UDC 004.81
DOI: 10.15587/1729-4061.2024.318600

DEVELOPMENT OF A METHOD FOR MANAGING A GROUP OF UNMANNED AERIAL VEHICLES USING A POPULATION ALGORITHM

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The object of the study is a group of unmanned aerial vehicles (UAVs). The subject of the study is the decision-making process in management tasks using:

– an improved brown bear algorithm (BBA), which achieves the determination of the optimal UAV movement route based on the given optimization criterion (the probability of completing the flight task), described by complex multimodal functions;

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

The originality of the method lies in using additional improved procedures that allow:

– the initial BBA population and their initial position on the search plane are determined considering the degree of uncertainty in the data on the UAV group movement route;

– the initial speed of each BBA is considered, enabling the prioritization of searches in the respective search plane (height, latitude, and longitude);

– the suitability of the UAV group's flight route for performing the flight task is determined, considering a set of external factors, thereby reducing the decision search time;

– the universality of BBA food search strategies allows classifying a set of conditions and factors affecting the completion of the flight task.

This aids in identifying the most feasible movement options for the UAV group based on the defined optimization criterion for movement route. Modeling the operation of the proposed method has shown that the increase in decision-making efficiency reaches 15–18 %. The enhancement in the method's efficiency is achieved through additional procedures and ensuring the reliability of the decisions at a level of 0.9

Keywords: unmanned aerial vehicles, unimodal functions, multimodal functions, destabilizing factors, flight task

Received 04.10.2024
Received in revised form 25.11.2024
Accepted 06.12.2024
Published 27.12.2024

How to Cite: *Alkhafaji, M. J. A., Kashkevich, S., Shyshatskyi, A., Sova, O., Nalapko, O., Buyalo, O., Yula, O., Shaposhnikova, O., Matsyi, O., Dvorskyi, M. (2024). Development of a method for managing a group of unmanned aerial vehicles using a population algorithm. Eastern-European Journal of Enterprise Technologies, 6 (9 (132)), 108–116. https://doi.org/10.15587/1729-4061.2024.318600*

1. Introduction

Optimizing the movement of a group of unmanned aerial vehicles (UAVs) during the execution of a flight mission is a complex process for determining a set of solutions for the optimal mission task [1–3]. This complexity arises from numerous destabilizing factors that impact the UAV flight mission process, including:

– meteorological conditions of the surrounding environment;

– inhomogeneities in the terrain and discrepancies with cartographic services providing planning information for the flight mission;

– a complex electromagnetic setting in the area of mission execution.

Additionally, challenges in managing the flight of a UAV group include the diversity of software and hardware used by UAVs when performing joint flight tasks and more.

In solving optimization tasks for executing a UAV mission, decision variables are determined so that UAVs execute the mission according to the best-defined optimization criteria regime.

Taking into account the diversity of destabilizing factors, the varied dimensional indicators describing them, and the necessity for processing large sets of diverse data for managing the flight of a UAV group, population algorithms (swarm algorithms) are proposed [4–6].

Swarm intelligence algorithms are based on swarm movement and imitate the interaction of the swarm with its environment to enhance knowledge about the surroundings, such as finding new food sources [7, 8]. The most well-known swarm algorithms include Particle Swarm Optimization, Artificial Bee Colony, Ant Colony Optimization, Wolf Pack Optimization, and the Sparrow Flock Algorithm.

However, most of the aforementioned basic population algorithms struggle to balance the exploration and exploitation phases, leading to unsatisfactory performance in real-world complex optimization tasks.

This drives the implementation of various strategies to improve the convergence speed and accuracy of basic population algorithms when managing a UAV group. One method to enhance decision-making efficiency in managing the movement of a UAV group with population algorithms is their further refinement.

Therefore, scientific research aimed at improving UAV group management efficiency is indeed relevant.

2. Literature Review and Problem Statement

In work [9], a cognitive modeling algorithm is presented. The main advantages of cognitive tools are identified. A drawback of this approach is the lack of consideration for the type of uncertainty about the state of the analysis object.

Work [10] explores the essence of cognitive modeling and scenario planning. A system of complementary principles for building and implementing scenarios is proposed, with various approaches to scenario construction highlighted, and a scenario modeling procedure using fuzzy cognitive maps described. The approach proposed by the authors does not account for the type of uncertainty about the analysis object's state and ignores initial data noise.

In work [11], an analysis of the main approaches to cognitive modeling is conducted. Cognitive analysis allows for the investigation of problems with fuzzy factors and interconnections; it considers changes in the external environment and uses objectively formed developmental trends to its advantage. However, the issue of describing complex and dynamic processes remains unexplored in this work.

Work [12] presents a method for analyzing large data arrays, focused on uncovering hidden information within them. The method includes operations for generating analytical baselines, reducing variables, detecting sparse features, and applying rules. A drawback of this method is its inability to account for various strategies for decision evaluation and the absence of consideration for the uncertainty type in input data.

Work [13] describes a mechanism for transforming information models of construction objects into their equivalent structural models. This mechanism automates necessary operations for transformation, modification, and supplementation during information exchange. The approach's disadvantages include the inability to assess the adequacy and reliability of the information transformation process and to appropriately correct the obtained models.

In work [14], the development of an analytical web platform for researching the geographical and temporal distribution of incidents is presented. The web platform includes several information panels with statistically significant results across territories. 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. Additionally, a lack of solution search directionality is noted.

Work [15] involves developing a method for fuzzy hierarchical evaluation of library service quality. This method allows for assessing library quality based on multiple input parameters. However, its disadvantages include the inability to assess the adequacy and reliability of the evaluation and to determine the evaluation error accordingly.

In work [16], an analysis of 30 algorithms for processing large data arrays is conducted, highlighting their advantages and disadvantages. It is established that big data analysis should be layered, occur in real-time, and have the capability for self-learning. Noted disadvantages of these methods are high computational complexity and the inability to verify the adequacy of the obtained estimates.

Work [17] presents an approach to input data evaluation for support and decision-making systems. The essence of the proposed approach lies in clustering the basic set of input data, analyzing them, and then training the system based on this analysis. The drawbacks include the gradual accumulation of evaluation and training errors due to the inability to assess the adequacy of decisions made.

Work [18] describes an approach to processing data from various information sources, allowing for the processing of diverse data. However, the approach suffers from low accuracy in the obtained evaluations and the inability to verify the credibility of these evaluations.

In work [19], a comparative analysis of existing decision support technologies is conducted, specifically: the Analytic Hierarchy Process, neural networks, fuzzy set theory, genetic algorithms, and neuro-fuzzy modeling. Advantages and disadvantages of these approaches are outlined, and their areas of application are defined. It is shown that the Analytic Hierarchy Process works well with complete initial information but requires expert comparison of alternatives and choice of evaluation criteria, leading to a high degree of subjectivity. For forecasting tasks under risk and uncertainty, the use of fuzzy set theory and neural networks is justified.

Work [20] indicates that the most popular evolutionary bio-inspired algorithms are the so-called "swarm" procedures (Particle Swarm Optimization - PSO), including promising ones like Cat Swarm Optimization (CSO) for their speed and ease of implementation. These algorithms have proven their effectiveness in solving a number of complex tasks and have undergone several modifications, such as harmonics-based search, fractional derivatives, search parameter adaptation, and "crazy cats." However, these procedures have drawbacks that impair the process of searching for a global extremum.

The analysis of works [9–20] shows that the common disadvantages of the above studies are:

– lack of a hierarchical system of indicators for managing the flight of a UAV group;

– absence of consideration for computational resources in UAV group flight management systems;

– lack of mechanisms for the correction of flight management system indicators;

– absence of mechanisms for deep learning of knowledge bases;

– high computational complexity;

– failure to account for available computational (hardware) resources in the system;

– lack of priority in search in specific directions.

Thus, the unresolved problem remains the management of a UAV group under conditions of uncertainty and dynamic environmental changes across multiple indicators and a defined efficiency criterion.

3. The aim and objectives of the study

The aim of the study is to develop a method for managing a group of unmanned aerial vehicles (UAVs) using a population algorithm. This will enhance the efficiency of managing the flight of a UAV group with predetermined reliability and facilitate the development of subsequent management decisions. This approach will enable the creation of software for managing the flight of a UAV group.

To achieve this aim, the following objectives were set:

– define the algorithm for implementing the method;

– provide an example of the method's application in managing the flight of a UAV group.

4. Materials and methods

The object of the study is a group of unmanned aerial vehicles (UAVs). The problem addressed in the research is enhancing the decision-making efficiency in managing the movement of a UAV group, ensuring a specified reliability regardless of the number of UAVs in the group. The subject of the study is the decision-making process in management tasks using a set of improved procedures.

The research hypothesis is that it is possible to increase decision-making efficiency in managing the movement of a UAV group with specified evaluation reliability using an improved Brown Bear Algorithm (BBA). The algorithm is inspired by the behavior of brown bears, such as group following, identifying food locations, and establishing a living range. This behavior is mainly based on marking with scent and sniffing. The algorithm enables obtaining soft solutions for the search space of optimal UAV group movement routes, regardless of the type of UAVs in the group or the number of input variables.

The proposed method's operation was simulated using the Mission Planner version 1.3.849.20539 software (USA) and MathCad 14 (USA), along with Microsoft Visual Studio 2022 (USA). The task addressed during the simulation was determining the optimal route for the UAV group's movement. The research hardware was an AMD Ryzen 5.

Main parameters of the UAV group:

– number of airplane-type UAVs: 20 units;

– flight duration: 2 hours;

– UAV movement route length: 100 km;

– wind speed: 5 m/s;

– terrain type: urban area;

– air temperature: 5 °C;

– interference level on the UAV group's flight mission route affecting the input of the global satellite positioning system receiver: 15 dBm.

Parameters for BBA operation:

– number of iterations: 100;

– number of individuals in the swarm: 20;

– feature space range: [–300, 300].

This represents a set of possible values for each flight task undertaken by the UAV group.

5. Development of a method for managing a group of unmanned aerial vehicles using a population algorithm

5. 1. Algorithm for the method of managing a group of unmanned aerial vehicles using a population algorithm

The method for managing a group of unmanned aerial vehicles (UAVs) using a population algorithm consists of the following sequence of Steps:

Step 1. Input initial data. At this stage, initial data about the UAVs composing the group, the route for executing the flight mission, information about the environment, terrain, and more are introduced.

Step 2. Initialization and formation of the BBA population. At this stage, initial random sets of solutions representing the BBA populations are generated, with the scents marked on the paws of individual BBAs serving as decision variables from the set of possible solutions. The mathematical representation of a randomly selected BBA group within their specific territory is provided by the following equation:

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

where λ – a random number in the range from 0 to 1, $P_{i,j}$ – i-th scent marking of the j-th BBA population. The BBA population is placed in ascending order of $f(P_i)$, selecting the best $\left(P_i^{best}\right)$ and worst decisions $\left(P_i^{worst}\right)$, γ – represents the degree of uncertainty in the data about the UAV group's route. At this stage, the objective function $f(P)$, the population size (m) of the BBA swarm, the number of variables (n), variable constraints (LB, UB) and the algorithm's termination criterion $\left(FE'_{\max}\right)$. The group of brown bears is considered part of the BBA population (i=1, 2, ..., m), and the BBA levels in the group are treated as decision variables (j=1, 2, ..., n).

Step 3. Numbering BBAs in the population, i, $i\epsilon[0, S]$. Each BBA in the population is assigned a serial number at this stage.

Step 4. Determining initial speed of BBAs in the population.

The initial speed v_0 of each BBA in the population is determined by the following expression:

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

Determining the initial speed of each search agent in the population is necessary to set the movement speed in a specific direction for solving the task in the search space for each agent in the BBA swarm. In this approach, one search agent in the BBA population represents one UAV.

In the planning of the proposed approach, the position of the BBA population in the problem-solving space is updated based on modeling exploration and exploitation strategies.

Step 5. Preliminary Evaluation of the BBA search area.

In this procedure, the search area in natural language is defined as the habitat range of the BBA. Considering the diversity of BBA food sources, let's sort the quality of the food.

Step 6. Classification of food sources for BBA.

The location of the best food source (i.e., minimal suitability) is considered (FS_{ht}) plant food: berries, acorns, nuts, roots, tuberous grasses, which are nearby and require the least energy to find and obtain. The delicacy food-honey-is marked as FS_{at}. The procedure for classifying food for BBA in this study represents the priority of selecting the flight direction for each UAV in the UAV group according to its priority.

Other non-priority food sources (food necessary for the survival of individuals) are marked as FS_{nt}.:

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

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

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

Step 7. Selection of BBA gait technique (choice of UAV maneuver type on route). The physical essence of this procedure for the UAV group involves describing the set of maneuvers performed during the flight task by each UAV in the group.

Step 7. 1. Turning legs while walking (investigating the route with the payload of leading UAVs in the group).

This step involves a special walking technique where BBAs turn their legs to avoid previous depressions in the ground and carefully step toward the desired location. This special walking behavior is most often observed in male BBAs. Mathematically, this behavior can be modeled as:

$$P_{i,j,k}^{new}=P_{i,j,k}^{old}-\left(\theta_k\alpha_{i,j,k}P_{i,j,k}^{old}\right), \tag{6}$$

where $P_{i,j,k}^{new}$ – the updated scent mark of the paw in the k-th iteration of the i-th group, created by the j-th scent mark;

θ_k – the repeatability coefficient, taking values from 0 to 1;

$\alpha_{i,j,k}$ – a random number in the range from 0 to 1.

Step 7. 2. Cautious step of BBA (repeating the movement path of the leading UAV in the group).

The characteristic of a cautious step of the BBA involves repeating paw prints by checking previously marked paws. This behavior helps effectively warn other group members. Equation (7) presents the mathematical formulation of the cautious step technique observed in BBA:

$$P_{i,j,k}^{new}=P_{i,j,k}^{old}+F_k\left(P_{j,k}^{best}-L_kP_{j,k}^{worst}\right), \tag{7}$$

where F_k – the step coefficient; $P_{j,k}^{best}$, $P_{j,k}^{worst}$ – j-th best and worst estimates of the BBA paw in the k-th iteration; L_k – the length of the BBA step in a given iteration.

Step 7. 3. Twisting of BBA paws (creating route markers for UAV movement in the group).

The third unique walking behavior observed in brown bears is the twisting of paws. Male brown bears typically twist their legs into previously formed paw prints, making them deeper and more pronounced for easier identification. The choice of paw print type is based on the worst and best paw scent tracks of the BBA, as determined in the previous iteration. The mathematical representation of the twisted legs behavior is described by equation (8):

$$P_{i,j,k}^{new}=P_{i,j,k}^{old}+\omega_{i,k}\left(P_{j,k}^{best}-P_{i,j,k}^{old}\right)-\omega_{i,k}\left(P_{j,k}^{worst}-P_{i,j,k}^{old}\right), \tag{8}$$

where $\omega_{i,k}$ – the angular velocity of the legs at the i-th paw mark and the k-th iteration.

Step 8. Placement of the BBA population. At this stage, BBAs are placed in order of increasing values of the objective function $f(P_i)$, and the best $\left(P_i^{best}\right)$ and worst $\left(P_i^{worst}\right)$ decisions are chosen. In this study, the objective function is represented as the safest route for executing the flight mission for each UAV in the group, based on a set of defined indicators.

Step 9. Creation of a New BBA Population:

$$P_{i,k}^{new}=P_{i,k}^{old}-\left(\theta_k\alpha_{i,k}P_{i,k}^{old}\right), \tag{9}$$

where $F_k=\beta_{1,k}\,\theta_k$, L_k=1+$\beta_{2,k}$ and $\beta_{1,k}$, $\beta_{1,k}$ – random numbers in the range [0; 1].

Step 10. Placement of the BBA set. At this stage, BBAs are placed in order of increasing values of the objective function $f(P_i)$ and the best $\left(P_i^{best}\right)$ and the worst decisions $\left(P_i^{worst}\right)$ are chosen.

Step 11. Sniffing of BBA. The essence of BBA behavior is that they sniff each other to follow the scent trails of their group members in the right direction. Additionally, BBAs use sniffing to establish their own territory and avoid being misled by the scent trails of other BBAs' paws. The physical essence of the proposed management method is to repeat the movement trajectory of UAVs that are guiding a defined number of other UAVs. The mathematical model of the sniffing behavior is given by formula (10):

$$P_{m,j,k}^{new}=\begin{cases}P_{m,j,k}^{old}+\lambda_{i,k}\left(P_{m,j,k}^{old}-P_{n,j,k}^{old}\right), \text{if } f\left(P_{m,k}^{old}\right)\langle f\left(P_{n,k}^{old}\right),\\ P_{m,j,k}^{old}+\lambda_{i,k}\left(P_{n,j,k}^{old}-P_{m,j,k}^{old}\right), \text{if } f\left(P_{n,k}^{old}\right)\langle f\left(P_{m,k}^{old}\right),\end{cases} \tag{10}$$

where $\lambda_{i,k}$ – a uniformly distributed random number in the range from 0 to 1; $P_{m,j,k}^{new}$ – the updated paw scent location $m \neq n$;

$P_{m,k}^{old}$ and $P_{n,k}^{old}$ – the fitness function values for the k-th iteration of the m and n groups respectively. The update process for all described steps is applied to each BBA population until the required criterion is met.

Step 12. Checking the stop criterion. The algorithm ends if the maximum number of iterations is reached. Otherwise, the behaviors of generating new locations and checking conditions are repeated.

Step 13. Training the knowledge bases of BBA. In this study, the method of learning based on evolving artificial neural networks, developed in research [2], is used to train the knowledge bases of each BBA. This method is utilized to modify the movement characteristics of each BBA for more accurate analysis results in the future.

Step 14. Determining the required computational resources and intelligent decision support system.

To prevent computation loops in steps 1–10 of this method and enhance calculation efficiency, the system's load is additionally assessed. If the computational complexity exceeds a defined threshold, the number of software and hardware resources that need to be additionally involved is determined using the method proposed in work [20].

End of the algorithm.

5. 2. Example of applying the proposed method for determining the optimal flight of a group of unmanned aerial vehicles

The proposed method for managing a group of unmanned aerial vehicles using a population algorithm. To determine the effectiveness of the proposed method, its operation was modeled to address the task of managing a group of UAVs under given initial conditions.

To evaluate the effectiveness of the method proposed in the study, a software application was developed in the Microsoft Visual Studio 2022 programming environment, which is presented below.

```
#include <iostream>
#include <vector>
#include <cmath>
#include <ctime>
#include <cstdlib>
struct Bear {
    double x, y;
    double speed;
    double fitness;
    Bear() : x(0), y(0), speed(0), fitness(0) {}};
class BrownBearAlgorithm {
private:
    std::vector<Bear> population;
    int population_size;
    double search_area_x_min, search_area_x_max;
    double search_area_y_min, search_area_y_max;
    double alpha;
    int max_iterations;
    double stopping_criteria;
public:
    BrownBearAlgorithm(int population_size, double x_min, double x_max, double y_min, double y_max,
        double alpha, int max_iterations, double stopping_criteria)
    : population_size(population_size), search_area_x_min(x_min), search_area_x_max(x_max),
    search_area_y_min(y_min), search_area_y_max(y_max), alpha(alpha),
    max_iterations(max_iterations), stopping_criteria(stopping_criteria) {
        srand(time(0));}
    void initializePopulation() {
        population.clear();
        for (int i = 0; i < population_size; ++i) {
            Bear bear;
            bear.x = search_area_x_min + (rand() % 100) / 100.0 * (search_area_x_max - search_area_x_min);
            bear.y = search_area_y_min + (rand() % 100) / 100.0 * (search_area_y_max - search_area_y_min);
            bear.speed = 0;
            bear.fitness = calculateFitness(bear);
            population.push_back(bear); } }
    double calculateFitness(const Bear& bear) {
        return -(bear.x * bear.x + bear.y * bear.y);}
    void moveBear(Bear& bear, const Bear& best_bear) {
        bear.speed = alpha * (rand() % 100) / 100.0;
        bear.x += bear.speed * (best_bear.x - bear.x);
        bear.y += bear.speed * (best_bear.y - bear.y);
        bear.fitness = calculateFitness(bear);  }
    Bear findBestBear() {
        Bear best_bear = population[0];
        for (const auto& bear : population) {
            if (bear.fitness > best_bear.fitness) {
                best_bear = bear;}  }
        return best_bear;}
    void checkStoppingCriteria(const Bear& best_bear) {
        if (best_bear.fitness >= stopping_criteria) {
            std::cout << "Algorithm is complete, find the best result:: " << best_bear.fitness << std::endl;
            exit(0);}}
    void estimateResources() {
        std::cout << "Assessment of computing resources " << population_size * max_iterations << " operations." << std::endl; }
    void optimize() {
        initializePopulation();
        for (int iter = 0; iter < max_iterations; ++iter) {
            Bear best_bear = findBestBear();
            for (auto& bear : population) {
                moveBear(bear, best_bear); }
            checkStoppingCriteria(best_bear);
        estimateResources();}}};
int main() {
    int population_size = 50;
    double x_min = -10, x_max = 10, y_min = -10, y_max = 10;
    double alpha = 0.5;
    int max_iterations = 1000;
    double stopping_criteria = -0.01;
    BrownBearAlgorithm algorithm(population_size, x_min, x_max, y_min, y_max, alpha, max_iterations, stopping_criteria);
    algorithm.optimize();
    return 0;}
```

The implementation of the software application in the Microsoft Visual Studio 2022 programming environment is shown in Fig. 1–3.

The effectiveness of the method for managing a group of unmanned aerial vehicles using a population algorithm is compared using functions, as shown in Table 1, which includes unimodal and multimodal functions with the CEC2019 test functions set.

Table 2 (probabilistic value) presents the results of the reliability assessment of decisions made for each of the optimization methods for managing a group of unmanned aerial vehicles.

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

As seen from Tables 1, 2, an increase in decision-making efficiency is achieved at the level of 15–18 % through the use of additional procedures and ensuring the reliability of decisions at a level of 0.9.

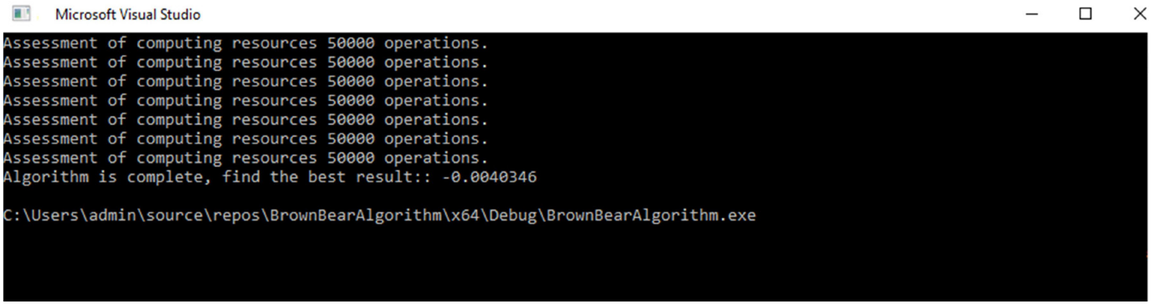

Fig. 1. Implementation of the software application in the Microsoft Visual Studio 2022 programming environment

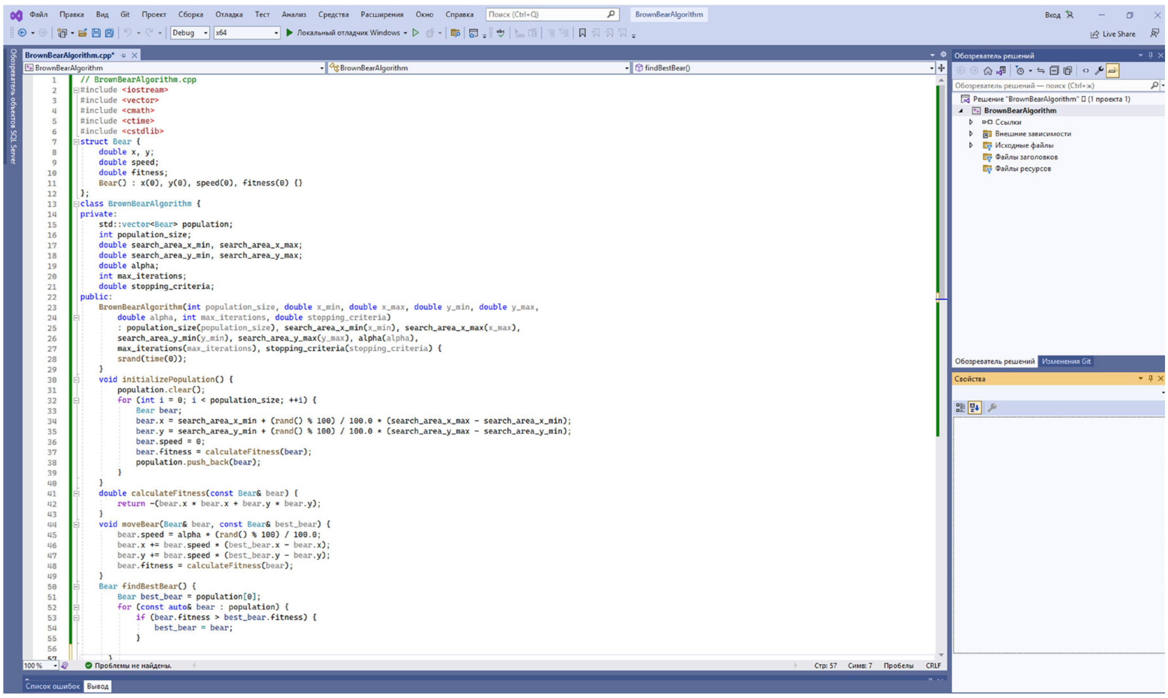

Fig. 2. Implementation of the software application in the Microsoft Visual Studio 2022 programming environment

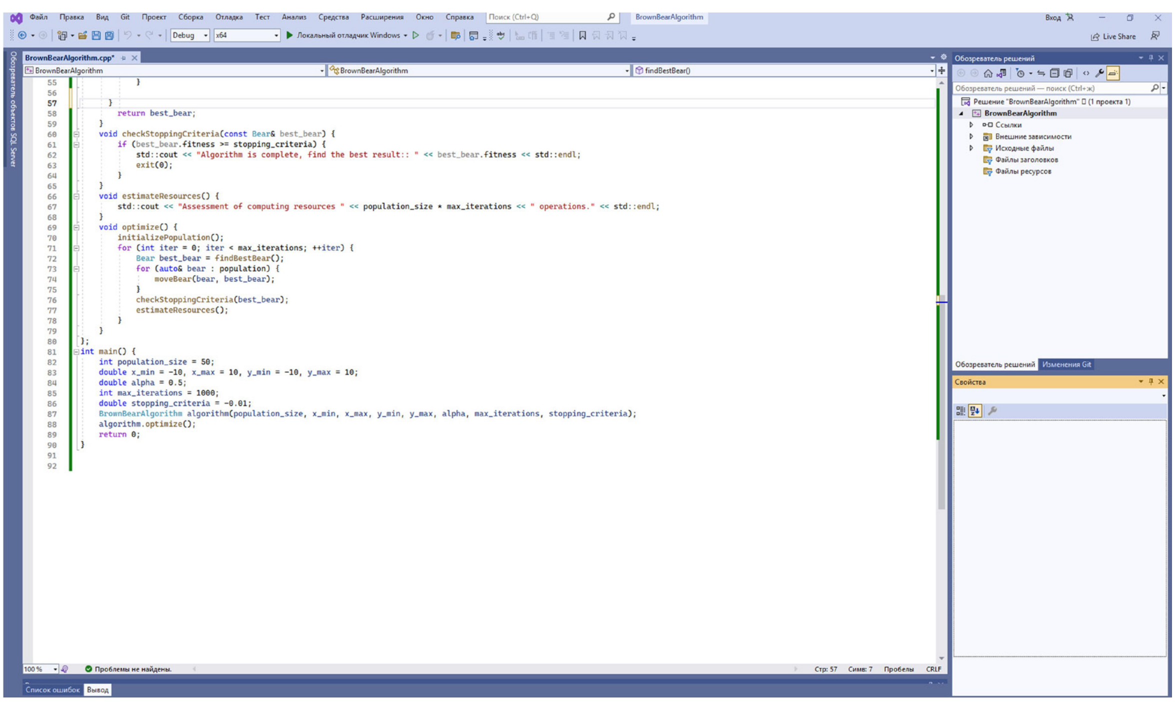

Fig. 3. Implementation of the software application in the Microsoft Visual Studio 2022 programming environment

Table 1

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

Function Name	Metric	Particle Swarm Optimization Algorithm [21]	Ant Colony Algorithm [21]	Black Widow Algorithm [21]	Gray Wolf Pack Algorithm [21]	Canonical Brown Bear Algorithm [21]	Improved Brown Bear Algorithm
F1	Average value (ms)	300.000	300.000	300.000	300.000	300.000	300.000
	Standard value (ms)	2.17547E-07	1.94448E-07	1.73866E-07	1.73121E-07	1.51021E-07	1.72168E-07
F2	Average value (ms)	400	400.265772	400.7973158	400.265772	400.3986579	400.5315439
	Standard value (ms)	4.9898E-08	1.011427534	1.621892282	1.011427535	1.216419212	1.378343398
F3	Average value (ms)	600.0071815	600.0644622	600.0240021	600.012832	600.031303	600.0449987
	Standard value (ms)	0.021632777	0.184980091	0.115606243	0.053463097	0.147011513	0.101164243
F4	Average value (ms)	826.5653461	827.3281442	823.8789639	826.3000191	826.2668486	825.7693662
	Standard value (ms)	9.13817552	8.364210734	11.30806963	8.186625055	9.136107323	10.05991317
F5	Average value (ms)	900.743876	900.9504411	900.9726169	900.8007883	900.5452042	901.2016312
	Standard value (ms)	0.781626306	1.424558753	1.275779755	0.903385622	0.635781924	1.598982565
F6	Average value (ms)	1888.524629	1874.869967	1876.294359	1847.184924	1888.926953	1842.878175
	Standard value (ms)	127.2561383	91.22185049	69.00003268	32.76980351	140.693674	31.32108747
F7	Average value (ms)	2027.479588	2030.758499	2029.556604	2032.238674	2028.177978	2029.128603
	Standard value (ms)	6.106897592	8.027195324	5.81348717	7.446489204	8.003968446	8.197733191
F8	Average value (ms)	2223.108804	2223.537417	2222.070633	2223.140251	2220.888475	2220.690533
	Standard value (ms)	4.749655105	2.963408213	4.895282849	3.995669404	5.451654006	6.337353983
F9	Average value (ms)	2510.930321	2510.930321	2536.358938	2498.216012	2523.644629	2498.216012
	Standard value (ms)	65.93880108	65.93880108	85.778947	48.38585173	77.58997694	48.38585173
F10	Average value (ms)	2594.615905	2596.833927	2585.256107	2591.210109	2605.304194	2619.308989
	Standard value (ms)	48.2013289	49.71807546	57.1034079	56.36586785	42.57395199	34.10382553
F11	Average value (ms)	2695.981932	2685.587394	2733.855734	2710.621315	2700.168413	2715.332781
	Standard value (ms)	116.3652035	110.1475838	146.333679	118.5098748	113.7913849	109.3008673
F12	Average value (ms)	2857.067086	2858.742176	2854.959949	2861.414681	2859.407788	2860.718769
	Standard value (ms)	9.364347909	14.88960231	5.539104327	17.96133754	15.00545163	16.34731781

Table 2

Evaluation of the effectiveness of the proposed management method based on the criterion of information processing reliability (probabilistic value)

Function Name	Metric	Particle Swarm Optimization Algorithm [21]	Ant Colony Algorithm [21]	Black Widow Algorithm [21]	Gray Wolf Pack Algorithm [21]	Canonical Brown Bear Algorithm [21]	Improved Brown Bear Algorithm
F1	Average value (ms)	0,66	0,73	0,67	0,68	0,8	0,9
	Standard value (ms)	0,7	0,73	0,68	0,69	0,83	0,91
F2	Average value (ms)	0,7	0,73	0,7	0,71	0,77	0,89
	Standard value (ms)	0,71	0,73	0,72	0,72	0,76	0,9
F3	Average value (ms)	0,68	0,73	0,7	0,71	0,76	0,92
	Standard value (ms)	0,69	0,73	0,69	0,73	0,77	0,91
F4	Average value (ms)	0,67	0,74	0,7	0,72	0,78	0,93
	Standard value (ms)	0,67	0,72	0,67	0,72	0,79	0,92
F5	Average value (ms)	0,6	0,71	0,64	0,73	0,8	0,91
	Standard value (ms)	0,61	0,72	0,64	0,74	0,88	0,92
F6	Average value (ms)	0,64	0,73	0,66	0,77	0,85	0,93
	Standard value (ms)	0,66	0,75	0,66	0,78	0,83	0,92
F7	Average value (ms)	0,67	0,72	0,68	0,75	0,81	0,9
	Standard value (ms)	0,68	0,71	0,69	0,74	0,83	0,9
F8	Average value (ms)	0,68	0,74	0,69	0,75	0,84	0,93
	Standard value (ms)	0,65	0,74	0,67	0,77	0,81	0,91
F9	Average value (ms)	0,64	0,75	0,66	0,69	0,83	0,91
	Standard value (ms)	0,7	0,72	0,71	0,71	0,84	0,93
F10	Average value (ms)	0,69	0,71	0,7	0,72	0,8	0,94
	Standard value (ms)	0,68	0,71	0,7	0,73	0,8	0,91
F11	Average value (ms)	0,67	0,71	0,69	0,71	0,82	0,91
	Standard value (ms)	0,67	0,72	0,68	0,74	0,91	0,91
F12	Average value (ms)	0,63	0,73	0,65	0,75	0,82	0,91
	Standard value (ms)	0,62	0,74	0,66	0,76	0,83	0,91

6. Discussion of the results from the UAV group management method using a population algorithm

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

– the initial BBA population and their starting positions on the search plane are determined considering the degree of uncertainty in the initial data about the UAV group's route (1) using appropriate corrective coefficients, compared to works [9, 14, 20];

– the initial speed of each BBA is considered (2), allowing for prioritization of the search in the respective search plane (height, latitude, and longitude), compared to works [9–15];

– the suitability of the UAV group's flight route is determined when performing the flight task, taking into account external factors, thereby reducing decision search time (Step 5), compared to works [14, 16, 17];

– the universality of BBA food location search strategies allows classifying the set of conditions and factors affecting the completion of the flight task (Step 6), compared to works [14, 16, 17]. This enables the determination of the most suitable movement options for the UAV group based on the defined route optimization criteria;

– the ability to explore solution spaces of functions described by atypical functions through the use of BBA gait technique selection procedures (Step 7), compared to works [9, 12–18];

– the replacement of unsuitable search entities by updating the BBA population (Steps 9, 10), compared to works [9, 12–18];

– the ability for simultaneous solution searches in different directions (Steps 1–14, Tables 1, 2);

– the capability of deep learning for BBA knowledge bases (Step 10), compared to works [9–20];

– the ability to calculate the required number of computational resources needed if calculations cannot be carried out with existing resources (Step 18), compared to works [9–20].

The disadvantages of the proposed method include:

– loss of informativeness in managing the flight of a UAV group due to the construction of the membership function;

– lower accuracy of evaluation for an individual parameter in assessing the state of UAV group movement routes;

– loss of reliability in obtained decisions when searching in multiple directions simultaneously;

– lower accuracy of assessment compared to other methods of managing UAV group flights.

The proposed method allows for:

– determining the optimal flight route for a UAV group based on a defined optimization criterion;

– identifying effective measures to enhance the management efficiency of a UAV group;

– increasing the speed of managing a UAV group while ensuring a specified reliability in decision-making for managing the movement route of the UAV group;

– reducing the use of computational resources in decision support systems.

The research limitations include the necessity of having an initial database on the UAV group movement route, and the need to account for the time delay in collecting and transmitting information from UAV group monitoring technical means.

The proposed approach is advisable for solving UAV group flight management tasks characterized by a high degree of complexity.

7. Conclusions

1. An algorithm for implementing the method has been defined, thanks to additional and improved procedures that allow:

– the initial BBA population and their starting positions on the search plane are determined considering the degree of uncertainty in the initial data about the UAV group route;

– the initial speed of each BBA is considered, allowing prioritization of the search in the respective search plane (height, latitude, and longitude);

– the suitability of the UAV group's flight route is determined when executing the flight mission, taking into account external factors, thereby reducing decision search time;

– the universality of BBA food location search strategies allows classifying conditions and factors affecting the completion of the flight mission. This enables determining the most suitable movement options for the UAV group based on the defined route optimization criteria;

– the ability to explore solution spaces of functions described by atypical functions, using BBA gait technique selection procedures;

– replacing unsuitable search individuals by updating the BBA population;

– simultaneous solution search in different directions;

– the capability of deep learning for BBA knowledge bases;

– calculating the necessary number of computational resources needed if calculations cannot be carried out with existing resources.

2. An example of using the proposed method, applied to constructing a UAV group movement route, demonstrated an increase in decision-making efficiency by 15–18 % through the use of additional procedures and ensuring decision reliability at a level of 0.9.

Conflict of interest

The authors declare that they have no conflicts of interest regarding this research, including financial, personal, authorship, or any other type that could affect the research and its results presented in this article.

Funding

The research was conducted without financial support.

Data availability

The manuscript has associated data in a data repository.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies in creating the presented work.

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