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METHOD FOR PREDICTING THE FLIGHT PATH OF LONG-RANGE UNMANNED AERIAL SYSTEMS BASED ON THE ELITE ANTS ALGORITHM

Abstract. The **subject matter** of the article is a method for predicting the flight path of long-range unmanned aerial systems based on the elite ants algorithm. The **goal** is to develop a method for predicting the flight path of long-range unmanned aerial systems. The **tasks** are: analysis of existing methods for laying flight paths, development of a method for predicting the flight path of long-range unmanned aerial systems based on the elite ant algorithm, practical verification of the operation of the developed method, conducting experimental studies on predicting the flight path of movement using the method based on a simple ant algorithm and based on the elite ant algorithm, conducting a comparative analysis of the obtained experimental results. The **methods** used are: graph modeling, multi-criteria optimization, simple ant algorithm, ant algorithm based on elite ants, computer modeling, and comparative analysis of results. The following **results** are obtained. The methods of laying flight paths are analyzed depending on the approach to optimization, taking into account the specified flight restrictions. They are divided into four main groups, and their main advantages and disadvantages are determined. We will give a formal description of the problem of predicting the path of long-range unmanned aerial systems based on the ant algorithm. A simple ant algorithm and an elite ant algorithm are considered. A method of predicting the path of long-range unmanned aerial systems based on the elite ant algorithm is developed. Experimental studies are conducted on the operation of the method of predicting the path of long-range unmanned aerial systems. A comparative assessment of the efficiency of the simple ant algorithm and the ant algorithm based on elite ants in solving the problem of predicting the optimal path of long-range unmanned aerial systems is carried out. **Conclusions.** Analysis of experimental studies showed that the use of the elite ant algorithm is more appropriate for the task of predicting the flight path of long-range unmanned aerial systems. The direction of further research is to optimize the input parameters of the elite ant's algorithm to solve the problem of predicting the flight path of long-range UASs in order to increase its accuracy and stability.

Keywords: long-range unmanned aircraft system; UAS; flight path; unmanned aerial vehicle; UAV; ant simple algorithm; elite ant's algorithm.

Introduction

Formulation of the problem. Modern trends in unmanned technology development are driving rapid growth in the role of long-range unmanned aerial systems (UASs) across both the military and civilian spheres. Active scientific research and development in the field of UASs, driven by the growing need for their use, is expanding the list of tasks they can perform every day. These studies help expand the range of UASs, increase their autonomy, and enhance their functionality [1, 2].

When using long-range UASs, additional restrictions are imposed on task performance, as tasks are conducted in dynamic situations and with information uncertainty. These may include changes in the meteorological and radio-electronic environment, as well as the presence of prohibited (dangerous) zones and other additional influences [3, 4]. The presence of such zones significantly affects the prediction of the path of movement of long-range UASs, since prohibited (dangerous) zones can be not only permanent, but also temporary, can be closed entirely or with partial restrictions (for example, by height, time, with the approval of relevant institutions, etc.) [5]. That is, these restrictions when laying the path are constantly changing and require an adaptive response to changes in external conditions in real time [3, 5].

The experience of using long-range UASs has shown that the success of assigned tasks largely depends on the quality of the flight path. Strict requirements are imposed on the flight path [3, 6]. This is the minimization of flight time and energy consumption of the unmanned aerial vehicle (UAV), with strict adherence to navigational and technical restrictions during the flight. An additional requirement for performing military tasks is to achieve the maximum reduction in the probability of detection and/or destruction of the UAV in the presence of potential threats [6, 7].

Therefore, in this regard, predicting the optimal flight path for long-range UASs that account for the full range of external factors and their potential dynamic changes is relevant.

Analysis of recent research and publications. A detailed analysis of the literature shows that today, when predicting flight paths for both UASs and aircraft, various path-planning methods are used. The analyzed methods for laying flight paths, depending on the optimization approach and the specified flight restrictions, can be conditionally divided into several main groups. Let us consider them and identify the main disadvantages and advantages of these groups.

The first group is methods based on classical optimization algorithms. They are based on deterministic mathematical models and are used to construct trajectories by minimizing certain indicators. To solve the problem, these indicators are flight time, distance, energy consumption, etc. In [8], the classical Dijkstra algorithm and its detailed study are considered. In [8], the A* algorithm is considered, an improvement over the classical Dijkstra algorithm. Method [8] is a classical deterministic method for finding the shortest path in a weighted graph with non-negative edge weights. Method [9] is supplemented with a heuristic function that significantly reduces the search area and speeds up the search for the optimal path. But for such an accelerated search, it is necessary to consider approximate estimates of the distance to the path's final point. Therefore, using method [8] guarantees finding the globally optimal path from the initial vertex to the final one, but at the expense of large computational and time costs. At the same time, the use of the method [8] guarantees high computational speed and a short time to construct a trajectory from the initial to the final point, but does not guarantee its optimality.

When the weight for graphs is negative (e.g., fines for entering dangerous or prohibited areas), another method based on classical optimization algorithms can be used. This is the Bellman-Ford method. In [10], the authors provide a generalization of the classical shortest-path problem. At the same time, instead of minimizing only the total edge weight, the authors introduce an input metric that, in addition to edge weight, also accounts for the path length and other characteristics of the movement trajectory along the graph. The main advantage of [10] is the ability to take into account the negative value of the graph weights. However, the main disadvantage of [10] is the dependence of the result of the method on the correct choice of weight coefficients.

In [11], the methods considered above were compared with each other, all belonging to the group of classical optimization algorithms. The comparison was carried out using indicators such as time and computational cost when calculating the shortest path. Thus, according to the study's results, Dijkstra's algorithm is guaranteed to find the shortest path in a graph with non-negative weights, but it explores a significant portion of the graph. This significantly reduces its efficiency in problems with large volumes. The A* algorithm is faster because it uses a heuristic function that guides the search to the goal state. At the same time, optimality is preserved with correct heuristics. The Bellman-Ford algorithm is slower than the previous two algorithms. However, it has the advantage of working with negative weights.

The second group is stochastic and probabilistic methods. In [12], a probabilistic planning approach, the Probabilistic Roadmap (PRM), is proposed for planning a UAV's path. The essence of [12] is to form a graph of achievable path options by probabilistic selective placement of graph nodes in free space, with their subsequent connection taking into account the probability of encountering obstacles (prohibited (dangerous) zones). The advantages of [11] include efficient routing in complex, large spaces with prohibited (dangerous) zones, as well as the ability to path in three-dimensional space. The disadvantages of [12] include the method's dependence on the sample's density and distribution, and the need to adapt the algorithm to rapidly changing conditions.

In [13], the authors investigated the feasibility of implementing the Rapidly-Exploring Random Trees (RRT) algorithm for real-time trajectory prediction of a UAV. This study was conducted on an STM32 microcontroller, which, in turn, has limited computing resources, and aimed to demonstrate the suitability of this algorithm for embedded autonomous systems in a UAV. The essence of the method is to build a tree of possible UAV trajectories by randomly generating points in its flight space. The tree is then sequentially expanded until the final point is reached. The main advantage of the proposed approach [13] is the ability to implement the trajectory prediction algorithm in real time with limited computing resources. The main disadvantages of [13] are the lack of a guarantee of obtaining the optimal trajectory and the dependence of the quality of the method's result on the sampling parameters.

The third group is methods based on artificial intelligence algorithms.

In [14], a deep reinforcement learning (DRL) approach is proposed to predict a UAV's path. The authors proposed representing the UAV as an agent that constantly learns through interaction with the external environment. According to the results of such training, it receives a reward if it quickly and safely reaches the final point of the path. Thus, the algorithm builds a database of the agent's correct navigation decisions by analyzing possible states. The analysis takes into account information on obstacles, the distance to the path's final point, prohibited areas, etc. The advantage of [14] is the adaptability of the proposed approach to environmental changes in three dimensions. The main disadvantage of [14] is the need for a large number of simulations for reinforcement learning, which, in turn, increases preparation time and computational resources.

In [15], a method for predicting dangerous (prohibited) flight zones for a UAV in an urban environment using a deep neural network (DNN) is proposed. The essence of [15] is to train a neural network on data about urban topology, building heights, weather conditions, and potential restricted areas. The advantage of [15] is that it yields good results in predicting dangerous (prohibited) zones when planning a path before actually approaching them. The disadvantages of [15] are that path prediction is performed only for the urban environment, only obstacles characteristic of it are considered, and there is no guarantee of finding the optimal path.

In [16], an approach to predicting a UAV's flight trajectory using a recurrent neural network of the GRU (Gated Recurrent Unit) type is proposed. The essence of [16] is to use such data about the flight state of the aircraft, as coordinates, its flight speed, changes in the external environment, etc., to predict its possible positions in real time. The GRU network is trained on data collected from past UAV flights. The advantage of [16] is adaptation to dynamically changing environmental conditions. The disadvantages of [16] are that such a prediction depends directly on the quality and representativeness of the training data, and there is no guarantee that the optimal UAV flight path will be laid.

The fourth group is methods that imitate the behavior of living organisms or natural processes to effectively search for the optimal path (bioinspired algorithms, swarm intelligence algorithms).

This group of methods is constantly expanding and supplemented with new algorithms. The most popular and most studied among them are the genetic algorithm, the artificial bee colony algorithm, the particle swarm algorithm, the ant colony algorithm, the firefly algorithm, etc.

In [17], a genetic algorithm is proposed as an optimization method for segmenting satellite images. The essence of [17] is to imitate natural selection, evolving the population of solutions through selection, crossing, and mutations to find the best or a close-to-optimal result. The advantages of the approach proposed in [17] are the study of an ample parameter space, global search for a solution, and implementation of the algorithm on parallel computing. At the same time, the disadvantages of [17] include high computational complexity and slow convergence.

In [18], the particle swarm optimization algorithm is proposed to solve the optimization problem in image segmentation. The essence of [18] is to model the collective behavior of particles to find the optimal parameters of the problem being solved by updating their positions based on their own experience and the experience of neighboring particles of the swarm. The advantages of [18] include a relatively fast rate of convergence and effective adaptation to dynamic conditions. At the same time, the disadvantages of [18] are the possibility of falling into local extrema and the dependence of the algorithm's result on the correct choice of swarm parameters.

Another algorithm from the fourth group of methods is presented in [19]. This is the algorithm of an artificial bee colony. The essence of [19] is to imitate the behavior of bees, when "employed bees" explore the solution space, and "scout bees" orient the further search to the most promising solutions. The advantages of [19] include the ability to find optima in complex multidimensional spaces effectively and to adapt to dynamic conditions. The disadvantages of [19] are the possibility of getting "stuck" in local optima and sensitivity to the choice of algorithm parameters.

In [20], a method is proposed to determine the optimal path for the arrival of special service units to the emergency scene. The essence of [20] is to represent the transport network as a weighted graph, the vertices of which are road infrastructure nodes, and the edges are road sections with corresponding weight coefficients. The method involves multi-criteria optimization of the path. For this purpose, a simple ant algorithm is used. The advantages of [20] are the ability to determine the optimal path in real time. At the same time, the method has certain limitations, namely that the algorithm's effectiveness depends on the correct setting of the input parameters.

Experimental studies of the results of swarm algorithms have shown that for solving the problem of determining the optimal path of vehicles, the ant algorithm is one of the most promising.

To date, a significant number of modifications of the ant algorithm have already been presented in the literature.

In [21], one of the modifications of the simple ant algorithm is considered, namely the max-min algorithm. This algorithm is proposed to be used to solve the problem of determining the path of vehicles in the presence of prohibited (dangerous) zones. The peculiarity of [21] is that the algorithm generates permissible paths taking into account the presence of prohibited (dangerous) zones. If the path passes through a prohibited zone, it is either rejected or receives a significant penalty value for the edge weight. The advantage of [21], in addition to those indicated in the analysis of [20], is the ability to take into account such restrictions as prohibited (dangerous) zones when laying the path. The disadvantages of [21] are the increase in computational complexity with a large number of forbidden (dangerous) zones.

Taking the above into account, it is advisable to further analyze and develop methods based on modifications to the ant algorithm to predict the paths of long-range UASs.

Thus, the **goal** of this article is to develop a method for predicting the flight path of long-range unmanned aerial systems based on the elite ants algorithm.

Main results

Let us provide a formal description of the task of predicting the flight path of long-range UASs using the ant algorithm.

In general, airspace can be represented as a weighted directed graph (1):

$$AS = (N, E), \tag{1}$$

where $N = \{n_1, n_2, ..., n_t\}$ – the set of graph nodes. In this task, these are the coordinates of the location of the UAS; $E = \{e_1, e_2, ..., e_l\}$ – the set of edges of the graph. In this task, these are the permissible movements of the UAS between the graph's nodes.

At the same time, in the task of predicting the path of long-range UASs, the following indicators are assigned to each edge of the graph $(i, j) \in E$:

d_{ij} – the length of the path of movement of the UAS between nodes;

c_{ij} – energy cost, i.e., the energy costs of the UAS on this path;

r_{ij} – risk; in this problem, these are prohibited (dangerous) zones;

t_{ij} – time to travel this path.

In the task of predicting the path of long-range UASs based on the ant algorithm, it is necessary to find a path P that would minimize the multi-criteria objective function (2):

$$F(P)=\omega\cdot\sum_{(i,j)\in P} d_{ij}+ \\ +\xi\cdot\sum_{(i,j)\in P} c_{ij}+\gamma\cdot\sum_{(i,j)\in P} r_{ij}+\mu\cdot\sum_{(i,j)\in P} t_{ij}, \quad (2)$$

where P – the path of movement of a UAS, i.e., the sequence of transitions between the nodes of the graph; ω – weighting factor of the spatial length of the path; ξ – weighting factor of energy cost; γ – weighting factor of risk component; μ – weighting factor of the time factor.

Let us introduce a "pheromone" model, where $\tau_{ij}(t)$ is the amount of pheromone on the edge, $\eta_{ij}(t)=\frac{1}{L_{ij}(t)}$ this is the heuristic appeal on the edge ($L_{ij}(t)$ local cost of transition).

The probability of the transition of an ant a from node i of the graph to node j occurs with the probability according to (3) [20]:

$$p_{ij}^{a}(t)=\frac{\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}}{\sum_{l\in N_i}\tau_{ij}^{\alpha}(t)\cdot\eta_{ij}^{\beta}}, \quad (3)$$

where t – the iteration sequence number; T – total number of iterations; N_i – permissible transitions from node i; α – the weight of the pheromone, i.e., its influence; β – the influence of the heuristic.

Let us consider a modification of the simple ant algorithm, namely, the elite ant algorithm. The main difference of this modification is the reinforcement of the best path found.

The evaporation of the pheromone at each subsequent iteration is calculated according to expression (4) [20]:

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t), \quad (4)$$

where $\rho\in(0;1)$ – pheromone evaporation coefficient.

In this modification, the total number of ants is divided into two classes: ordinary and elite. The number of elite ants is determined at the start of the method and included in the input data.

The pheromone update for these two classes of ants is calculated using different expressions.

The pheromone update for ordinary ants is updated according to (5) and (6) [20]:

$$\Delta\tau_{ij}^{a}=\begin{cases}\dfrac{Q}{F(P_k)}, & \text{if the edge graph belongs } P_a;\\ 0, & \text{otherwise,}\end{cases} \quad (5)$$

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\sum_{a=1}^{A}\Delta\tau_{ij}^{a}, \quad (6)$$

where A – total number of ants.

The pheromone update for elite ants is updated according to (7) and (8) [22, 23]:

$$\Delta\tau_{ij}^{elite}=e\cdot\frac{Q}{F(P^*)}, \quad (7)$$

$$\tau_{ij}(t+1)=(1-\rho)\cdot\tau_{ij}(t)+\sum_{a=1}^{A}\Delta\tau_{ij}^{a}+\Delta\tau_{ij}^{elite}, \quad (8)$$

where P^* – globally best ant movement path; e – number of elite ants.

The condition for the completion of the algorithm based on elite ants is the fulfillment of condition:

$$\left|F(P_t^*)-F(P_{t-1}^*)\right|<\varepsilon, \quad (9)$$

where ε – accuracy is set [24].

Another condition may be reaching the maximum number of iterations of the algorithm defined in the input data [25].

We will conduct experimental studies on the predicting of the paths of long-range UASs using the considered algorithms.

The optimal (shortest) path is predicted from the starting point of the path – point A (lower left corner, Fig. 1) to the final point of the path – point B (upper right corner, Fig. 1). The path from point A to point B passes through the turning points of the path – one of the points of the set Ω_1 (a total of 100 possible points) and one of the points of the set Ω_2 (a total of 100 possible points). Path prediction is reduced to finding two optimally located points among the points of the sets Ω_1 and Ω_2.

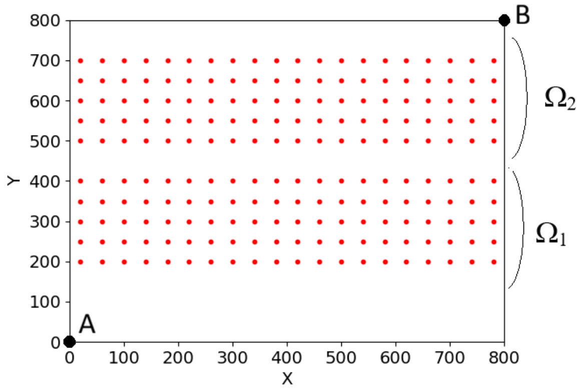


Fig. 1. Coordinates of the position of the turning points of the sets Ω_1 and Ω_2

Naturally, in this case, the shortest path between point A and point B is a straight line. Therefore, the best solutions would be to choose points from sets Ω_1 and Ω_2 that are closest to the straight line AB (Fig. 2).

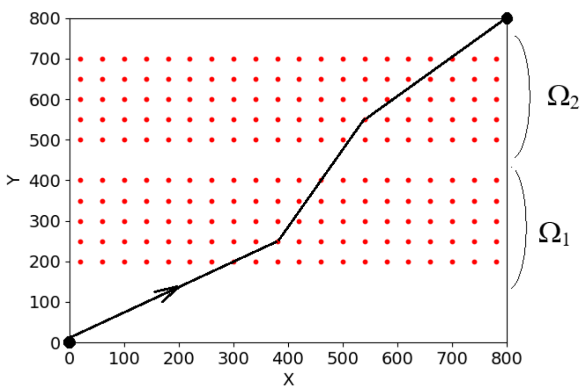


Fig. 2. Possible path planning option

Let us consider the prediction of the path of long-range UASs based on a simple ant algorithm and based on the elite ant's algorithm.

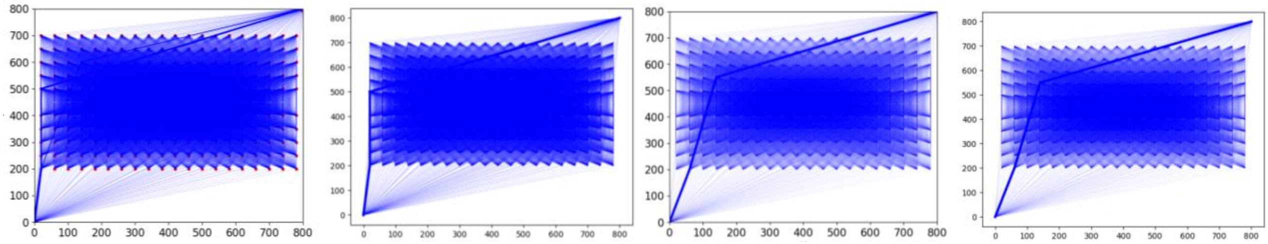
Let us define the input data for modeling the method for predicting the flight path of long-range UASs based on a simple ant algorithm:

$$\alpha = 1{,}5,\ \beta = 1,\ \rho = 0{,}1,\ A = 30,\ T = 200.$$

Two runs of the algorithm for the method of predicting the flight path of long-range UASs using a method based on a simple ant algorithm were performed.

At the first run, the algorithm was stopped after the 100th (Fig. 3, a) and 200th iteration (Fig. 3, b) of its operation.

A second run of the algorithm was performed. On the second run, the algorithm was stopped after the 100th (Fig. 3, c) and 200th iteration (Fig. 3, d) of its operation.



a – 100 iterations b – 200 iterations c – 100 iterations d – 200 iterations

Fig. 3. Results of the method for predicting the flight path of long-range UASs using a method based on a simple ant algorithm: a, b – 1st run of the algorithm; c, d –2nd run of the algorithm

According to the results of experimental studies of the method of predicting the path of long-range UASs using a simple ant algorithm, it can be concluded that the main disadvantages are:

– the results of predicting the path of long-range UASs are unsatisfactory; the paths found are not optimal;

– increasing the number of iterations (from 100 iterations to 200 iterations) does not lead to finding the optimal path;

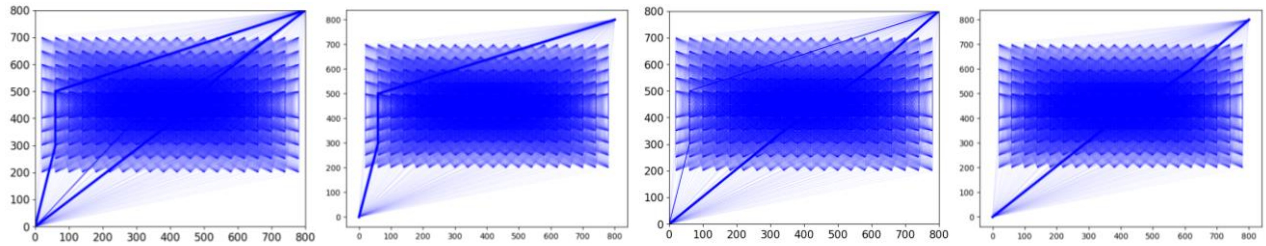
– in the first steps, the method of predicting the path of long-range UASs using a simple ant algorithm selects one of the shortest segments from the initial point of the path A to the intermediate point of the path of the set Ω_1 and enhances the attractiveness of this segment with pheromones. At the same time, the position of this segment is far from the optimal direction. In the future, this segment "suppresses" other possible paths. In this case, changes in the parameters α and β do not lead to success.

Let us define the input data for modeling the method for predicting the flight path of long-range UASs based on the elite ants algorithm:

$$\alpha = 1{,}5,\ \beta = 1,\ \rho = 0{,}1,\ e = 100,$$
$$A = 30,\ T = 200.$$

Two runs of the algorithm for the method of predicting the flight path of long-range UASs using a method based on the elite ant's algorithm were performed. At the first run, the algorithm was stopped after the 100th (Fig. 4, a) and 200th iteration (Fig. 4 ,b) of its operation.

A second run of the algorithm was performed. On the second run, the algorithm was stopped after the 100th (Fig. 4, c) and 200th iteration (Fig. 4, d) of its operation.



a – 100 iterations b – 200 iterations c – 100 iterations d – 200 iterations

Fig. 4. Results of the method for predicting the flight path of long-range UASs using a method based on on the elite ants algorithm: a, b – 1st run of the algorithm; c, d –2nd run of the algorithm

Experimental studies (Fig. 3, Fig. 4) were conducted using the high-level programming language Python 3.14.

The main goal was to conduct a comparative assessment of the efficiency of the simple ant algorithm and the ant algorithm based on elite ants in solving the task of predicting the flight path of long-range UASs.

The simulation was performed for runs of the algorithms with 100 and 200 iterations.

Comparison of the results shown in Fig. 3, a and Fig. 4, a (1st run of the algorithm, 100 iterations) showed that the simple ant algorithm forms a path that is not optimal and has noticeable deviations from the shortest trajectory between points A and B (Fig. 2).

This is due to the premature concentration of pheromone on a locally attractive, but globally suboptimal direction of movement. At the same time, the algorithm based on elite ants demonstrates a significantly better result after 100 iterations: the path is located closer to the straight line AB, and the pheromone concentration more clearly reflects the promising search direction.

Analysis of the results shown in Fig. 3, b and Fig. 4, b (1st run of the algorithm, 200 iterations) confirmed the above.

Increasing the number of iterations for the simple ant algorithm does not lead to a fundamental improvement in the result, which indicates that the algorithm has reached a local extremum (Fig. 3, b). At the same time, the elite ants algorithm at 200 iterations provides stabilization of the path (Fig. 4, b), which practically coincides with the optimal trajectory (Fig. 2).

Thus, additional iterations in the modification of the ant simple algorithm are used more productively.

The 2nd run of the algorithm of the two considered algorithms was also performed.

The analysis of Fig. 3, c and Fig. 4, c (2nd run of the algorithm, 100 iterations) showed that even at the initial stage of the iteration process, the algorithm with elite ants demonstrates faster convergence to the global minimum of the objective function (Fig. 4, c).

At the same time, the simple ant algorithm with the same input data did not provide pheromone concentration along the optimal trajectory of movement.

Similar conclusions are confirmed when analyzing Fig. 3, d and Fig. 4, d (2nd run of the algorithm, 200 iterations).

For the algorithm based on elite ants, complete stabilization of the globally optimal path and a clear concentration of pheromone along it are observed.

In the case of a simple ant algorithm, even after 200 iterations, deviations from the optimal direction of movement may persist, indicating slower convergence and greater dependence on initial random factors.

Therefore, the obtained results of experimental studies allow us to conclude that the use of the elite ant algorithm is more appropriate for the task of predicting the flight path of long-range UAVs.

Its main advantages are:

– faster selection of the best path;

– higher convergence speed;

– reducing the influence of local extrema of the objective function;

– increasing the stability of results under different launch options.

These advantages reduce the time required to predict the path of long-range UAVs and increase the efficiency of decision-making in dynamically changing conditions.

Conclusions and the directions of further research

Thus, it was found that the task of predicting the optimal path of long-range UASs, taking into account a set of external factors and their possible dynamic changes, is relevant.

Methods for laying flight paths were analyzed based on the chosen optimization approach and the specified flight restrictions.

They were conditionally divided into four main groups:

methods based on classical optimization algorithms;

stochastic and probabilistic methods;

methods based on the use of artificial intelligence algorithms;

methods that simulate the behavior of living organisms or natural processes.

Their main advantages and disadvantages were determined.

Swarm intelligence methods that simulate the behavior of living organisms were selected for further research, namely: the ant algorithm.

A formalized description of the problem of predicting the paths of long-range UASs using the ant algorithm is presented. A simple ant algorithm and one of its modifications, the elite ant algorithm, are considered. A method for predicting the paths of long-range UASs using the elite ant algorithm is developed.

Experimental studies have been conducted on the operation of the method for predicting the path of long-range unmanned aerial vehicles. Experimental studies were conducted using the high-level programming language Python 3.14. Simulations were performed for two runs of the algorithm with the number of iterations equal to 100 and 200.

Comparative assessments of the efficiency of the simple ant algorithm and the ant algorithm based on elite ants were carried out when solving the problem of predicting the optimal path of long-range unmanned aerial vehicles.

The results of the experimental studies indicate that the elite ants algorithm is more expedient for predicting the path of long-range unmanned aerial vehicles.

The direction of further research is to optimize the input parameters of the elite ants algorithm to solve the problem of predicting the flight path of long-range UASs in order to increase its accuracy and stability.

Conflicts of interest

The authors declare that they have no conflicts of interest in relation to the current study, including financial, personal, authorship, or any other, that could affect the study, as well as the results reported in this paper.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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Метод прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії на основі алгоритму елітних мурах

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Анотація. Предметом вивчення в статті є метод прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії на основі алгоритму елітних мурах. **Метою** є розробка методу прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії. **Завдання:** аналіз існуючих методів прокладання маршрутів польоту, розробка методу прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії на основі алгоритму елітних мурах, практична перевірка роботи розробленого методу, проведення експериментальних досліджень щодо прогнозування маршруту руху методом на основі простого мурашиного алгоритму та на основі алгоритму елітних мурах, проведення порівняльного аналізу отриманих результатів експерименту. Використовуваними **методами** є: графового моделювання, багатокритеріальної оптимізації, простий мурашиний алгоритм, мурашиний алгоритм на основі елітних мурах, комп'ютерне моделювання та порівняльний аналіз результатів. Отримані такі **результати.** Проаналізовано методи прокладання маршрутів польоту в залежності від підходу до оптимізації та врахування зазначених обмежень польоту, розділено їх на чотири основні групи, визначено їх основні переваги та недоліки. Наведемо формалізований опис задачі прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії на основі мурашиного алгоритму. Розглянуто простий мурашиний алгоритм та алгоритм елітних мурах. Розроблено метод прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії на основі алгоритму елітних мурах. Проведено експериментальні дослідження щодо роботи методу прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії. Проведено порівняльної оцінки ефективності роботи простого мурашиного алгоритму та мурашиного алгоритму на основі елітних мурах при розв'язанні задачі прогнозування оптимального маршруту руху авіаційних безпілотних комплексів дальньої дії. **Висновки.** Аналіз експериментальних досліджень показав, що застосування алгоритму елітних мурах є більш доцільним для задачі прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії. Напрямом подальших досліджень є оптимізація вхідних параметрів алгоритму елітних мурах для вирішення задачі прогнозування маршруту руху авіаційних безпілотних комплексів дальньої дії з метою підвищення його точності та стійкості.

Ключові слова: авіаційний безпілотний комплекс дальньої дії; БпАК; траєкторія польоту; безпілотний літальний апарат; БпЛА; простий мурашиний алгоритм; алгоритм елітних мурах.