UDK 355.40 DOI: 10.63978/3083-6476.2025.2.2.06

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USING ARTIFICIAL INTELLIGENCE METHODS IN TASKS OF DECENTRALIZED CONTROL OF A GROUP OF UNMANNED AERIAL VEHICLES

Abstract. *For solving tasks dangerous to humans, a group of unmanned aerial vehicles (UAVs) has advantages over a single device. The greatest result is the implementation of decentralized control of a group of UAVs. The work considers the problem of decentralized control of a group of UAVs for the effective solution of strategically important tasks in conditions of uncontrolled situations using swarm intelligence methods. The work presents a structural diagram and implements a method of decentralized control of a group of UAVs. Practical results – modeling the behavior of drones in a group.*

Keywords: *agent, artificial intelligence, decentralized management, Python programming language, unmanned aerial vehicle.*

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ВИКОРИСТАННЯ МЕТОДІВ ШТУЧНОГО ІНТЕЛЕКТУ В ЗАДАЧАХ ДЕЦЕНТРАЛІЗОВАНОГО УПРАВЛІННЯ ГРУПОЮ БЕЗПІЛОТНИХ ЛІТАЛЬНИХ АПАРАТІВ

Анотація. *Для вирішення небезпечних для людини задач група безпілотних літальних апаратів (БПЛА) має переваги щодо поодинокого квадрокоптеру. Однак найбільшу цінність представляє можливість децентралізованого управління групою БПЛА, коли єдиний центр управління пристроями або оператор відсутні. Таке рішення дозволяє вирішувати стратегічно важливі завдання у різних сферах: військовій, логістичній, побутовій, рятувальній, моніторингу місцевості. В даній роботі розглядається задача децентралізованного управління групою безпілотних літальних апаратів для ефективного вирішення завдань в умовах неконтрольованих ситуацій з використанням методів штучного інтелекту, а саме колективного розуму та ройового інтелекту. Метою роботи є дослідження ройових методів, методів децентралізованого управління групою БПЛА, адаптивних алгоритмів для ефективного вирішення завдань в умовах неконтрольованих ситуацій. У роботі представлено структурну схему і реалізовано метод децентралізованого управління групою БПЛА. У рамках практичних результатів проведено моделювання поведінки дронів у групі. Представлені результати роботи полягають в забезпеченні контролю над групою БПЛА, необхідність групового управління обумовлена тим, що багато задач виконуються швидше, точніше та з меншими ресурсними витратами. Зростанню актуальності використання децентралізованого управління для вирішення практичних завдань сприяє здешевлення елементної бази з одночасним* *зменшенням її розмірних характеристик, що робить можливим використання великих груп БПЛА. Також підвищенню ефективності використання децентралізованих методів сприяє зростання складності завдань, покладених на БПЛА, збільшення частки невизначеності в умовах виконання місії, а також зростання рівня довіри до систем управління групами пристроїв. Зазначені фактори сприяють необхідності оперативного прийняття рішення і максимізації самостійності дій БПЛА.*

Ключові слова: *агент, безпілотний літальний апарат, децентралізоване управління, мова програмування Python, штучний інтелект.*

Introduction

Modern military conflicts demonstrate a transition to a new paradigm of warfare, where information technology and automated systems play a key role. Artificial intelligence (AI) is one of the leading tools that can significantly change the nature and course of military operations. With the ability to analyze large amounts of data in real time, make predictions, and autonomously perform tasks, AI provides an advantage in high-tech conflicts.

Artificial intelligence encompasses a set of technologies that enable the performance of tasks that traditionally require human intelligence: pattern recognition, natural language processing, decision-making and learning from experience. The current development of AI is based on such areas as: machine learning, deep learning, neural networks, computer vision, natural language processing (NLP), and robotics.

In the civilian sector, these technologies are already widely used in medicine, transportation, industry, financial systems, and education. The military sector is largely adopting these developments, adapting them to solve specific tasks: from detecting enemy objects to controlling autonomous systems.

Information advantage in modern wars is no less important than the numerical advantage of troops. AI allows for effective processing of data from various sources: satellite images, radio intelligence signals, data from unmanned aerial vehicles and sensor systems. Autonomous systems are one of the most promising areas of application of AI. Unmanned aerial vehicles (UAVs), which perform reconnaissance, target strikes and communications have gained the greatest popularity. Intelligent algorithms allow such autonomous devices to independently navigate in space, avoid obstacles and work in groups (swarm methods).

Drones and unmanned aerial vehicles are modern software and hardware devices that have become an integral aspect of modern society and are expanding into various industries, which allows them to solve a number of complex or dangerous tasks for humans. For example, in the domestic sphere – these are the tasks of the “Smart Home”, in the commercial sphere – these are the tasks of delivery and logistics, in the scientific or applied sphere – research into the chemical and biological composition of organisms, as well as in the military, police and rescue spheres. The use of drones in cities for solving local monitoring tasks is also very useful.

Let’s consider the basic definitions [1, p. 3-5].

A drone is any mobile unmanned transport vehicle, i.e. without a pilot on board, pre-programmed to perform a specific task in the air, on land or under water. Thus, the term “drone” refers not only to the modern recreational quadcopter, but also to sea (for example, a submarine) or land-based autonomous vehicles, as well as to remotely controlled vehicles. When using drones for aerial missions, this term is mainly used by mass media to refer to a simple aircraft. They are mainly available as ready-made solutions [1, p. 3-5].

An unmanned aerial vehicle is a vehicle that flies without a pilot, either remotely and fully controlled from another location (ground, another aircraft, space) or programmed and fully autonomous. This refers to large unmanned aerial vehicles with autopilots, which have found widespread use in the civil and defense sectors [1, p. 3-5].

The use of both terms depends on the characteristics of the aircraft, as well as the scope of application.

An unmanned aerial vehicle complex is a set of several devices that include the unmanned aerial vehicle itself, as well as the equipment necessary for its operation: a ground control station, an antenna system, and catapults.

This paper considers the devices of unmanned aerial vehicles (agents or boids).

Advantages of using unmanned aerial vehicles are [2, p. 140-145]:

speed – the necessary information on unmanned aerial vehicles can be provided to the client faster using special cameras and data channels, rather than using traditional shooting methods, which can sometimes be slow;

economy – data is obtained faster than with the help of conventional collection methods, so various missions can be performed in a shorter period of time, thus, the cost is lower than when using other devices;

safety – UAV operators do not need to be in territory that may be dangerous for various reasons;

high level of accuracy – an unmanned aerial vehicle can receive high-speed data. This is due to the duplication of information received during the flight – the more rewrites, the more accurately the recorded information;

to carry out a mission or task, there is no need to involve a qualified pilot, since they are unmanned, and all systems are designed in such way that human intervention in the work is minimized;

An unmanned aerial vehicle is capable of flying and collecting information in rain, fog, foggy weather, and high temperatures.

According to the principle of controlling groups of agents (UAVs), centralized and decentralized systems can be considered.

Centralized management of all elements of the group is carried out from a single coordination center, the policy clearly delimits types of activities or operations.

Decentralized management implies the absence of a single control center for the formation of coordination teams for each of the group elements.

The work explores methods of swarm intelligence, methods of decentralized control of a group of unmanned aerial vehicles in uncontrolled situations.

Swarm intelligence is the collective behavior of individuals (agents) in a system that is self-organizing without a defined control center, that is, in a decentralized group [3, p. 6-12]. One of the fundamental rules of swarm intelligence is the fact that it requires a fairly large number of agents capable of interacting with each other and the environment.

A single agent follows simple rules that are inherent in it (either by physical laws or genetics). Despite the absence of a command center that would indicate what each of the fighters should do, their random interactions lead to the fact that the general behavior of the group becomes clearly intelligent. At the same time, each specific fighter does not necessarily behave intelligently. Such behaviors are demonstrated, for example, by ants, bees, termites, wolves, water droplets, the human immune system, bats, etc.

To achieve a specific goal set by a group of unmanned aerial vehicles in the case of centralized control each drone can perform a certain sequence of actions known in advance.

In the case of decentralized control, which is more flexible, this sequence must be found by the control system of a group of agents in the process of achieving the goal, while the actions of a group of unmanned aerial vehicles must be coordinated in some way.

Statement of the problem.

Thus, the aim of the work is implementation of method of decentralized control of a group of unmanned aerial vehicles. This task consists in implementing the control system by agents of the sequence of actions of all group members when solving the task.

To achieve this goal in work:

a study of swarming methods and algorithms was conducted, and the bee method was selected for the implementation of a UAV group control system;

a structural scheme for decentralized management of the UAV group is presented;

the implementation of a method for decentralized control of a group of unmanned aerial vehicles was presented;

a practical implementation is presented.

Analysis of recent research and publications.

The biggest advantage of unmanned aerial vehicles is the ability to perform tasks that may be dangerous or impossible for humans to execute. In this sense, the use of UAVs is more suitable for performing tasks of photo or video monitoring, data reconnaissance, and combat operations.

The disadvantages of UAVs include limited payload and flight time. As for the use of UAVs, the problem may be the presence of various obstacles, accidental or intentional. But these disadvantages can be solved by using a group of vehicles. There are certain problems with this approach, namely the coordination and interaction of certain UAV units in a group and the distance of communication with the remote control.

The actuality of this work consists in providing control over the UAV group, specifically, the UAV group has certain advantages over a single UAV:

1) increased awareness of the environment for communication within the group;
2) interchangeability of UAVs due to the replacement citation;
3) increased reliability;
4) speed of task completion;
5) the ability to collectively perform more complex tasks.

When performing the assigned tasks, the UAV group may encounter certain obstacles that must be overcome by the entire group or to reduce the number of disabled UAVs. After completing the task, it is necessary (if required by the task) to return to the starting point of departure [4, p. 1256-1260].

Since the tasks are performed by a group of UAVs, it is necessary to use a mechanism for transmitting data about threats between certain UAV units. This is necessary in order to reduce the chance of each UAV in the group colliding with a threat.

Moreover, if one of the UAVs in the group loses contact with the operator controlling it (or the entire group), it is necessary for this unit to be able to continue the execution of the task set thanks to another UAV in the group that has contact with the operator. That is, if the UAV loses contact with the operator, by default, it will return to the operator’s side until contact is restored. In the context of completing the task, this is incorrect behavior, since it is necessary to be in the UAV group, avoid threats, and achieve the task. For this reason, the neighboring UAV, which has not lost contact with the operator, will provide him with information about new commands or threats, which the “lost” UAV will execute according to its initial task [4, p. 1256-1260].

The need for group management is due to the fact that many tasks are performed faster, more accurately, and with less resource costs.

Let's consider the choice and justification of the UAV behavior model.

The technology of UAV behavior can be based on the general theory of technical systems control [5, p. 40-45; 6, p. 22-30]. Behavior can be considered as a special case of the general theory of optimal control of objects. In such formulation, the UAV appears as an abstract discrete control system, which based on its actions and the reaction to these actions of the environment chooses the optimal strategy of behavior.

In many real-world situations, the choice of options has to be made under conditions of a priori uncertainty, when based on the available data, it is not possible to specify in advance which of the possible options should be chosen to ensure the achievement of a given goal. In this case, achieving a given goal is possible only on the basis of the application of an adaptive approach [7, p. 50-55], the meaning of which is to use current information obtained as a result of individual selection actions, which allows to compensate for the lack of information and implement the optimal management strategy for the class of systems.

Let us consider the general formulation of the adaptive selection problem, presented in Fig. 1.

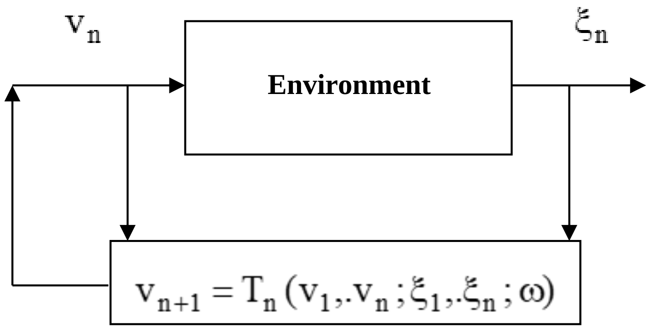

Fig. 1. Scheme of adaptive selection of options
Source: developed by the authors based on data from [7, p. 50-55].

The meaning of the approach is as follows: at each of the successive moments in time $t_n(n = 1,2\ldots)$ you must choose an option v_n from a finite set of possible options V.

As a result of the choice made, the system loses ξ_n is a random variable – elementary result function ω, and depend on v_n and, possibly, the states of the system. A sequence of options is implemented $\{v_n\}$ should be such that the set goal, which is formulated in terms of the limit values of current average losses, is achieved.

The presence of a priori uncertainty, which consists in the lack of accurate information about the losses of the system and its characteristics, leads to the fact that the formation of a sequence of options $\{v_n\}$, which ensures the achievement of the target condition of the problem being solved, should be carried out in accordance with the adaptive approach. In this case, the choice of the next option v_{n+1} is carried out based on the sequence of losses obtained at the current time $\xi_1, \xi_2, \ldots, \xi_n$, the corresponding implemented sequence of options $v_1, v_2, \ldots, v_n$. This means that v_{n+1} is a function of $v_1, v_2, \ldots, v_n$, $\xi_1, \xi_2, \ldots, \xi_n$ and maybe from time to time n and elementary result ω. Thus

$$v_{n+1} = T_n(v_1, v_2, \ldots, v_n; \xi_1, \xi_2, \ldots, \xi_n; \omega), n = 1,2, \ldots, \quad (1)$$

where ξ_n depending on the task a scalar or a vector.

Function T_n we will call the option selection rule v_{n+1}. This function can be either deterministic or random. Sequence $\{T_n\}$ selection rules determines the strategy for selecting options or the management strategy [8, p. 60-65; 9, p. 310-315].

Let's consider existing systems of centralized and decentralized management of groups of autonomous intellectual objects.

At work [10, p. 74-80] the task of automating the work of a group of quadcopters in a location where drones take off, land, and fly along a given trajectory is considered. Quadcopters under the control of an operator can perform tasks of various complexity, such as filming materials for a film or a search operation, but the greatest value is the possibility of automating the task performed, when only one operator is needed to monitor the clear execution of the work, a watchman, i.e. a centralized control system is considered. It is possible to automate the process of cargo delivery, spot scanning, as well as shipping and handling operations.

The work provides a review of group management, in particular group management methods and strategies used in practice. Based on the analysis of group management, the method of quadcopter system design is selected.

Work [11, p. 403-408] is devoted to a topical problem of mathematical modeling and control theory: the task of decentralized control by multi-agent system consisting of agents modeling autonomous robots, with the aim of providing a fixed group of agents with a system that has a given geometric shape.

For an even distribution of agents in the mission zone, maintaining stable communication among the group, and preventing collisions, a certain geometric structure of the system must be maintained during the mission (a certain position relative to each other or relative to the center of mass of the group, which creates certain geometric figures).

To solve this problem, the following approaches are used:

1) to set the desired distance between pairs of agents and apply graph stiffness theory [12, p. 215-217; 13, p. 88-94];

2) to set the desired position of the agent with respect to its neighbors and vectors and to create rules of consensus (averaging) [14, p. 989-995; 15, p. 1860-1863; 16, p. 171-176];

3) at every moment, it is necessary to transmit information to the agents about the structure and direction of the request form, on the basis of which each agent can configure the request person and follow him [17, p. 2011-2014].

When developing algorithms based on one of the three approaches described above, as a rule, serious difficulties arise in processing the following citations:

1) the departure of one or several agents with the subsequent loss of the ability to transmit information, especially the leader agent;

2) interruption of communication with an agent who, on the way to the target point, found himself in the zone of information exchange with other agents;

3) communication problems with the coordination center (in cases where it is envisaged to continuously or periodically transmit information important for management from this center to agents).

At work [18, p. 1468-1473] a mathematical model is presented that describes a group of workers, and a fully decentralized control rule and algorithm are developed that allow for effective control of a group of agents while preserving the geometric shape of the system (certain mutual distances relative to each other) under the conditions of complete autonomy of the agent and the possibility of obtaining information only from its closest neighbors. In this case, the rule of thumb is to avoid the occurrence of the described extraneous citations.

An original decentralized management rule is proposed, which combines some principles of consensus (average), as well as elements of the approach using virtual leaders.

New elements for the field are used: criteria for the formation of a pattern corresponding to a given geometric structure with the necessary accuracy are formulated, based on the concepts of geometric structure of a pattern and virtual leaders introduced in this work, taking into account the complexity of various constraints. A distinctive feature of the generated control rules is that the set of virtual leaders is individual for each agent, the agent can independently coordinate virtual leaders and their preferences with the original generated rules, which allows choosing a place in the geometric structure of the formation dynamically without a fixed binding of the agent to a particular position in the geometric structure of the formation.

Thus, the analysis of research and publications demonstrates the relevance of using decentralized management of a group of agents.

Purpose of the article.

The purpose of the work is to study swarm methods, methods of decentralized control of a group of UAVs, adaptive algorithms for effective task solving in uncontrolled situations.

Presentation of the main material

Various swarm intelligence methods can be used to formalize UAV group flights: the particle swarm method, ant and bee algorithms [19, p. 1215-1220; 20, p. 1943-1946; 21, p. 12-18].

Despite their sufficient efficiency, particle swarm and ant swarm algorithms have some drawbacks. Due to the large number of parameters that can be adjusted, the considered methods are quite sensitive to their choice and require careful tuning. The influence of such settings has an ambiguous effect on the efficiency of the algorithm and requires research when solving each specific problem.

The process of selecting settings does not have sufficient theoretical justification and in most cases is reduced to "fitting" the values. It is also necessary to have a fairly large amount of relevant information about the associated problem in order to select the values of the parameters responsible for local and global convergence. The strength of these methods is their high efficiency when successfully selecting the parameters to be adjusted, as well as the simplicity of program implementation.

In connection with the noted shortcomings of the particle swarm and ant swarm algorithms, let us consider the bee swarm method, which is less sensitive to parameters, but has a more complex logic of operation.

An artificial bee colony operate an algorithm similar to the extraction of nectar by honey bees. Instead of a field of flowers, let's consider a solution domain. Instead of nectar, let's use the criteria of an optimization problem, the objective function [22, p. 460-465].

At each iteration of the algorithm, regions with the best value of the objective function are selected and called "best". From the remaining regions, those considered "promising" are also selected. It is possible to set a certain minimum distance between two neighboring regions. In this case, if overlap occurs, the region with the worst value of the objective function is rejected. Another region is selected instead. The data of the area is remembered and during the next iteration, a certain number of bees are sent to it.

Algorithmic work can be divided into two stages [22, p. 460-465]:

1. Initialization:
   – upon initialization, initial positions are generated for n agents;
   – in the simplest case, the random sampling method is used.
2. Local search:
   – after forming lists of the best and most promising areas, "worker bees" are sent to their vicinity;
   – in some variants of the algorithm, the number of bees sent depends on the quality of the region from the point of view of the objective function. This dependence can be linear or determined by more complex rules;
   – in this case, a fixed number of bees is sent to each area, depending on the class to which the area belongs;
   – for each iteration, the "scouts beers" are sent to new areas.

With the given algorithm, several parameters are created:

1) the number of scouts;
2) a number of the best and most perspective;
3) a radius of the local scouting;
4) the number of bees for each area class,
5) minimum possible distance between neighboring areas.

The quality of the obtained solutions depends significantly on the choice of these parameters. In addition, the speed of the algorithm also depends on this choice.

There are countless modifications of this algorithm. They improve the quality of the results and the speed of it's work. This is mainly due to the reduction of dependence on the selected parameters.

The structural scheme of decentralized management of a group of UAVs based on the bee swarm method is shown in Fig. 2. The group of UAVs is represented in the form of a swarm of bees.

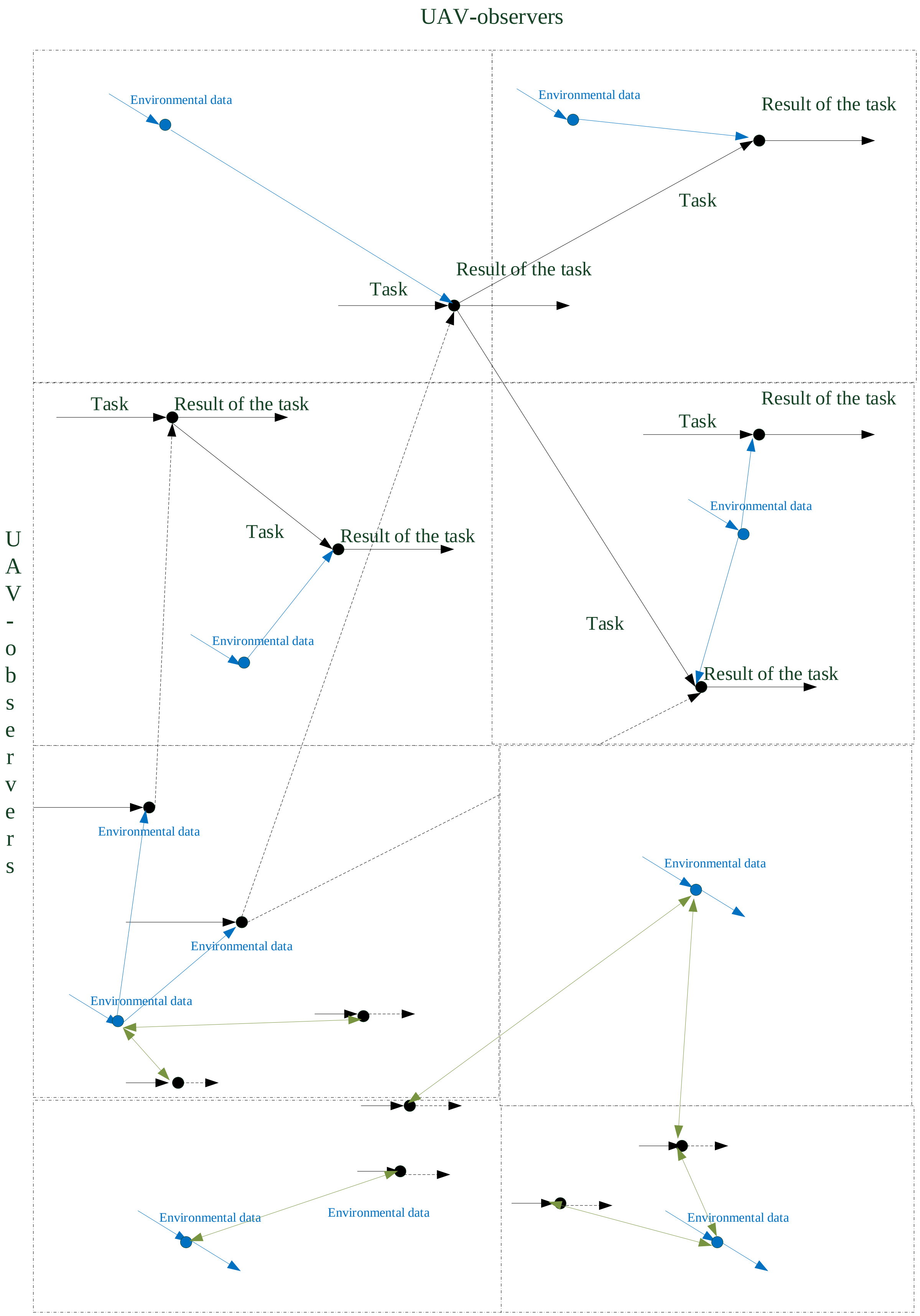

Fig. 2. Structural scheme of decentralized management of the UAV group
Source: developed by the authors

There are 3 groups of UAV-bees represented on the map:

UAV-scouts (first to conduct areas exploration, collect data on the environment);

UAV-observers (explore larger areas in the search area than the scouts);

UAV-workers (directly perform the assigned task, for example, armed or unarmed drones).

UAV-scouts collect data about the environment and transmit it to UAV-observers and UAV-workers for safe task performance.

UAV-observers also collect data about the environment, but they are exploring large areas in a search pattern (squares), compared to scouts and transmit the data to UAV-workers.

UAV-workers are considered the most valuable and strategically important devices that directly perform the task to achieve the goal. They use the received data about the environment and receive input for the task, which is performed decentralized, for example, from the cloud. The result of the task is similarly corrected.

Let's consider the main stages of implementing the adaptive bee algorithm.

1. Algorithm initialization. At the initialization stage, it is necessary to find or set several starting points and calculate the value of the objective function at them.

The group of UAVs, or bee swarms, is a vector of uniformly distributed random variables X, $X \epsilon D_x$.

The task is to find the point x_{nom} in the middle of the plane of Dx in the n-dimensional space

$$x_{nom} = \underset{x \epsilon Dx}{\arg\max} \operatorname{dist}(x, \partial D_x), \quad (2)$$

Let's consider three types of UAVs:

s_j – UAV-scouts;

w_k – UAV-workers;

q_l – UAV-observers (explore larger areas in the search area than the scouts).

A swarm of UAVs represents the multitude

$$SW_{UAV} = \{s_j \cup w_k \cup q_l\}, j = 1, S; k = 1, W; l = 1, Q, \quad (3)$$

All particles act individually, following the general principle of the best personal and best joint position. The essence of the algorithm lies in the repeated undirected random search method (the process of UAV dispatch) in limited areas of the search path, called sections [22, p. 460-465].

For each type of UAV the parameter r(0;1] is set, which corresponds to the size of the investigated area. For UAVs, this parameter takes the following values:

$r_{sj} = 1$– UAV-scouts are exploring the whole environment;

$r_{wk} = 0.1$ or 10% – from the initial size of the search area for UAV-observers;

$r_{ql} = 0.05$, or 5% for UAV-workers.

At the initialization stage it is necessary to find or set several starting points for the location of the UAV X_i in the area D_x, such that $X_i = \text{random}(Dx)$, for example, $X_1(x_1,y_1,\ldots,z_n)$, $X_2(x_2,y_2,\ldots,z_n)$, $X_3(x_3,y_3,\ldots,z_n)$ (see Fig. 3) and calculate the value of the objective function $\operatorname{dist}(x, \partial D_x)$ in them.

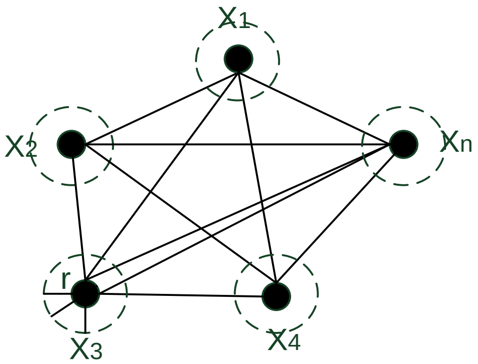

Fig. 3. UAV locations and their surroundings
Source: developed by the authors based on data from [22, p. 460-465].

2. Local search.
Depending on the objective function $\mathrm{dist}(x, \partial D_x)$, in the area D_x are selected areas:
b – the best ones, corresponding to the largest values of the objective function;
g – the good ones, that correspond closest to the best values of the objective function.
Then UAV-workers are sent to the b areas.

$$p_w = \frac{W}{b}, \quad (4)$$

UAV-observers are sent to the areas g.

$$p_q = \frac{Q}{g}, \quad (5)$$

The general recommendation for choosing the number of plots and bees is as follows. Each of the best plots should have more bees than the good plots, and the area should be smaller [22, p. 460-465].

It is important to note that the UAV-workers are not sent exactly to the place where the UAV-scouts and UAV-observers have found perspective and best places, but in their vicinity. In addition, the vicinity which defines the area where the UAV can be sent, can be reduced as the iteration number increases, so that the step-by-step solution approaches the "end" of the extreme. But if the cloud is reduced too quickly, then the writing can "get stuck" in local extremes [22, p. 460-465].

The size of the search area can be set both statically and dynamically, depending on the number of iterations. When implementing a dynamically changing search area, the convergence speed of the algorithm increases, but there is a possibility of the algorithm getting stuck in a local extremum. In this case, the global optimum may not be found. Based on this, when implementing this algorithm, fixed values were chosen for these parameters [22, p. 460-465].

After the UAV group explores the found areas, the areas are again sorted in descending order of the objective function among the UAVs participating in the search process, then a further selection of the best and most efficient areas is carried out and a new UAV dispatch is carried out. These steps are repeated until the stopping criterion is satisfied – achieving the set goal of the UAV group.

There can be several stopping criteria. For example, if the value of the objective function at the global extremum is known, then the algorithm can be repeated until the function reaches some value close to the desired one. If the value of the function at the extremum is unknown, then the algorithm steps can be repeated until the solution found does not improve after a sufficiently large number of iterations.

In the Fig.4 the graphs of the convergence of the bee swarm method depending on different sets of adjustable parameters are given. The abscissa axis shows the iterations, the ordinate axis shows the value of the objective function. From these graphs it is clear that the choice of algorithm parameters is not a critical factor in solving the optimization problem.

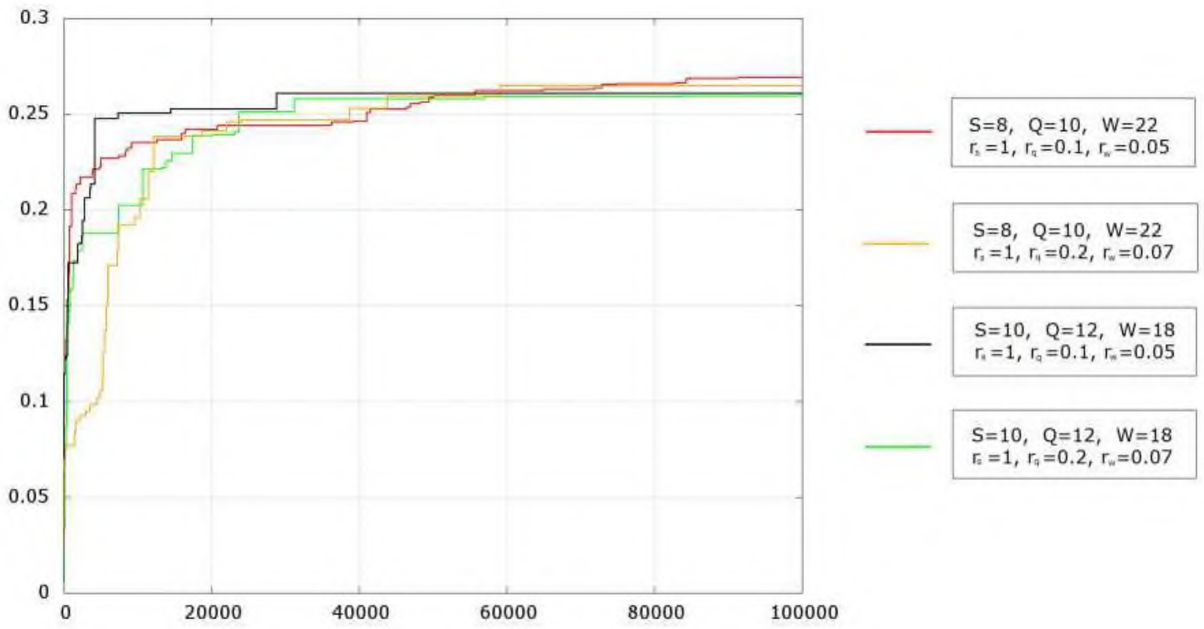

Fig. 4. The work of the swarm algorithm with different parameter sets
Source: developed by the authors

Thus, the task of ensuring the reliability of the technical devices of the UAV group against failures, which must be written at the stage of system design is considered. This is due to the incompleteness of the relevant information about possible external processes that may arise (the appearance of an obstacle for the UAV). The bee swarm method considered in the work, despite the rather complicated logic of the work and the process of organizing the calculation, in comparison with other methods, shows its effectiveness.

The main difficulties in using other search methods of this group are the selection of adjustable parameters. There is no universal set of parameters and it is not always possible to select different combinations of settings in order to choose the best one for each new task [23, p. 83-86].

In the work a modification of the bee swarm method is proposed, which simplifies the logic of its work and program implementation. This modification has shown its effectiveness and versatility. The considered method depends to a lesser extent on the quality of parameter settings.

Thus, if we consider all the criteria in the complex, from the point of view of the best solution to the task, limited time and computational resources, the absence of the possibility of fine-tuning the parameters of the algorithms, the absence of information about the associated task, then using the bee swarm method is the best for solving the problem of controlling a group of UAVs with decentralized control.

In Fig. 5 (a, b, c, d, e, f) you can see how the UAV agents gradually accumulate around one best solution.

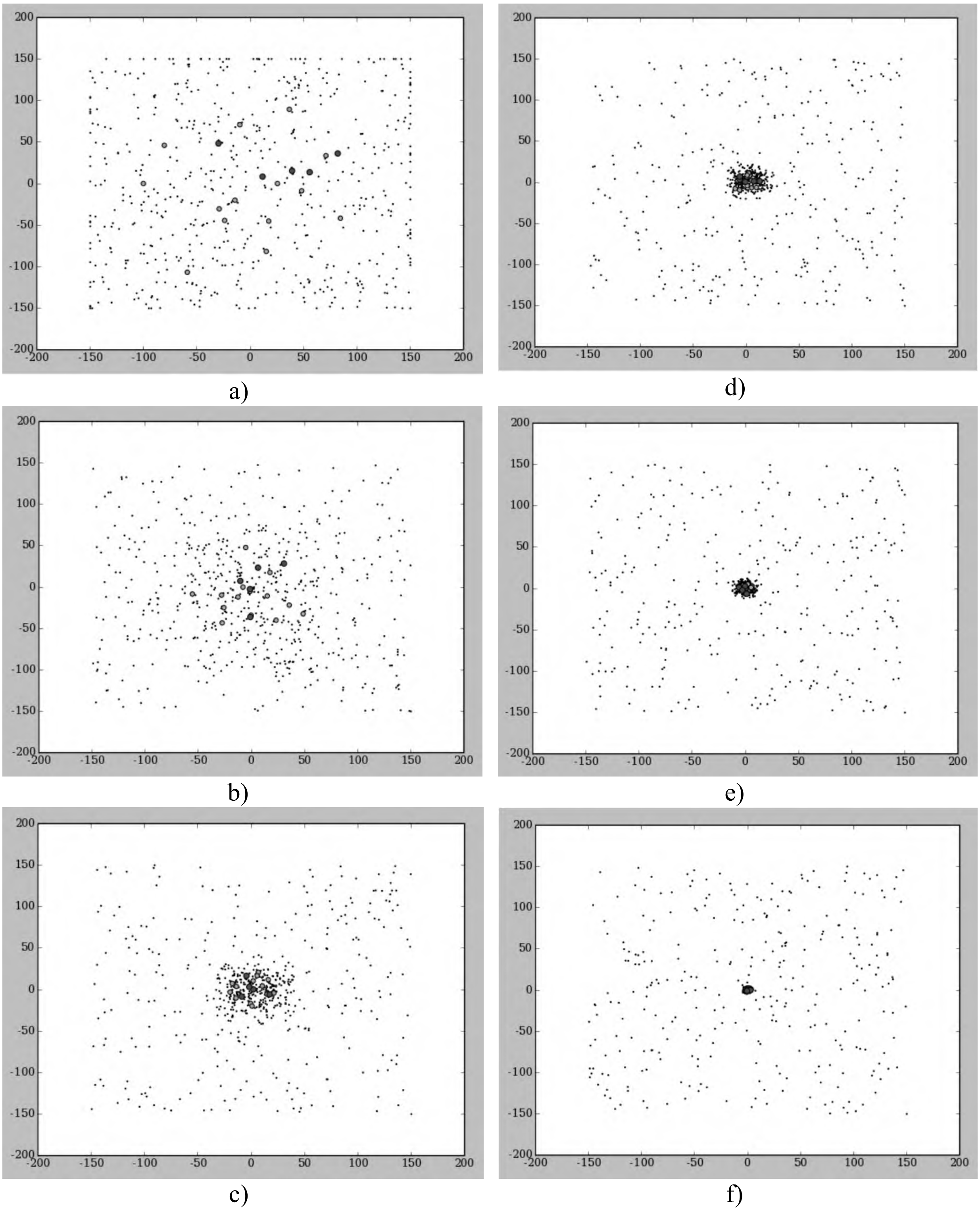

Fig. 5. Gradual accumulation of UAV agents around a single best solution
Source: developed by the authors

In this figure the red dots are the UAV bees that found the best solutions, the yellow dots are the are the chosen solutions and the black dots are other UAV bees, including the UAV-scouts that are randomly selected.

Conclusions

Thus, the main advantage of using the decentralized system proposed in this work is the absence of a single agent management center, since it can potentially be destroyed.

To implement an agent-based UAV control system, reliable and unconditional task performance and achievement of the set goal are provided. During the task performance, various obstacles may arise, both accidental and intentional, therefore it is necessary to use protective conditions for unmanned aerial vehicles. One such condition for increasing the reliability of task performance is the organization of UAVs into groups. Another option is to use special UAV-scouts and UAV-observers, who will constantly collect data about the environment and transmit it to UAV-workers for successful task completion, maintaining the integrity of the devices, and returning to the original point of departure.

In such scenarios, drones are often used as mobile sensors, which are used to collect data, which is then processed in a cloud service.

But, considering the technologies for creating autonomous drones, both armed and unarmed, the ethical and legal aspects of the use of artificial intelligence when used in combat situations become relevant. One of the most important challenges is the issue of responsibility for the actions of autonomous systems. International humanitarian law does not contain clear provisions on the use of combat drones. Therefore, in international community there is a need to regulate the activities of agent-based artificial intelligence technologies, creation of a regulatory framework that will regulate the limits of their application.

Ethical issues also include the problem of making decisions about the use of force by autonomous devices. Developers emphasize the need for “human control”, when the final decision to defeat the target remains with a person.

Humanity is rapidly approaching the point when autonomous systems can begin to act against humanity, and human intervention in this system will become difficult or even almost impossible.

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