (or improvement) of software for processing heterogeneous data in organizational and technical systems.

To achieve the aim, the following objectives were set:

– to define the algorithm for implementing the method;

– to provide an example of applying the method to heterogeneous data processing in organizational and technical systems.

4. Materials and methods of the study

The object of the study is heterogeneous data circulating in organizational and technical systems. The problem addressed in the research is improving the responsiveness of heterogeneous data processing in organizational and technical systems while ensuring a specified reliability level, regardless of the volume of input data. The subject of the study is the process of heterogeneous data processing through:

– an improved combined algorithm, which enhances responsiveness through a competition strategy among the individuals of the combined algorithm;

– evolving artificial neural networks, used for deep learning of the knowledge base within the multi-agent system by training both the parameters and the architecture of the artificial neural networks.

The combination of the above approaches allows for enhanced responsiveness in heterogeneous data processing through multidirectional search, and improved reliability by comparing the results of the two algorithms. The increase in data processing reliability is also achieved through the training of agents within the swarm of the combined algorithm.

The hypothesis of the study is the possibility of improving decision-making responsiveness in the processing of heterogeneous data, given a specified level of reliability, by using an improved combined algorithm.

The modeling of the proposed method was carried out using Microsoft Visual Studio 2022 (USA). The task solved during the modeling of heterogeneous data processing was the determination of the composition of a military (forces) grouping. The hardware used in the research was based on an AMD Ryzen 5 processor.

Parameters of the improved algorithm:

– number of iterations – 50;

– number of individuals in the swarm – 25;

– feature space range – [–150, 150].

5. Results of the method for improving the responsiveness of heterogeneous data processing in organizational and technical systems

5. 1. Algorithm of the method for improving the responsiveness of heterogeneous data processing in organizational and technical systems

The method for improving the responsiveness of heterogeneous data processing in organizational and technical systems consists of the following sequence of actions:

Action 1. Input of initial data.

At this stage, the available initial data concerning the organizational and technical system are entered, including the means of destructive influence, specifically:

– quantity and type of components that make up the organizational and technical system;

– quantity and type of means exerting destabilizing influence on the organizational and technical system;

– technical characteristics of the components of the organizational and technical system;

– architecture (connection topology) between the elements of the organizational and technical system;

– technical characteristics of the means exerting destabilizing influence on the organizational and technical system;

– architecture (connection topology) among the means exerting destabilizing influence on the organizational and technical system;

– type of data circulating within the system;

– available computing resources;

– information about the application environment, etc.

Action 2. Initialization and formation of the general population of agents in the swarm of the combined algorithm.

At this stage, initial random sets of solutions representing groups of agents of the combined algorithm are generated. The combined algorithm implies the simultaneous use of two metaheuristic algorithms: the dung beetle algorithm and the osprey algorithm.

The mathematical representation of a randomly selected group of agents from the combined algorithm out of the set of possible agents within a given territory (in this case) is mathematically described as follows:

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

where λ – a random number in the range from 0 to 1, P_{ij} – i-th designation of the j-th group of agents of the combined algorithm as previously described. The placement of the agent population of the combined algorithm is performed in ascending order based on the function values $f(P_i)$, selecting the best and worst solution, $\left(P_i^{best}\right)$ and $\left(P_i^{worst}\right)$, γ – the degree of uncertainty in the data regarding the means of destabilizing influence on the organizational and technical system. The correction coefficient γ is necessary to reduce the number of computations during the operation of the combined algorithm. At this stage, the objective function of the combined algorithm $f(P)$, the population size (m) of the swarm, the number of variables (n), the variable boundaries (LB, UB), and the termination criterion of the algorithm $\left(FE'_{\max}\right)$ are also determined.

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

At this stage, each agent of the combined algorithm's swarm is assigned a sequential number. This procedure is necessary to determine the search priority for each agent in the overall solution search space.

Action 4. Determination of the initial speed of agents of the combined algorithm in the population. This procedure is used to optimize the utilization of computational resources by adjusting the speed of exploration for each agent of the swarm within the search space.

The initial speed v_0 of each agent in the population is defined by the following expression:

$$v_i=(v_1, v_2... v_S),\ v_i=0. \tag{2}$$

Action 5. Preliminary evaluation of the search area by agents of the swarm of the combined algorithm.

In this procedure, the search area is defined in natural language as the aureole for each group in the swarm of the combined algorithm.

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

The location of the best food source (i.e., minimum fitness) is considered (FS_{ht}) food that is nearby and requires minimal energy expenditure to be found and obtained.

The gourmet food, which requires the highest expenditure to obtain, is denoted as FS_{at}.

Other non-priority food sources (food necessary for individual survival) are denoted as $FS_{nt.}$:

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

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

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

Action 7. Execution of computations by individual groups within the swarm of the combined algorithm.

Action 7. 1. Execution of computations by agents from the dung beetle swarm.

This algorithm simulates the specific behavior of dung beetles in nature. The Dung Beetle Algorithm (DBA) divides the entire population into four corresponding segments based on this behavior.

Action 7. 1. 1. Ball-rolling procedure.

When dung beetles roll their dung ball, they must ensure that their path is straight, aligned with the positions of celestial bodies. To simulate this behavior, in the algorithm, the individuals move in a specified direction across the entire search space. It is assumed that sunlight intensity influences the path of individual dung beetles. This process alters the agent's position, as shown in Equation (6) below:

$$X_n^{i+1}=X_n^i+a\cdot k\cdot X_n^{i-1}+b\cdot\Delta x, \tag{6}$$

$$\Delta x=\left|X_n^i-X^{\omega}\right|,$$

where X_n^{i+1} – the position of the n-th dung beetle at the i-th iteration, $k\in(0, 0.2]$ – the deviation coefficient (assigned the value 0.1 in the code); $b\in(0, 1)$ – a natural coefficient (assigned the value 0,3 in the code); x – the degree of change in light intensity, X^{ω} – the worst position of the dung beetle agent within the current population; a – a natural coefficient assigned the value 1 or –1, where $a=1$ indicates that the natural environment does not affect the original direction, while $a=-1$ indicates a deviation from the initial direction. This coefficient in the study characterizes the degree of data noise caused by the impact of destructive factors on the organizational and technical system.

In nature, when dung beetles encounter an obstacle in their path, they rotate their bodies to change direction and bypass the obstacle. In this case, the described procedure models the rerouting of information transmission in the event of an element failure within the organizational and technical system due to destabilizing factors and is described as:

$$X_n^{i+1}=X_n^i+\tan\alpha\left|X_n^i-X_n^{i-1}\right|, \tag{7}$$

$$0\le\alpha\le\pi,$$

where α – the deflection angle between the new direction of the dung beetle and its initial direction.

Action 7. 1. 2. Beetle reproduction procedure.

When the dung ball returns to the nest, the beetles must choose an appropriate site to lay their eggs in order to ensure a safe environment for their offspring. Based on the discussion above, the algorithm implements a strategy for selecting boundaries to model the region where females lay eggs, which is determined as follows:

$$LB_1=\max\left(X^t\cdot\left(1-T\right),LB\right), \tag{8}$$

$$UB_1=\min\left(X^t\cdot\left(1+T\right),UB\right),$$

where X^t – the current local optimum, LB_1 and UB_1 – the lower and upper bounds of the breeding area, LB and UB are the lower and upper bounds of the search space, and the inertia weight $R=1–t/T_{\max}$, where $T_{\max}$ – the maximum number of iterations during the algorithm's run.

In the context of this study, the described procedure identifies the elements of the organizational and technical system that are least affected by the destructive influence.

The boundary range of the egg-laying area by beetle agents changes dynamically, preventing the algorithm from getting trapped in a local optimum. Therefore, during the iteration process, the hatching ball positions may also change. This process can be described as:

$$X_n^{i+1}=X^t+B_1\cdot\left(X_n^i-LB_1\right)+B_2\cdot\left(X_n^i-UB_1\right), \tag{9}$$

where X_n^i – the position of the n-th hatching dung ball at iteration t-th, B_1 and B_2 – are two independent random matrices, D – the dimensionality of the algorithm.

Action 7. 1. 3. Hatching of dung beetles.

When young dung beetles successfully hatch, they emerge in groups to search for food. The food search process also involves a restricted search range. For these small dung beetles, the optimal foraging territory is defined as follows:

$$LB_2=\max\left(X^{tb}\cdot\left(1-T\right),LB\right), \tag{10}$$

$$UB_2=\min\left(X^{tb}\cdot\left(1-T\right),UB\right),$$

where X^{tb} – the global optimum, and LB_2 and UB_2 – the lower and upper bounds of the area, respectively. After determining the location of the small dung beetle, it can be updated as follows:

$$X_i^{n+1}=X_i^n+C_1\cdot\left(X_i^n-LB_2\right)+C_2\cdot\left(X_i^n-UB_2\right), \tag{11}$$

where X_i^{n+1} – the information about the location of the i-th small dung beetle at iteration t, C_1 – a random number following a Gaussian distribution, and C_2 – a value belonging to the interval (0, 1).

Action 7. 1. 4. Execution of the thief strategy.

In dung beetle populations, some beetles steal dung balls from others – these beetles are referred to as thieves. As mentioned above, X^s – the globally optimal position, i.e., the best location for food. Thus, it can be assumed that the neighborhood of X – the most competitive food zone. The positions of the thief dung beetles are updated during the iteration process as follows (12):

$$X_n^{i+1} = X^s + P \cdot d \cdot \left(\left| X_n^i - X^t \right| + \left| X_n^i - X^- \right| \right), \tag{12}$$

where d – a random vector of size $1 \cdot D$, that follows a normal distribution, and P=const.

Action 7. 2. Execution of computations by agents from the osprey swarm.

Action 7. 2. 1. Global exploitation.

To model the first phase of updating the osprey agent population, the natural hunting behavior of ospreys was simulated. Equation (13) is used to determine the position of each osprey:

$$OS_n = \left\{ X_t \mid t \in \{1,2,...,N\} \wedge O_t < O_n \right\} \cup \left\{ X^* \right\}, \tag{13}$$

where OS_n – the set of locations occupied by the n-th osprey, and X^* – the exact location of the optimal osprey. The osprey independently identifies the location of a fish and begins its attack. The calculation of the osprey's new position relative to the fish is based on simulating the osprey's movement, as described in Equation (14). If the objective function shows improvement, the new position replaces the previous one:

$$x_{i,j}^{P1} = xi, j + ri, j \cdot \left(SF_{i,j} - I_{i,j} \cdot x_{i,j} \right),$$
$$x_{i,j}^{P1} = \begin{cases} x_{i,j}^{P1}, lb_j \le x_{i,j}^{P1} \le ub_j; \\ lb_j, x_{i,j}^{P1} < lb_j; \\ ub_j, x_{i,j}^{P1} > ub_j, \end{cases} \tag{14}$$
$$X_i = \begin{cases} X_i^{P1}, F_i^{P1} < F_i; \\ X_i, \text{also}, \end{cases}$$

where $x_{i,j}^{P1}$ – the new position in the j-th dimension of the i-th osprey during the first stage, $F_{i,j}$ – the corresponding fitness value of the osprey's position, $SF_{i,j}$ – a random number in the interval [0, 1], and $I_{i,j}$ – a random integer from the set 1, 2.

Action 7. 2. 2. Local exploitation.

When an osprey catches a fish, it transports it to a safe location to consume it. The second phase of updating the population involves using simulation methods to replicate the osprey's natural behavior. The process of transporting the fish to a designated location results in slight adjustments to the osprey's position in the search space. This, in turn, improves the algorithm's local search capability and transitions toward a more optimal solution in the vicinity of the determined solution. This position is considered "suitable for fish consumption" and is defined using the following equation:

$$x_{i,j}^{P2} = x_{i,j} + \frac{lb_j + r \cdot \left(ub_j - lb_j \right)}{t}, \tag{15}$$

$$i = 1,2,...,N,\ j = 1,2,...,m,\ t = 1,2,...,T,$$

$$x_{i,j}^{P2} = \begin{cases} x_{i,j}^{P2}, lb_j \le x_{i,j}^{P2} \le ub_j; \\ lb_j, x_{i,j}^{P2} < lb_j; \\ ub_j, x_{i,j}^{P2} > ub_j, \end{cases} \qquad X_i = \begin{cases} X_i^{P2}, F_i^{P2} < F_i; \\ X_i, \text{also}, \end{cases}$$

where $x_{i,j}^{P2}$ – the new position in the j-th dimension of the i-th osprey during the second stage; $F_{i,j}^{P2}$ – the fitness value of the updated position; r – a random number in the range [0, 1]; t and T – current and maximum number of iterations, respectively.

Action 8. Integration of the search strategies of both algorithms.

After generating the initial population, each agent is assigned a population size equal to half of the initial population, as defined in the referenced work. The application of metaheuristic operators is simplified by sequentially applying the behavior of the osprey swarm algorithm and the dung beetle swarm algorithm according to their respective procedures. The procedure for combining the two behavioral strategies is modified as follows:

$$x_{i+1}^k = x_i^k \alpha + 1 - \alpha x_{best}^k M_i^k, \tag{16}$$

where x_{i+1}^k – the new candidate solution position x_i^k. The scaling coefficient α is set to 0.1 in this study; x_{best}^k – the best solution at iteration k; M_i^k – the modulation variable from the agent swarm. Equation (16) defines the unified population of the combined swarm algorithm agents that demonstrates the highest performance.

Action 8. 1. Modulation of metaheuristic operators.

In this study, the influence of each metaheuristic operator is modulated not only by the traditional comparison with the best candidate solution but also through analysis of its elite behavior. This competition begins with identifying the solution x_c^k relative to the actually obtained result x_i^k. The only restriction on obtaining x_c^k is that it must be different from x_i^k.

Action 8. 2. Pairwise competition of agent groups within the combined algorithm.

The procedure for agent group competition in the combined algorithm is described by Equation (17):

$$\text{if} f\left(x_i^k\right) < f\left(x_c^k\right) \text{ then } x_i^k = x_c^k \text{ and } M_i^k; \tag{17}$$

$$\text{if } f\left(x_i^k\right) > f\left(x_c^k\right) \text{ and } Pr > r \text{ then } x_i^k = G\left(x_c^k\right) \text{ and } M_i^k = M_c^k.$$

In addition, the probabilistic threshold is defined by the difference in performance between the obtained and the best solution and varies across iterations. This threshold is calculated by the following equation:

$$\Pr = \left| \frac{f\left(x_i^k\right) - f\left(x_c^k\right)}{BF} \right|, \tag{18}$$

where Pr – the probabilistic threshold, x_i^k – the actual solution, x_c^k – the reference solution, and BF – the cost (fitness) of the obtained solution. The new position x_i^k established based on the Euclidean distance between x_i^k and x_c^k. The position is updated using Equation (19):

$$r \cdot dist - x_c^k, \tag{19}$$

where r – a normally distributed random number, and $dist$ – the Euclidean distance between x_i^k and x_c^k. It is worth noting that this procedure promotes the exploration of new regions in the solution search space x_i^k. It prevents premature convergence and allows for analysis of the computational capabilities of the algorithm.

Action 9. Verification of the stopping criterion for the agents of the combined algorithm's swarm.

The algorithm terminates when the maximum number of iterations has been reached. Otherwise, new candidate positions are generated, and the conditions are re-evaluated.

Action 10. Training the knowledge base of the agents in the combined swarm algorithm.

In this study, the training of each agent's knowledge base in the combined algorithm swarm is performed using an evolving artificial neural network learning method, as developed in [2]. This method is employed to adapt the movement behavior of each swarm agent to obtain more accurate analytical results in future iterations.

Action 11. Determination of the required computational resources for the intelligent decision support system.

To prevent computational loops from persisting through Actions 1–10 of the method and to enhance computational responsiveness, the system's load is additionally assessed. If the defined computational complexity threshold is exceeded, the number of required hardware and software resources is determined using the method proposed in [20].

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

To evaluate the effectiveness of the proposed method, its performance was modeled for solving the task of processing heterogeneous data under the initial conditions defined in Section 4.

The efficiency of the heterogeneous data processing method in organizational and technical systems is compared using benchmark functions – outlined in Table 1.

Based on the analysis of Table 1, it can be concluded that the proposed method ensures stable algorithm performance for key test functions of both unimodal and multimodal types.

Additionally, from the analysis of Table 1, it is evident that the improvement in decision-making responsiveness is achieved at the level of 13–15 % due to the application of additional procedures and the ensured decision reliability at a level of 0.9.

Table 1

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

Function name	Metric	Canonical dung beetle swarm algorithm [20]	Ant colony algorithm [20]	Black widow algorithm [20]	Grey wolf swarm algorithm [20]	Canonical osprey swarm algorithm [20]	Proposed method
U22-1	Mean value	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00	0.00E+00
	Standard deviation	5.22E-294	1.94448E-07	1.04E-45	7.47E-46	4.36E-45	1.72168E-07
B22-2	Mean value	400	400.265772	400.7973158	400.265772	400.3986579	400.5315439
	Standard deviation	4.9898E-08	1.011427534	1.621892282	1.011427535	1.216419212	1.378343398
B22-3	Mean value	5.23E-171	1.58E-148	1.033E-45	5.41E-150	2.88E-149	2.22E-26
	Standard deviation	0.021632777	0.184980091	0.115606243	0.053463097	0.147011513	0.101164243
B22-4	Mean value	826.5653461	827.3281442	823.8789639	826.3000191	826.2668486	825.7693662
	Standard deviation	9.13817552	8.364210734	11.30806963	8.186625055	9.136107323	10.05991317
B22-5	Mean value	900.743876	900.9504411	900.9726169	900.8007883	900.5452042	823.2016312
	Standard deviation	0.781626306	1.424558753	1.275779755	0.903385622	0.635781924	1.558982565
B22-6	Mean value	1,888.524629	1,874.869967	1,876.294359	1,847.184924	1,888.926953	1,811.878175
	Standard deviation	127.2561383	91.22185049	69.00003268	32.76980351	140.693674	27.32108747
H22-7	Mean value	2,027.479588	20,30.758499	2,029.556604	2,032.238674	2,028.177978	2,010.128603
	Standard deviation	6.106897592	8.027195324	5.81348717	7.446489204	8.003968446	7.197733191
H22-8	Mean value	2,223.108804	2,223.537417	2,222.070633	2,223.140251	2,230.888475	2,216.190533
	Standard deviation	4.749655105	2.963408213	4.895282849	3.995669404	5.451654006	5.331353983
H22-9	Mean value	2,510.930321	2,510.930321	2536.358938	2,498.216012	2,523.644629	2,415.216012
	Standard deviation	65.93880108	65.93880108	85.778947	48.38585173	73.58997694	41.31585173
C22-10	Mean value	2594.615905	2,566.833927	2,585.256107	2,591.210109	2,305.304194	2,610.301989
	Standard deviation	48.2013289	49.71807546	57.1034079	56.36586785	43.57395199	30.10382553
C22-11	Mean value	2,695.981932	2,685.587394	2,733.855734	2,310.621315	2,300.168413	2,700.332781
	Standard deviation	116.3652035	110.1475838	146.333679	118.5098748	113.7913849	100.3008673
C22-12	Mean value	2,857.067086	2658.742176	2,654.959949	2,361.414681	2,859.407788	2,299.718169
	Standard deviation	9.364347909	14.88960231	5.539104327	17.96133754	15.00545163	14.34111781

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

The advantages of the proposed method are determined by the following:

– the initial population of agents in the combined swarm algorithm and their initial placement in the search space is defined with consideration of the uncertainty degree of input data regarding the information circulating in the organizational and technical system (Action 1). This is achieved through the use of appropriate correction coefficients, in contrast to the approaches in [9, 14, 20]. This reduces the time required for initial configuration of the heterogeneous data processing subsystem;

– the initial velocity of each agent in the swarm of the combined algorithm is considered (Action 2), enabling the determination of search priority in the corresponding search space (by elements and components of the organizational and technical system), compared to the approaches in [9, 11, 15];

– the feasibility of the obtained decisions is assessed in heterogeneous data processing with consideration of external factors, reducing the time needed to find a solution (Action 5), in comparison with [14, 16, 17];

– the universality of food source search strategies used by agents in the combined algorithm swarm enables the classification of various conditions and factors affecting the heterogeneous data processing process (Action 6), in contrast with [14, 16, 17]. This facilitates the selection of the most suitable solution options based on the defined optimization criterion;

– consideration of the impact degree of destabilizing factors (Action 7. 1) that influence heterogeneous data processing in the organizational and technical system allows the identification of system elements with the highest data processing reliability, compared to [9, 12, 18];

– accounting for malfunctioning elements of the organizational and technical system that are unsuitable for heterogeneous data processing (Action 7. 1) enables the optimization of the processing topology, compared to [14, 16, 17];

– the capability to conduct a comparative evaluation of processing efficiency using the modulation procedure of metaheuristic operators (Action 8. 1), compared to [20];

– the ability to conduct parallel search in different directions (Actions 1–11, Table 1);

– the capability for deep learning of the knowledge bases of agents within the combined algorithm swarm (Action 10), compared to [9, 10, 20];

– the ability to calculate the necessary amount of computational resources to be engaged in case of insufficient existing computing resources (Action 11), compared to [9, 11, 20].

The disadvantages of the proposed method include:

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

– lower accuracy in estimating individual parameters that describe the state of heterogeneous data processing;

– reduced reliability of obtained decisions when conducting multi-directional solution searches simultaneously;

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

The proposed method makes it possible to:

– determine the optimal efficiency indicator for heterogeneous data processing based on a specific optimization criterion;

– identify effective measures for improving heterogeneous data processing efficiency;

– optimize the topology of heterogeneous data processing in organizational and technical systems;

– take into account the influence of destabilizing factors both during initial deployment of the swarm agents and throughout the data processing cycle;

– increase the speed of heterogeneous data processing while ensuring the required reliability of decision-making;

– reduce the consumption of computational resources in decision support systems.

The limitations of the study include the necessity of having information about the degree of uncertainty regarding the data circulating in organizational and technical systems, and the need to account for delays in the collection and delivery of information from components of such systems.

The proposed approach is appropriate for solving problems involving the processing of heterogeneous data characterized by a high degree of complexity.

7.Conclusions

1. An implementation algorithm of the method has been defined, which, due to additional and improved procedures, enables the following:

– initialization of the initial population of agents in the combined algorithm swarm and their initial placement in the search space, taking into account the degree of uncertainty of input data circulating in the organizational and technical system. This is achieved through the use of appropriate correction coefficients. This approach reduces the time required for initial configuration of the heterogeneous data processing subsystem;

– consideration of the initial velocity of each agent in the combined algorithm swarm, enabling the determination of search priority within the relevant search space (across elements and components of the organizational and technical system);

– assessment of the feasibility of decisions made during heterogeneous data processing considering external factors, which reduces solution search time;

– classification of the set of conditions and factors influencing heterogeneous data processing through the universality of agent food source search strategies within the combined algorithm swarm. This makes it possible to determine the most suitable solutions for heterogeneous data processing based on a specified optimization criterion;

– replacement of unfit agents through population updates in the combined swarm algorithm;

– consideration of the reliability level of data processed by each element of the organizational and technical system;

– consideration of the influence of destabilizing factors both during the initial agent deployment and in the process of processing heterogeneous data;

– comparative evaluation of the effectiveness of heterogeneous data processing using the metaheuristic operator modulation procedure;

– possibility of parallel solution searches in multiple directions;

– capability for deep learning of the knowledge bases of the agents in the combined algorithm swarm;

– ability to calculate the required number of computing resources to be engaged if the current computational capabilities are insufficient.

2. A practical example of using the proposed method was carried out on the case of processing heterogeneous data within a military operational unit. The example demonstrated an improvement in decision-making responsiveness at the level of 14–20 %, due to the use of additional procedures and the ensured decision reliability at the level of 0.9.

Conflict of interest

The authors declare no conflict of interest in relation to this study, including financial, personal, authorship-related, or any other form of conflict that could influence the research or its results as presented in this article.

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Data availability

This manuscript is associated with 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 work.

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