Multicriteria adaptation of agricultural spraying drones

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Abstract. The article proposes a method for searching for the best configurations of robots under new and previously unknown operating conditions, which makes it possible to find solutions close to optimal using a limited number of full-scale tests. The problem of processing agricultural crops using liquid-spraying UAVs is considered. The time required for a given UAV to process a given landing area under arbitrarily specified external conditions was selected as a performance indicator of the UAV configuration. The search algorithm is based on multicriteria analysis of vector characteristics of UAVs using the criteria importance theory. Previous studies have used information about the relative importance of criteria. In this work, we additionally evaluate the value of gradations of the criteria scale and construct a value function for UAV configurations. Using a simple simulation model, a numerical experiment was carried out for 1000 different operating conditions. The effectiveness of the proposed method is confirmed by the small size of deviations of the found solutions from the optimal ones.

1. Introduction

Currently, mobile robots are widely used in the national economy, in particular in agriculture. Mobile robots are used to perform a wide variety of tasks, both under the control of an operator and independently controlled by artificial intelligence (AI) using machine learning (ML) systems. A special place is occupied by unmanned aerial vehicles (UAVs) – drones [1]. The following tasks performed by UAVs in agriculture can be noted: harvesting; drawing up field maps; control (monitoring) of harvesting; monitoring the spread of weeds, pests/diseases, spring shoots, soil moisture conditions; treating fields with pesticides/fertilizers, etc.

Cultivation of fields is an extremely urgent task, since there is a short period of time when it (processing) is permissible: absence of wind, certain humidity, temperature, absence of direct sunlight, etc. (Fig. 1). As a rule, these are morning/evening hours. The fields are divided into specific areas. Processing can be done by one drone or several. It is very important to select a UAV with certain characteristics and parameters. Here we have a parametric optimization problem.

Fig. 1. Unmanned aerial vehicle spraying fields with pesticides.

When processing fields with several devices, we have the task of group control of robots, i.e. the most efficient division of the processed surface, distribution of tasks between UAVs, minimization of processing time. The trajectories of the drones should not intersect; each can be launched from different areas, or all in turn from one. The task is set to process the field in the minimum time. During operation, some devices may fail or run out of the substance being processed, so the possibility of redistributing their tasks should be provided. Thus, we have the task of optimal selection of parameters, optimal control when conditions change during operation, and the task of creating adaptable systems.

Scientists all over the world are working to study UAVs, increase their mobility, productivity and gain new capabilities through flight characteristics and the use of artificial intelligence. The advantages and disadvantages, the use of drones in agriculture and an

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assessment of their importance for the industry are discussed in [2, 3]. The work [4] summarizes research on unmanned aerial vehicles in agriculture and suggests directions for future research. The analysis shows that remote sensing, precision agriculture, artificial intelligence, machine learning are the most important topics related to agricultural drones.

The use of drone remote sensing (RS) and machine learning (ML) has significantly changed precision agriculture. In paper [5] evaluates the use of these methods in precision agriculture, including their advantages and effective application. There is also recognition of the challenges associated with implementing these technologies, such as cost, data management and regulatory issues. In paper [6] discusses remote sensing (RS) methods and algorithms using drones, which are very effective for quickly identifying plant diseases in their early stages. The benefits of drone technology include high spatial resolution (as there are multiple sensors on board), high efficiency, flexibility of use, and most importantly, rapid detection of plant diseases over a large area while being low cost, reliable, and providing high-resolution data.

In agriculture, UAVs are also used for mapping. For example, in work [7] presented the development of the Drone-based Geographical Information System (GIS) Mapping of Cassava Pythoplasma Disease (CPD) for Precision Agriculture is an effective and innovative tool in detecting CPD in order to prevent the spread of the disease. Drone-based Geographical Information System (GIS) Mapping of Cassava Pythoplasma Disease (CPD) for Precision Agriculture was an effective tool in detecting the presence of Cassava Phytoplasma disease in cassava plantations using the different techniques and methodologies. In work [8], mapping and monitoring of corn fields using UAVs is considered, a system proposal is presented that will ensure the efficiency of using drones in image processing, which can be used as monitoring and mapping on corn farms in Indonesia, which will improve the efficiency of harvesting levels in certain area. In paper [9] uses high-resolution RGB data collected by a camera-equipped drone flying over an olive tree field in Extremadura (Spain) for land cover classification purposes. Such tasks require a large amount of random access memory (RAM). To address this problem, a new approach is proposed for olive tree canopy mapping by applying a spatial partitioning methodology, which consists of automatically dividing the image before processing. Experimental results demonstrate that the proposed methods avoid labor-intensive field work by facilitating the analysis of agricultural fields using UAV flights, resulting in high classification accuracy.

Fig. 2. The use of UAVs for mapping.

Trajectory planning for UAVs and collision avoidance is another area that receives considerable attention and the work of researchers. Obstacle avoidance is a desirable capability for unmanned aircraft systems (UAVs)/drones that prevents accidents and reduces pilot fatigue, especially when operating beyond visual line of sight (BVLOS). [10,11]. Group control (swarm) of robots, swarm models, and intelligence are of great importance because they ensure the collective behavior of self-organizing systems. Boids model is a fundamental framework for studying emergent behavior in swarms systems. It addresses problems related to simulating the emergent behavior of autonomous agents, such as alignment, cohesion, and repulsion, to imitate natural flocking movements. In [12] a method is considered that gives to enable drone swarms to quickly and effectively adapt to dynamic external environments. It is based on the Q-learning network to improve the cohesion and repulsion parameters in the Boids model to achieve continuous obstacle avoidance and maximize spatial coverage in the simulation scenario.

When designing robotic systems, the problem often arises of finding ways to achieve goals under dynamically changing operating conditions and limited capabilities (resources). The most promising approach to solving such problems is the design of adaptable systems that, through real-time reconfiguration mechanisms, can adapt to new goals, requirements and external conditions, increasing the efficiency of the entire system with available resources. In the most complex tasks, it is impossible to calculate and provide in advance all possible states and scenarios for the reconfiguration of robotic systems. Therefore, there is a need to solve in real time the problem of finding the configuration that is most suitable and effective under the emerging conditions. In this sense, methods of multicriteria decision making analysis [13,14], based on the criteria importance theory [15-18], have shown their effectiveness. The authors proposed a multicriteria approach to designing groups of robots, which allows, by

assessing the performance of a relatively small number of reference robots, to significantly reduce the search area for the best solutions and offer optimal or close to optimal solutions [19-21]. This work is a continuation of these studies. In addition to information about the relative importance of the criteria, this work evaluates the values of the criteria scale gradations and constructs a value function for UAV configurations.

2. Simulation and Optimization Problem

Variable parameters x of the spraying drones include the geometry and dimensions of the body, the diameter and material of the propellers, the number and power of engines, the number and power of liquid spray nozzles, and the volume of liquid collected at one time.

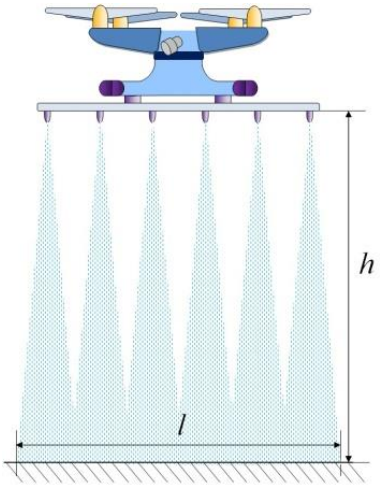

Fig. 3. Unmanned aerial vehicle spraying fields with pesticides.

The characteristics of an individual spraying drone depend on these parameters:
v – maximum flight speed (with average load), from 6 to 15 m/s;
q – maximum spraying speed, from 2 to 4 l/min;
c – score of flight controllability, from 0 to 9;
s – score of flight stability when spraying liquid, from 0 to 9;
m – payload, from 7 to 25 l.

Due to existing limitations, an individual spraying drone cannot achieve the best values for all characteristics at once. But we can select UAVs that will have better values of those characteristics that are more important to us, which will allow us to more effectively perform the task under the existing operating conditions.

Operating conditions λ are determined by the task specification (type of crop being processed, trajectory, flight altitude), as well as weather conditions:
λ_1 – required fluid flow per m^2, from 0.03 to 0.08 l;
λ_2 – total flight distance between plantings of agricultural crops, from 100 to 5000 m;
λ_3 – average additional distance for refueling UAVs, from 100 to 3000 m;
λ_4 – score of difficulty due to the height of spraying liquid, from 0 to 9;
λ_5 – score of difficulty due to weather conditions (wind, temperature, humidity), from 0 to 9.

The main indicator of UAV efficiency is the time during which a certain area S = 1000 m^2 of crop planting will be processed. The specified flight path of the UAV can be conditionally divided into 2 parts. On one part of the trajectory, the UAV performs useful work, i.e. sprays liquid over the plantings. In the second part of the trajectory, the UAV flies between planted areas or returning to refuel with liquid. With a decrease in the volume of loaded liquid m, the flight characteristics of the UAV improve, but the time spent on refueling increases. The total time to complete a task is the sum of the time spent on each section of the trajectory:

$$T(x,\lambda) = T_q(x,\lambda) + T_v(x,\lambda). \quad (1)$$

The time spent by the UAV on the working part of the trajectory is proportional to the total fluid requirement, inversely proportional to the spraying speed, and also depends on the altitude, weather conditions and the ability of the UAV to maintain stability in these conditions. To estimate this time, we will use a simplified model:

$$T_q(x,\lambda) = \frac{S\lambda_1}{q(x)} * \left(1 + \frac{5+\lambda_4+\lambda_5}{5+0.1c(x)+s(x)}\right). \quad (2)$$

The flight time of the UAV on idle sections of the trajectory is proportional to their total distance, inversely proportional to flight speed, and also depends on weather conditions and the ability of the UAV to maintain controllability in these conditions. The flight distance consists of the fixed part λ_2 and the return distance λ_3, multiplied by the required number of refuelings. To estimate this time, we will use a simplified model:

$$T_v(x,\lambda) = \frac{1}{v(x)}\left(\lambda_2 + \lambda_3 \frac{S\lambda_1}{m(x)}\right)\left(1 + \frac{5+2\lambda_5}{5+c(x)+0.1s(x)}\right). \quad (3)$$

The model (1)-(3) describes the objective function of the optimization problem. For given parameters λ, it is necessary to find a feasible UAV configuration x^* that provides the minimum value of the function $T(x^*,\lambda)$. Note that, despite its simplicity, the function $T(x,\lambda)$ is nonlinear and has discrete variables. In real conditions, it is intended to determine the operating time of the UAV experimentally. Therefore, when developing an optimization method, it is desirable to use as few calculations of the function $T(x,\lambda)$ as possible.

3. Multicriteria Decision Making

To solve the optimization problem, it is proposed to use methods of multicriteria analysis of decision making problems [12-13] and the criteria importance theory [14-17], in which the concepts of criteria importance are formally defined.

Let us consider the multicriteria problem of choosing the best vector score $y = (y_1, \ddot{U}, y_n)$, $n \geq 2$, from a finite set Y. Let the scale for each criterion $y_1, \ddot{U}, y_n$ consist of q gradations (scores) $\{1, \ddot{U}, q\}$. We will consider this

scale common to all criteria to be ordinal: for 1 □ $a < b$ □ q, we can say that score b is better (preferable) than score a, but we cannot say how much or how many times better. On the set of vector scores Y, the Pareto preference (dominance) relation can be introduced:

$$yP^{\varnothing}z \Leftrightarrow y_i \geq z_i, i = 1, \dots, n, y \neq z. \quad (4)$$

It is known that the best solution should be chosen among the Pareto-optimal vector scores $Y^{\varnothing}$, that are not dominated with respect to the Pareto relation (4) by any other vector score from the set Y. However, the Pareto set $Y^{\varnothing}$ usually contains many solutions. To narrow this set, the criteria importance theory uses information about the relative importance of criteria and the rate of growth of preferences along the scale of criteria.

Qualitative information Ω about the importance of criteria consists of messages $i \succ j$ – î the criterion with number i is more important than the criterion with number jï, as well as $i \sim j$ – î criteria with numbers i and j are equally importantï. Formally, this means the following [15]:

$$i \succ j \Leftrightarrow \forall y \in Y \rightarrow yP^{i \succ j}y^{ij}, y_i > y_j; \quad i \sim j \Leftrightarrow \forall y \in Y \rightarrow yI^{i \sim j}y^{ij}, y_i \neq y_j,$$

where the vector score y^{ij} is obtained by permuting the i-th and j-th components of the vector score y. Using information Ω, a preference relation P^{Ω} is built on a set of vector scores Y, expanding the Pareto relation $P^{\varnothing}$. As a result, the set of vector estimates Y^{Ω} that are not dominated by the relation P^{Ω} becomes smaller than $Y^{\varnothing}$.

Quantitative information about the importance of criteria consists of messages î the criterion with number i is more important than the criterion with number j by h_{ij} timesï [16]. Based on these degrees of superiority in importance, criteria importance coefficients α_i are calculated:

$$h_{ij} = \alpha_i/\alpha_j; \alpha_1 + \dots + \alpha_n = 1.$$

In addition to information about the importance of criteria, the theory uses information about the growth rate of preferences along the criteria scale {1, Ü , q}. Consider the values $v(k)$ of the scale gradation with the number k, as well as the value increments $\delta_k = v(k+1) - v(k)$, k = 1, Ü , q – 1. For the ordinal scale, we only know that $v(1) < \dots < v(q)$. If we arrange the value increments δ_k, then the scale of criteria will become the first ordinal metric scale [13]. In the criteria importance theory, there are methods for obtaining such information. For example, in the case of two equally important criteria [17]:

$$\delta_1 > \dots > \delta_{q-1} \Leftrightarrow (k,k)P(k-1,k+1), k = 2, \dots, q-1,$$
$$\delta_1 < \dots < \delta_{q-1} \Leftrightarrow (k-1,k+1)P(k,k), k = 2, \dots, q-1.$$

Using quantitative estimates of the importance coefficients α_i and values of gradations $v(k)$, an additive value function can be constructed [12-13, 15]:

$$V(y) = \sum_{i=1}^{n} \alpha_i v(y_i). \quad (5)$$

Then the best vector estimate y^V can be chosen by solving the problem of maximizing the function $V(y)$ on Y. If we additionally assume that $v(1) = 0$ and $v(q) = 1$, then the value function $V(y)$ will have a range of values [0; 1].

4. Multicriteria Search Method

We will use the listed 5 characteristics of spraying drones as criteria for the multicriteria problem of choosing the best UAV configuration. To do this, we bring them to a common 10-point scale {1, ..., 10}, using the following equations:

$$v = 5 + y_1, q = 2 + \frac{2}{9}(y_2 - 1), c = y_3 - 1, s = y_4 - 1, m = 5 + 2y_5. \quad (6)$$

Next, we will solve the problem of optimizing the function $T(y, \lambda)$, obtained from (1)-(3) using transformations (6), and selecting the best vector scores y = (y_1, Ü , y_5). Taking into account the constraints on UAV characteristics, 72294 feasible values of the vector $y(x)$ were obtained. Of these, 1893 are Pareto optimal (4). Since the function $T(y, \lambda)$ is decreasing in y_1, Ü , y_5, then for any values of the parameters λ the best solution will be found among the Pareto set $Y^{\varnothing}$. The search and selection of this best solution already depends on the specific values of the parameters λ. To evaluate the effectiveness of the proposed method, we will conduct 1000 computational tests in which the values of the vector λ will be generated randomly.

To evaluate information about the relative importance of criteria, we use the method previously proposed in [20]. To do this, the performance indicators are calculated for n + 1 = 6 reference UAV with vector scores:

$$e^0 = (a,a,a,a,a), e^1 = (b,a,a,a,a), e^2 = (a,b,a,a,a),$$
$$e^3 = (a,a,b,a,a), e^4 = (a,a,a,b,a), e^5 = (a,a,a,a,b). \quad (7)$$

Information Ω about the ordering of criteria by importance is obtained by pairwise comparison of UAV performance indicators with reference estimates e^1, Ü , e^5:

$$T(e^i, \lambda) > T(e^j, \lambda) \Rightarrow i \succ j; \quad T(e^i, \lambda) = T(e^j, \lambda) \Rightarrow i \sim j. \quad (8)$$

If $i \sim j$, then $h_{ij} = 1$ and $\alpha_i = \alpha_j$. Consider the case when $i \succ j$. Quantitative information about the importance of the criteria is obtained by comparing the performance of the UAV with the reference vector score e^j and the mathematical expectation of the UAVs performance, which has the vector score e^i with probability p_{ij}, and the vector score e^0 with probability $(1 - p_{ij})$. The equilibrium probability p_{ij}^* is calculated, at which these performance indices are equal:

$$T(e^j,\lambda) = p_{ij}^* T(e^i,\lambda) + \left(1 - p_{ij}^*\right) T(e^0,\lambda).$$

The degree of superiority in importance of the criterion with number *i* over the criterion with number *j* is the reciprocal of the calculated equilibrium probability p_{ij}^* (see [16, 20]):

$$h_{ij} = \frac{\alpha_i}{\alpha_j} = \frac{1}{p_{ij}^*} = \frac{T(e^0,\lambda) - T(e^i,\lambda)}{T(e^0,\lambda) - T(e^j,\lambda)}. \quad (9)$$

In addition to information about the importance of criteria, this paper proposes to determine information about the growth of preferences along the scale of criteria, namely, how the value increments δ_k, k = 1, Ü , 9 are related to each other. To do this, it will be necessary to evaluate the performance of an additional set of UAVs with specially selected vector scores. To form new reference vector scores, we will vary the scores for the first two criteria, and let the rest of the criteria scores be the same and equal to *d*. Let us introduce the notation for new reference vector scores:

$$g^k = (k, k, d, d, d), \quad k = 1, Ü , 9,$$
$$g^{k\pm} = (k+1, k-1, d, d, d),\ g^{k\mp} = (k-1, k+1, d, d, d), \quad k = 2, Ü , 9. \quad (10)$$

Qualitative estimates of the relationship between neighboring values δ_k, k = 2, Ü , 9, can be obtained as follows:

$$1\sim 2:\ T(g^k,\lambda) \geq T(g^{k\pm},\lambda) \Rightarrow \delta_k \geq \delta_{k+1},\ T(g^k,\lambda) \geq T(g^{k\pm},\lambda) \Rightarrow \delta_k \geq \delta_{k+1}.$$
$$1\succ 2:\ T(g^k,\lambda) \geq T(g^{k\pm},\lambda) \Rightarrow \delta_k > \delta_{k+1},\ T(g^k,\lambda) \leq T\left(g^{k\mp},\lambda\right) \Rightarrow \delta_k < \delta_{k+1}.$$
$$2\succ 1:\ T(g^k,\lambda) \geq T\left(g^{k\mp},\lambda\right) \Rightarrow \delta_k > \delta_{k+1},\ T(g^k,\lambda) \leq T(g^{k\pm},\lambda) \Rightarrow \delta_k < \delta_{k+1}.$$

If for all k = 2, Ü , 9 it turns out that $\delta_k > \delta_{k+1}$, then we can conclude that the growth of preferences along the scale of criteria slows down, and if $\delta_k < \delta_{k+1}$, then the growth of preferences along the scale of criteria accelerates [16]. In [20], only an assumption was made about the presence of such additional information about the scale of criteria, while no methods were proposed for obtaining and verifying it.

Let us now turn to a quantitative estimate of the value increments δ_k. For this, we assume that there is an additive value function (5). Comparing the value functions of reference vector scores for some k = 2, Ü , 9, we can conclude the following:

$$V(g^k) \geq V(g^{k\pm}) \Leftrightarrow \alpha_2 \delta_{k-1} \geq \alpha_1 \delta_k.$$

If the performance indicators T of two robots with vector scores g^k and $g^{k\pm}$ coincide, then we can assume that their value functions are equal. Then

$$\frac{\delta_{k-1}}{\delta_k} = \frac{\alpha_1}{\alpha_2}.$$

Let $T(g^k,\lambda) > T(g^{k\pm},\lambda)$. Let us use a technique similar to that used earlier in assessing the degrees of superiority in the importance of criteria. Let's compare the performance of the UAV with the reference vector score $g^{k\pm}$ and the mathematical expectation of the UAVs performance, which has a vector score g^k with probability p_k and a vector score g^{k-1} with probability $(1 - p_k)$. Calculate the equilibrium probability p_k^*, at which these performance indicators are equal:

$$T(g^{k\pm},\lambda) = p_k^* T(g^k,\lambda) + (1 - p_k^*) T(g^{k-1},\lambda).$$

Equating also the value function of the vector $g^{k\pm}$ and the mathematical expectation of the value functions of the vectors g^k and g^{k-1}, we get:

$$V(g^{k\pm}) = p_k^* V(g^k) + (1 - p_k^*) V(g^{k-1}),$$
$$\alpha_1 \delta_k = p_k^* \alpha_2 \delta_{k-1} + (1 - p_k^*) \cdot 0,$$
$$\frac{\delta_{k-1}}{\delta_k} = \frac{\alpha_1}{p_k^* \alpha_2} = \frac{T(e^0,\lambda) - T(e^1,\lambda)}{T(e^0,\lambda) - T(e^2,\lambda)} \frac{T(g^{k-1},\lambda) - T(g^k,\lambda)}{T(g^{k-1},\lambda) - T(g^{k\pm},\lambda)}. \quad (11)$$

For the case $T(g^k,\lambda) < T(g^{k\pm},\lambda)$, the same final formula (11) is obtained.

Having obtained the estimates of the importance coefficients α_i and the values $v(k)$, choose the vector estimate y^V with the maximum value function $V(y^V)$ among the Pareto-optimal solutions $Y^\varnothing$.

The proposed method for estimation of the values $v(k)$ requires the calculation of performance indices for additional $2q - 3 = 17$ robots with reference vector scores g^k, k = 1, Ü , $q - 1$, and $g^{k\pm}$, k = 2, Ü , $q - 1$. Thus, a total of $n + 2q - 2 = 23$ reference vectors will be required. Note that for a certain choice of the scores *a*, *b* and *d*, namely, $b = a + 2$ and $d = a$, the sets of reference vectors (7) and (10) intersect and contain a common vector $e^1 = g^{(a+1)\pm} = (a+2, a, a, a, a)$. This reduces the total number of reference vectors by one.

5. Results and Discussion

Thousand numerical tests were carried out, in which the values of the parameters λ were obtained using a random number generator. In each test, the optimal solution y^* was found by completely searching among 1893 solutions from the Pareto set $Y^\varnothing$. Among all Pareto-optimal solutions, the spread of values $\Delta T^\varnothing$ of the performance indicator was on average 129% relative to the optimal value $T(y^*,\lambda)$.

In the proposed method, the scores *a*, *b* and *d* should be selected so that all reference vector scores (7) and (10) are feasible and are as close as possible to Pareto-optimal. The maximum value of the score *d*, at which all reference vector scores (10) belong to the feasible set *Y*, is equal to 3. For parameters *a* and *b*, we first use the values a = 6, b = 9, at which 2 of the reference vector scores (7) belong to $Y^\varnothing$, and then values a = 3, b = 5, allowing to reduce the total number of reference vectors by one.

Table 1 presents the results obtained in the first 10 trials and the average of all 1000 trials for values of (*a*, *b*, *c*) equal to (6, 9, 3). The columns of Table 1 show the values of the vector parameter λ, the optimal vector score y^* and the value of its performance indicator

$T(y^*, \lambda)$. The following is information Ω about the ordering of criteria by importance obtained using (8), the number of vector estimates Y^{Ω} that are not dominated by the relation P^{Ω}, and the spread of values ΔT^{Ω} of the performance indicator on this set. Following is the vector score y^V found by the proposed method, which has the maximum value of the value function $V(y^V)$ (5). The next column shows the deviation of the performance indicator of the found solution from the optimal one, in absolute and percentage terms. The last column shows the difference between the values of the value function of the found solution and the optimal one.

Table 1. Results obtained in the first 10 trials and the average of all 1000 trials for (a, b, d) = (6, 9, 3).

$\boldsymbol{\lambda}$	$\boldsymbol{y^*}$	$\boldsymbol{T(y^*, \lambda)}$	$\boldsymbol{\Delta T^{\varnothing}}$	$\boldsymbol{\Omega}$	$\boldsymbol{\lvert Y^{\Omega} \rvert}$	$\boldsymbol{\Delta T^{\Omega}}$	$\boldsymbol{y^V}$	$\boldsymbol{V(y^V)}$	$\boldsymbol{T(y^V, \lambda) - T(y^*, \lambda)}$	$\boldsymbol{V(y^V) - V(y^*)}$
(73.5, 4412, 941, 6, 5)	(6, 7, 7, 8, 7)	77.8917	84.1 (108%)	2≻4≻1≻3≻5	182	52.6 (68%)	(6, 7, 7, 8, 7)	0.9541	0	0
(69.5, 1521, 2507, 9, 6)	(6, 7, 7, 7, 8)	93.4746	131.2 (140%)	2≻5≻4≻1≻3	151	53.6 (57%)	(6, 7, 7, 7, 8)	0.9328	0	0
(44.5, 5000, 2362, 5, 5)	(7, 6, 7, 7, 8)	64.6648	86.1 (133%)	1≻2≻3≻5≻4	203	40.1 (62%)	(7, 6, 8, 7, 7)	0.8051	0.0187 (0.03%)	0
(31.5, 1570, 1492, 1, 4)	(6, 7, 7, 7, 8)	29.8323	32.4 (108%)	2≻1≻5≻4≻3	203	17.9 (60%)	(6, 7, 7, 7, 8)	0.9138	0	0
(56, 1717, 187, 7, 9)	(5, 8, 6, 10, 4)	51.6359	89.2 (173%)	2≻4≻3≻1≻5	151	24.7 (48%)	(6, 8, 7, 8, 5)	0.9983	1.2169 (2.3%)	0.0019
(73, 5000, 1724, 4, 7)	(7, 6, 7, 8, 7)	95.6214	114.6 (120%)	1≻2≻4≻3≻5	203	56.9 (59%)	(7, 6, 7, 8, 7)	0.6305	0	0
(32.5, 1913, 1637, 8, 5)	(6, 7, 7, 8, 7)	39.9749	39.9 (100%)	2≻4≻1≻5≻3	182	30.3 (76%)	(6, 7, 7, 8, 7)	0.9278	0	0
(45.5, 2011, 100, 2, 2)	(6, 9, 6, 8, 3)	27.4796	36.6 (133%)	2≻4≻1≻3≻5	182	15.3 (56%)	(6, 8, 7, 8, 5)	0.9971	0.6618 (2.35%)	0.0024
(73, 2354, 2391, 4, 1)	(6, 8, 5, 7, 8)	66.4844	86.5 (130%)	2≻1≻5≻4≻3	203	28.8 (43%)	(6, 7, 7, 7, 8)	0.9288	0.2066 (0.31%)	0.0036
(49, 4020, 999, 0, 1)	(8, 8, 5, 6, 6)	37.0952	29.8 (80%)	2≻1≻4≻5≻3	203	21.5 (58%)	(7, 7, 6, 7, 7)	0.8967	0.4862 (1.29%)	0.0012
average of all 1000 trials			129%		180	59%			0.4305 (0.83%)	0.0016

Figure 4 shows as an example the function $v(k)$ of the scale gradations obtained in the first two trials.

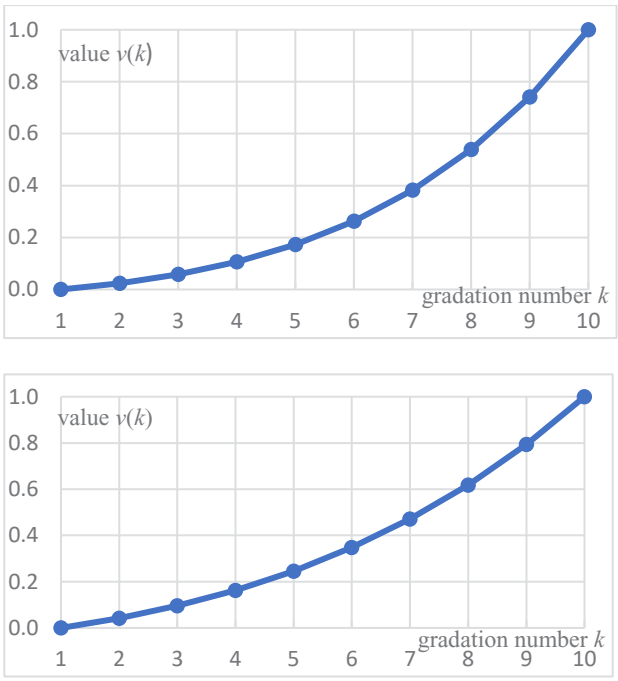

Fig. 4. The resulting graphs of the value $v(k)$ in the first two tests.

On average, information Ω about ordering criteria by importance made it possible to reduce the search area for the best solutions from $|Y^{\varnothing}|$=1893 to $|Y^{\varnothing}|$=180. At the same time, the spread of performance indicator values decreased from 129% to 59%. Let us recall that for this it was necessary to calculate the performance indicator for only 5 reference vector scores (7).

Figure 5 shows how the size of the search area for the optimal robot is reduced by calculating the performance indicator of the reference vector scores.

Fig. 5. The size of the search area for the optimal solution depending on the number of calculations of the performance indicator of the reference robots.

The results obtained show that the values (9, 6, 3) of the parameters (a, b, d) of the proposed method on average lead to a smaller error in finding the optimal solution than the values (3, 5, 3). In the first case, in 547 trials, the found solution differed from the optimal one, and the average deviation was 0.4305 min (0.83%). In the second case, in 821 trials, the found solution differed from the optimal one, and the average deviation was 0.6922 min (1.33%). This advantage on average can be explained by the fact that for large values of a and b, the reference vector scores e^i are closer to the Pareto set $Y^{\varnothing}$ and this makes it possible to more accurately estimate preferences in this area. In both cases, the deviations from the optimal solution turned out to be quite small, compared to the spread of performance indicator values $\Delta T^{\varnothing}$ = 129% among Pareto-optimal solutions and ΔT^{Ω} = 59% among solutions not dominated with respect to P^{Ω}. This confirms the high efficiency of the proposed method, at least on the considered simple simulation model.

The final deviations of the objective function $V(y^V) - V(y^*)$ are also of practical interest. On average, they turned out to be equal to 0.0016 and 0.0054, respectively. When optimizing the value function, you can set a certain amount of error ε and choose a set of vector scores $\{y|V(y^V) - V(y) < \varepsilon\}$. If we take the experimental maximum deviations of 0.0233 as ε, then this guarantees the inclusion of the optimal vector estimate y^* in the selected set.

6. Conclusion

The method proposed in the work, based on the criteria importance theory, made it possible, using a simple simulation model, to reduce the search area for the best solutions and find close to optimal solutions by calculating the objective function for only 23 specially selected options. Deviation from the optimal solution was recorded in 55% of cases and on average amounted to 0.83% of the optimal value of the objective function.

The described procedure for finding the best UAV configuration through testing reference UAVs can be carried out once at the very beginning, before performing the main work by a group of UAVs. In addition, it is possible to adapt UAVs online to changing operation conditions. To do this, in parallel with a group of UAVs with a îworkingï configuration, you can launch 23 reference UAVs and monitor changes in their performance indicators in real time. If there is a significant change in operation conditions and preferences, you can consider the option of changing the îworkingï configuration to a new one, more adapted to the changed conditions.

The methods proposed in this paper for searching the best configurations for spraying drones are quite general and can be applied to various reconfigurable robots.

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