This study considers a heterogeneous fleet of unmanned aerial vehicles (UAVs), consisting of two types of vehicles – main and auxiliary, operating under conditions of probabilistic medium resistance. The task addressed is to rationalize the informed selection of ratio between the main and auxiliary UAVs, which predetermines the survivability of the system, the level of possible losses, as well total resource costs.

A two-criteria discrete mathematical statement of the problem has been proposed, which minimizes the most probable number of losses of main vehicles and the number of auxiliary UAVs. Considering a heterogeneous fleet of UAVs, the probability of losing any element in this fleet is different, especially given the various types of UAVs in it. This significantly complicates the possibility of predicting the integrity of the system over a certain period of its operation; therefore, a simulation model was built by using the Monte Carlo method. It reproduces the sequential nature of events, taking into account the change in the composition of elements after each probable loss. In its architecture, modules for generating random scenarios, modeling losses of fleet elements, and statistical processing of results can be distinguished.

To verify the model, an analytical distribution was performed for the base scenario, and a Pareto-optimal set of heterogeneous fleet configurations was constructed. The maximum discrepancy between the empirical and analytical distributions is 0.49% at $N=50{,}000$ iterations. These results reflect the dependence on the reduction of losses for the main group of fleet elements and the number of auxiliary devices, which are considered cheaper and play the role of increasing stability for the system.

The results could prove useful for preliminary analysis when designing a heterogeneous UAV fleet with elements of different types, different functional purpose, and cost

Keywords: unmanned aerial vehicles, heterogeneous fleet, multi-criteria optimization, Monte Carlo method

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MULTI-CRITERIA OPTIMIZATION OF HETEROGENEOUS UAV FLEET COMPOSITION UNDER PROBABILISTIC COUNTERACTION FROM SURROUNDING ENVIRONMENT BASED ON MATHEMATICAL AND SIMULATION MODELING

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1. Introduction

The evolution of unmanned aerial vehicles (UAVs) accelerates every year, thereby changing approaches to performing both military and civilian tasks. The scope of application of modern UAVs is very diverse – from cargo delivery, use in the agricultural sector, video surveillance of territories, to performing automated missions under difficult environmental conditions. With the growth of UAV functionality, the principles of their application are becoming more complicated. Heterogeneous UAV fleets are becoming increasingly widespread, consisting of aircraft of different purposes, cost, and technical characteristics.

The concept of a heterogeneous fleet involves the joint use of several types of aircraft that work together as a single whole, complementing each other. A heterogeneous fleet is a fleet or group of different types of UAVs that operate as a single system. Among them, one can distinguish main UAVs that execute more important functions or whose quality (cost) is much higher, and auxiliary aircraft used to distribute the load, distract countermeasures, expand the surveillance zone, or increase the overall survivability of the group. Such an approach allows for greater flexibility in the use of the system and reduces the risk of losing key devices under difficult operating conditions.

The relevance of building heterogeneous UAV fleets is important due to the presence of various countermeasure factors when performing the tasks. As shown in papers [1-4,], the use of heterogeneous systems makes it possible to significantly improve the efficiency of executing complex operations. Among such factors are harsh weather conditions, different work of electronic warfare means, or any others, which leads to the loss of an element of the fleet [2]. The evolution of UAVs and their application are described in numerous studies, in particular [1, 4–6], which confirms the relevance of this topic.

Therefore, there is a need to rationalize a reasonable ratio between the number of main and auxiliary devices. On the one hand, increasing the number of auxiliary platforms makes it possible to increase the survivability of the system and reduce the loss of critically important UAVs. But on the other hand, this leads to an increase in the cost of the overall system, as well as the complexity of operation [7]. Therefore, there is a need to find balanced solutions that could make it possible to achieve the optimal ratio.

2. Literature review and problem statement

The basic theories and algorithms that help achieve joint coordinated actions of a group of objects are described in [1]. It is shown that the effectiveness of using a heterogeneous fleet of UAVs is largely explained by the principles of collective behavior, according to which complex actions of the system can be formed through a combination of simple actions of individual devices and their interaction with each other. However, there are unresolved issues regarding the consideration of object losses and how this would affect the task of the system as the study focuses on the self-organization of a UAV swarm and collision avoidance. The fleet devices are considered as equivalent elements, dividing them into local subgroups, between which information is exchanged. The disadvantage of such a model is that it does not take into account the losses of each device. The results do not make it possible to quantitatively assess the impact of losses by local subgroups on the success of the swarm in performing the task set, and are not suitable for substantiating its rational composition, which is the subject of this study.

In [7], mission reliability is considered as the ability of the swarm to perform a given task under given operating conditions, and the structure of the swarm is analyzed taking into account the possible failures of individual devices. As the size of the UAV fleet (or swarm) increases, the balance between mission reliability and the survivability of the system as a whole is important. However, for heterogeneous fleets, this contains additional complexity because devices perform different functions and have different values. The loss of UAVs belonging to the main group of the fleet can have a much greater impact on the result of the task than the loss of UAVs belonging to the auxiliary ones. At the same time, this does not make it possible to describe the scenario when the auxiliary devices take on the responsibility of the loss for the sake of preserving the main group of the fleet.

UAV losses can be a consequence of the influence of external factors, which are usually random in nature, calculated using a probabilistic approach. The calculation can be carried out using a hypergeometric distribution, which determines the probability of a given number of elements of a certain type in a sample from a finite population [8]. The disadvantage of the classical hypergeometric distribution for modeling losses is that it assumes the same probability of selecting elements of the fleet regardless of which group it belongs to. Therefore, the use of this distribution needs to be supplemented with simulation methods.

Regarding the reliability of UAV fleets, not only the technical condition of an individual device is important but also how the failure or loss of one element affects the functioning of the entire group. In [2], UAVs are considered as a complex air system consisting of a certain number of subsystems and components. To achieve the required level of reliability, high-quality components with reduced characteristics are used, in combination with a detailed selection of a backup subsystem. Study [3] is aimed at analyzing the UAV fleet, calculating the availability, reliability, and states of the elements of the fleet, in which a reserve UAV swarm is distinguished. Thus, both studies separately divide UAVs (or UAV subsystem) into main and auxiliary elements. However, the disadvantage of these papers is that they are aimed specifically at the redundancy of elements, when the backup element (UAV, or UAV subsystem) duplicates the functions of the main element and replaces it in case of failure. This logic does not foresee a situation where auxiliary reserve elements are purposefully spent for the sake of preserving others.

In [5], a review of studies on the reliability analysis and evaluation of UAV swarms (fleets) was conducted, in which most of them are performed for a single device, not a system. The study reports the analysis of the UAV fleet based on structural functions, provides characteristics that need to be taken into account when modeling a heterogeneous fleet. Among such characteristics are availability, measures of importance and dependence on topology. However, the study does not solve the problems of optimizing the composition of the UAV fleet, such as rationalizing the selection of ratio between main and auxiliary devices. An option for analyzing such systems can be the use of stochastic methods, Monte Carlo simulation modeling.

In work [6], Monte Carlo modeling is described, the essence of which is the repetition of the same processes, creating a series of events. After that, events are recorded according to their properties, which makes the method suitable for the analysis of stochastic systems. However, in [6], the Monte Carlo method is represented as a universal procedure that is not tied to a specific problem. Therefore, the method needs to be adapted so that it can be applied to a heterogeneous UAV fleet.

Analysis of the above papers reveals that despite the advancements in the considered topic of heterogeneous UAV fleets, the task of optimizing the fleet composition under probabilistic counteraction remains undefined. Existing approaches either consider the fleet devices as equivalent, dividing them into local subgroups [1], or as main and auxiliary [2, 3, 7]. However, auxiliary devices in this context perform backup functions. If the goal is to complete the task at the expense of the main elements of the UAV fleet, thus losing auxiliary UAVs for the sake of preserving the goal, the considered approaches are not suitable for this purpose. Probabilistic and simulation tools [6, 8] are represented in a general statement and are also not adapted to understand how exactly the number of losses of auxiliary elements could affect the provision of the UAV fleet goal.

In turn, study [5] argues that most work on the topic of heterogeneous fleets is really focused on the analysis of a single device, and not the system as a whole. The authors of [5] solve the task of analyzing the reliability of existing fleet configurations by introducing methods (Availability and Importance Measures) to assess the impact of individual drones on system failure. These methods are useful for maintenance planning and determining critical components of the fleet. However, the study does not consider the issue of synthesis and optimization of the configuration of a heterogeneous fleet.

A comparative analysis of mathematical models for assessing the reliability of a UAV swarm (fleet) is given in work [4], in which the binary and multi-state models are compared by the system readiness indicator and recommendations are compiled for choosing the appropriate model. However, similarly to [3, 5], the cited study assesses the reliability of a predetermined fleet structure and does not pose the task of choosing its composition. Auxiliary devices are also treated as reserve elements that duplicate the functions of the main ones, and not as those that are purposefully spent for the sake of preserving the main group.

These unresolved issues are directly addressed in our work, which considers the synthesis and optimization of a heterogeneous UAV fleet through a hypergeometric model, the Monte Carlo method, as well as multi-criteria optimization with the construction of a Pareto set.

3. The aim and objectives of the study

The aim of our work is multi-criteria optimization of the composition of a heterogeneous UAV fleet under conditions of probabilistic counteraction from the environment, which would allow for a reasonable choice of its configuration taking into account the compromise between the survivability of the main platforms and resource costs.

To achieve the set goal, it is necessary to solve the following tasks:

– to propose the architecture of a heterogeneous UAV fleet model and determine its parameters;

– to build mathematical (analytical hypergeometric) and simulation (based on the Monte Carlo method) models of losses in fleet elements;

– to verify the simulation model by comparing its results with the analytical hypergeometric distribution for the case of equal vulnerability of the devices;

– to build a Pareto-optimal set of configurations of fleet composition according to the criteria of the most probable number of losses of main devices and the number of auxiliary ones;

– to conduct a sensitivity analysis of the model for different scenarios of the ratio of the probabilities of losses of elements of the main and auxiliary groups of the fleet;

– to investigate the influence of the environment resistance resource on the number of losses in park elements.

4. The study materials and methods

4. 1. The object and hypothesis of the study

The object of our study is a heterogeneous fleet of UAVs, consisting of two types of devices – main and auxiliary, operating under conditions of probabilistic counteraction from surrounding environment. A heterogeneous fleet of UAVs can be interpreted from different aspects: either from the point of view of mission orientation, or from an abstract point of view – the presence of various functional features [9].

The principal hypothesis assumes that the addition of auxiliary UAVs, which take on part of the impact of the external environment, reduces the most likely number of losses of the main devices. At the same time, main devices perform critically important tasks and have a higher value for the mission. Such a structure makes it possible to model scenarios for the use of mixed groups of UAVs under conditions of probabilistic counteraction from surrounding environment.

Before building the models for this study, the following simplifications were adopted:

– the UAV fleet is divided into two groups of devices (main and auxiliary) without detailing the types within the groups;

– the surrounding environment resistance is represented by a sequence of independent events, as a result of each of which one device is lost with a given probability; however, the impact acting simultaneously on all elements is not considered;

– resource costs are estimated in a simplified manner for the number of auxiliary devices, without taking into account the full cost of the system.

To estimate the losses in a heterogeneous UAV fleet under the influence of external influences, a baseline scenario with the same vulnerability of devices was considered, in which an analytical model based on a hypergeometric distribution was applied. For the case when UAVs have different probability of loss, a simulation model was built using the Monte Carlo method.

4. 2. Software and hardware

To obtain computational results, the Python 3.12 programming language (Python Software Foundation, USA) was used applying the NumPy, SciPy, and Matplotlib libraries. To enable the Python code to be reproduced with the same results, a fixed value was used to generate pseudo-random numbers. For this purpose, the np.random.seed(42) function was used, which registers the initial state of the generators. The calculations were performed on an Apple (USA) personal computer with the MacOS operating system and the Apple M1 Pro processor.

5. Results of construction and investigation of models for optimizing the composition of a heterogeneous fleet of unmanned aerial vehicles

5. 1. Architecture of the model of a heterogeneous fleet of unmanned aerial vehicles

The architecture of the model is based on the division of all vehicles into two categories:

– UAV type 1: main platforms with a critically important objective function;

– UAV type 2: auxiliary platforms used for backup and increasing the stability of the fleet.

To describe the structure of the fleet, the following parameters are introduced:

– n_1 – number of main UAVs in the fleet (type 1);

– n_2 – number of auxiliary UAVs (type 2);

– n_R – resource of counteraction from the environment;

– p_1 – probability of losing a type 1 UAV in one counteraction event;

– p_2 – probability of losing a type 2 UAV;

– x_1 – number of lost main UAVs;

– x_2 – number of auxiliary UAVs, which acts as an optimization variable.

Since type 1 UAVs are basic in terms of functional characteristics, their value n_1 is considered static (constant) and is defined as the minimum required number to achieve the ultimate goal. The main characteristic is x_2, which characterizes the number of UAVs that need to be added to reduce the risk of losing main vehicles.

The surrounding environment's countermeasure resource parameter n_R characterizes the number of external impact events that can lead to the loss of vehicles. Thus, it shows how many times the means of destruction make an attempt that causes the loss of the vehicle. Taking into account the nature of kinetic countermeasures, n_R corresponds to the number of effective impacts of air defense assets on the fleet. Within the framework of the model, it was assumed that the impact of environmental countermeasures acts on each UAV randomly, and the probability of choosing a UAV of a specific type depends on the current number of active elements in the system. This allows us to take into account changes in the structure of the UAV fleet in the event of losses and to approach actual operating conditions.

Two criteria K_1 and K_2 were used to assess the effectiveness. A first criterion characterizes the most likely number of losses of main UAVs

$$K_1 = \arg\max P\left(x_1 \mid x_2\right) \rightarrow \min, \tag{1}$$

where $P(x_1 \mid x_2)$ is the probability of losing exactly x_1 type 1 devices, provided that the fleet contains x_2 type 2 devices.

A second criterion determines the number of auxiliary devices in the fleet and is considered as a simplified estimate of resource costs for system expansion

$$K_2 = x_2 \rightarrow \min. \tag{2}$$

Thus, the task is to find a compromise between reducing the losses of the main platforms and minimizing the number of auxiliary devices.

Since the number of UAVs is a discrete value, the space of admissible solutions is also discrete. The result of the optimization is a set of Pareto-optimal fleet configurations, among which each solution provides its own balance between the level of protection of the main platforms and the complexity of the system structure [10].

Initial data for modeling for the case of equal vulnerability: number of main UAVs $n_1 = 10$; number of auxiliary UAVs $n_2 = 8$; resource of counteraction from surrounding environment $n_R = 6$; number of runs involving the Monte Carlo method $N = 50000$.

5. 2. Loss models in a heterogeneous fleet of unmanned aerial vehicles

5. 2. 1. Basic hypergeometric model

The basic scenario assumes that each iteration is guaranteed to result in the loss of one vehicle, that is, when $p_1 = p_2 = 1$. Given that the targets are randomly selected, the probability that among the lost vehicles (n_R) there will be exactly x_1 vehicles of type 1 is calculated using the hypergeometric distribution [11]

$$P\left(x_1\right) = \frac{C_{n_1}^{x_1} \cdot C_{x_2}^{n_R - x_1}}{C_{n_1 + x_2}^{n_R}}, \tag{3}$$

where C_n^k is the binomial coefficient; n_1 is the number of main UAVs (type 1); n_2 is the number of auxiliary UAVs (type 2); n_R is the resource of environment's counteraction; x_1 is the number of lost main UAVs (type 1).

The domain of this function is described by the following conditions

$$\max\left(n_R - x_2, 0\right) \leq x_1 \leq \min\left(n_1, n_R\right), \tag{4}$$

where x_2 is the number of auxiliary UAVs.

5. 2. 2. Simulation model based on the Monte Carlo method

Given that the previous model is close to an idealized condition, the probability of loss of fleet elements will be different under actual conditions. After all, they are influenced by the external environment, especially when UAVs differ in characteristics and dimensions. There may also be other factors that will lead to the loss of devices. At the same time, auxiliary devices may have different materials or be of different sizes in advance.

Therefore, in this model, parameters p_1 and p_2 are introduced, which are not equal ($p_1\,^{1}\,p_2$). Analytical determination of the distribution of losses is significantly complicated, so the assessment is performed by the Monte Carlo method.

The architecture of the simulation model consists of three functional modules: generation of random counteraction scenarios, modeling of UAV losses, and statistical processing of simulation results (Fig. 1).

The simulation model implements a sequence of n_R counteraction events. At each step, the type of UAV that is exposed to environment is randomly determined, after which the fact of the loss of the device is simulated taking into account the corresponding probability p_1 or p_2. After the loss, a specific UAV is removed from the active platforms, which changes the current ratio between the types of devices and affects the further course of the simulation. The block diagram of this algorithm is shown in Fig. 2.

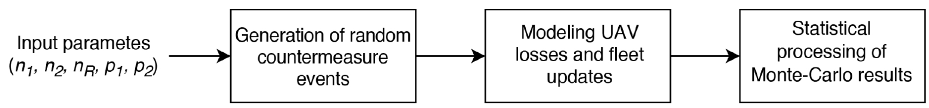

Fig. 1. Simulation model architecture

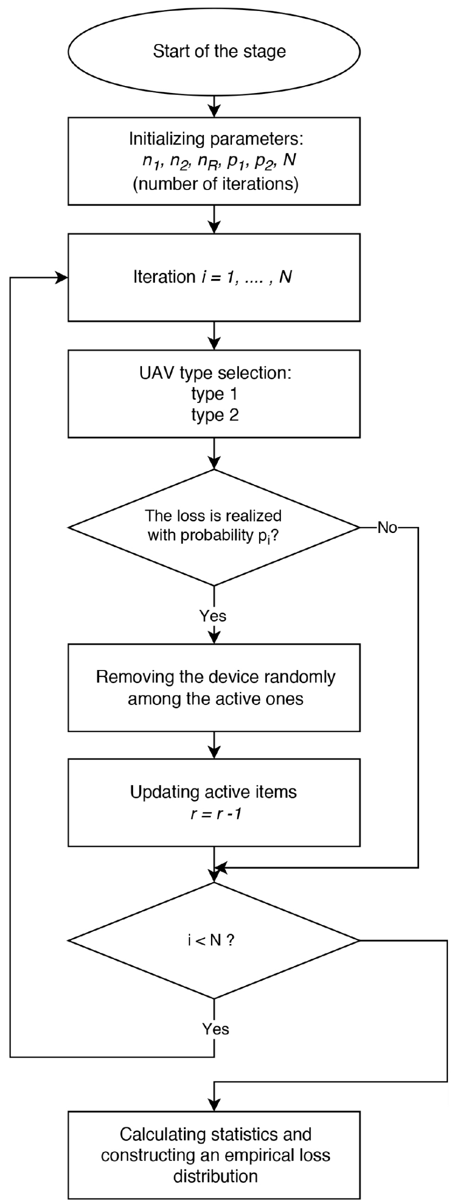

Fig. 2. Block diagram of the Monte Carlo simulation algorithm

After the iterations are completed, an empirical distribution of the number of losses of the main UAVs is performed. The result is used to estimate the most likely loss scenario and further analyze the effectiveness of different fleet configurations.

5. 3. Verification of the simulation model for the case of equal vulnerability of devices

To verify the correctness of simulation model implementation, the results from the Monte Carlo simulation were compared with the analytical hypergeometric distribution for the base case of equal vulnerability of the devices, that is, at $p_1 = p_2 = 1$. In this case, each counteraction event is guaranteed to lead to the loss of one UAV, which allows us to directly compare the results of the simulation and analytical approaches.

A fragment of the Python code of the analytical model is shown in Fig. 3.

A fragment of the Monte Carlo method code is shown in Fig. 4.

```python
import numpy as np
from scipy.stats import hypergeom


def analytical_loss_distribution(n1, n2, nR):
    M = n1 + n2
    if nR > M:
        nR = M
    rv = hypergeom(M, n1, nR)
    x_max = min(n1, nR)
    x_vals = np.arange(0, x_max + 1)
    probs = rv.pmf(x_vals)
    probs = probs / probs.sum()
    return x_vals, probs
```

Fig. 3. Type 1 loss probability distribution code block

The result of executing this code with the input data is shown in Fig. 5.

The maximum absolute difference between the analytical and empirical probability values did not exceed 0.49%, which indicates the correctness of the implementation of the simulation model and the sufficient accuracy of the Monte Carlo method for further computational experiments.

```python
import numpy as np

def simulate_losses_monte_carlo(n1, n2, nR, p1=1.0, p2=1.0, n_trials=10000):
    """Monte Carlo method for estimating type 1 loss distribution."""
    losses_type1 = np.zeros(n_trials, dtype=int)

    for trial in range(n_trials):
        active_type1 = np.ones(n1, dtype=bool)
        active_type2 = np.ones(n2, dtype=bool)
        events_left = nR

        while events_left > 0:
            n1_active = active_type1.sum()
            n2_active = active_type2.sum()
            total_active = n1_active + n2_active

            if total_active == 0:
                break

            if np.random.rand() < n1_active / total_active:
                if np.random.rand() < p1:
                    active_idx = np.where(active_type1)[0]
                    target = np.random.choice(active_idx)
                    active_type1[target] = False
            else:
                if np.random.rand() < p2:
                    active_idx = np.where(active_type2)[0]
                    target = np.random.choice(active_idx)
                    active_type2[target] = False

            events_left -= 1

        losses_type1[trial] = n1 - active_type1.sum()

    return losses_type1
```

Fig. 4. Monte Carlo method code block for estimating type 1 loss distribution

The results (Fig. 5) confirm that the simulation model adequately reproduces the behavior of the system in the case for which there is an analytical solution and therefore could be used to study more complex scenarios with unequal probabilities of losses of UAVs of different types.

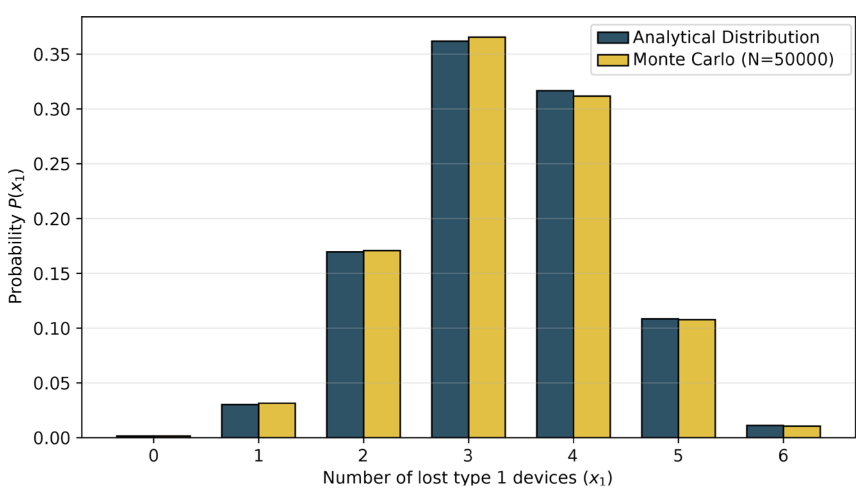

Fig. 5. Comparing the empirical Monte Carlo loss distribution to the analytical hypergeometric distribution

5. 4. Construction of a Pareto-optimal set

Optimization of the composition of a heterogeneous UAV fleet involves increasing the number of auxiliary UAVs, which makes it possible to reduce the probable losses of the main devices. However, this leads to an increase in the complexity of the system and resource losses.

For such problems in multi-criteria optimization, the concept of Pareto-optimality is used, which implies that we obtain as a result not a single optimal solution but a set of permissible compromise options [12]. The configuration of a heterogeneous UAV fleet is considered Pareto-optimal if there is no other permissible solution that simultaneously provides lower losses of the main UAVs and a smaller number of auxiliary ones.

Formally, configuration i belongs to the set of Pareto-optimal solutions if there is no configuration j for which the condition is met:

$$K_1(j) \leq K_1(i), \quad (5)$$

$$K_2(j) \leq K_2(i), \quad (6)$$

at least one of the inequalities is strict

$$K_1(j) < K_1(i), \quad (7)$$

or

$$K_2(j) < K_2(i), \quad (8)$$

The construction of such a set is carried out by enumerating the permissible values of the number of auxiliary UAVs and comparing the resulting values. Configurations that are worse than other options simultaneously by both criteria are excluded from consideration; the remaining solutions form a Pareto-optimal set. The resulting set of solutions allows us to assess the compromise between the level of protection of the main platforms and the number of auxiliary UAVs in the fleet.

Initial data for conducting a series of iterations with several scenarios to assess the impact of the relative vulnerability of the devices on the shape of the Pareto front:

– scenario A in which auxiliary devices are significantly more stable: $p1 = 0.95$, $p2 = 0.3$;

– scenario B, moderate difference: $p1 = 0.85$, $p2 = 0.5$;

– scenario C, with equal characteristics: $p1 = 0.7$, $p2 = 0.5$;

For each scenario, $N = 4{,}000$ iterations were performed.

To construct the Pareto-optimal set, a series of computational experiments were conducted for different configurations of a heterogeneous UAV fleet. Within the experiment, the number of main vehicles n_1 was considered fixed, while the number of auxiliary UAVs x_2 varied within a given range. For each configuration, the distribution of losses of the main platforms was estimated using the Monte Carlo method and the most probable value of the criterion K_1 was determined. A fragment of the code for constructing the Pareto-optimal set is shown in Fig. 6.

For each configuration, criteria K_1 and K_2 were formed, where K_1 characterizes the most likely number of losses of the main UAVs, and K_2 is the number of auxiliary devices in the fleet. Fig. 7 visualizes the result of code execution.

```python
def is_pareto_optimal(point, all_points):
    for other in all_points:
        if (other[0] <= point[0] and other[1] <= point[1] and
                (other[0] < point[0] or other[1] < point[1])):
            return False
    return True

def compute_pareto_front(n1_fixed, nR, p1, p2, x2_range, n_trials=5000):
    points = []
    for x2 in x2_range:
        losses = simulate_losses_monte_carlo(n1_fixed, x2, nR, p1, p2, n_trials)
        x_vals, probs = mc_distribution(losses, n1_fixed)
        k1 = int(x_vals[np.argmax(probs)])
        k2 = int(x2)
        points.append((k1, k2))

    pareto = [p for p in points if is_pareto_optimal(p, points)]
    pareto = sorted(set(pareto))
    return points, pareto
```

Fig. 6. Pareto-optimal set construction code block

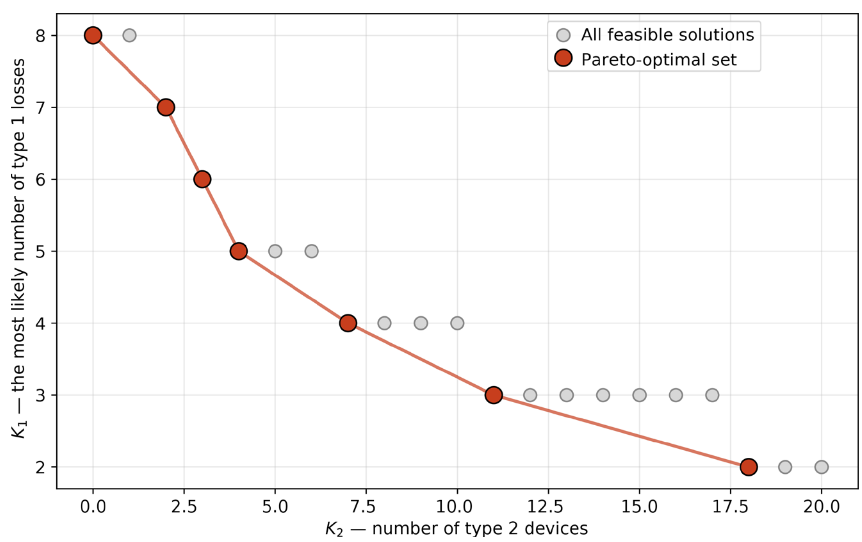

Fig. 7. Pareto-optimal set of fleet composition in the criteria space (K_1, K_2)

Based on the results in Fig. 7, the Pareto-optimal set decreases, forming a curve according to which we can conclude that an increase in the number of auxiliary devices leads to a decrease in the most probable number of losses of the main ones.

5. 5. Sensitivity analysis of the model for different scenarios of the ratio of probability of losses

To assess the impact of relative vulnerability of devices on the shape of the Pareto front, a series of iterations with several scenarios according to the input data was carried out. A code fragment is shown in Fig. 8.

A graphical comparison is shown in Fig. 9.

```python
scenarios = [
    ("A: p1=0.95, p2=0.30", 0.95, 0.30, "#2E5266"),
    ("B: p1=0.85, p2=0.50", 0.85, 0.50, "#6E8898"),
    ("C: p1=0.70, p2=0.70", 0.70, 0.70, "#C73E1D"),
]
# Plot generation
fig3, ax3 = plt.subplots(figsize=(9, 5.5))
for label, p1, p2, color in scenarios:
    _, pareto = compute_pareto_front(n1_base, nR_base, p1, p2, x2_range_base, n_trials=4000)
    if pareto:
        k2s, k1s = zip(*sorted(((p[1], p[0]) for p in pareto)))
        ax3.plot(k2s, k1s, '-o', color=color, linewidth=2, markersize=8, label=label)

ax3.set(xlabel='$K_2$ — number of type 2 devices',
        ylabel='$K_1$ — the most likely number of type 1 losses')
ax3.legend(fontsize=10); ax3.grid(True, alpha=0.3); plt.tight_layout()
plt.savefig('fig3_sensitivity.png', dpi=150, bbox_inches='tight'); plt.close()
```

Fig. 8. Model sensitivity analysis code block

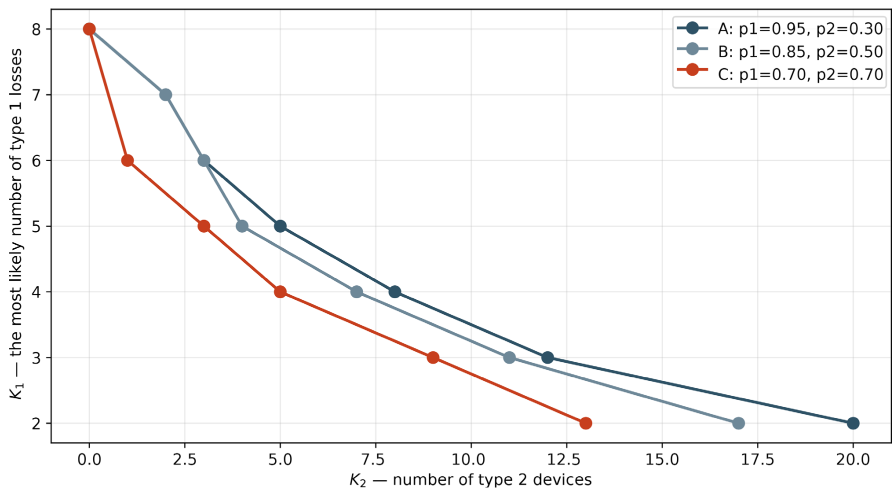

Fig. 9. Sensitivity of Pareto-optimal fronts to the probability ratio p_1/p_2

Analysis of our results reveals that the greater the relative stability of auxiliary devices (less p_2), the more of them are required in the fleet to achieve the same reduction in K_1. Scenario C (probability levels) demonstrates the best results with the smallest number of auxiliary devices. However, this does not mean that this scenario is optimal in practice – the $p_1 = p_2$ equality typically indicates the uniformity of devices and the loss of the very idea of a heterogeneous fleet. Scenario A is most characteristic of heterogeneous fleets with pronounced specialization.

5. 6. The influence of the resource of environment's countermeasure on the number of losses in fleet elements

To assess the stability of a heterogeneous fleet of UAVs under conditions of varying intensity of external influence, a study of the dependence of K_1 on n_R at different fixed n_2 values was conducted. A fragment of the code is shown in Fig. 10.

The results of the execution are shown in Fig. 11.

```python
nR_range = range(2, 21, 2)

def most_probable_losses(n2, nR):
    x_v, p_v = mc_distribution(
        simulate_losses_monte_carlo(n1_base, n2, nR, p1_base, p2_base, n_trials=3000),
        n1_base)
    return int(x_v[np.argmax(p_v)])

fig4, ax4 = plt.subplots(figsize=(8, 5.5))
for n2, color in zip([0, 4, 8, 12], ['#2E5266', '#6E8898', '#E2C044', '#C73E1D']):
    ax4.plot(list(nR_range), [most_probable_losses(n2, nR) for nR in nR_range],
             '-o', color=color, linewidth=2, markersize=7, label=f'$n_2 = {n2}$')

ax4.set(xlabel='$n_R$ — environmental countermeasure resource',
        ylabel='$K_1$ — the most likely number of type 1 losses')
ax4.legend(fontsize=10); ax4.grid(True, alpha=0.3); plt.tight_layout()
plt.savefig('fig4_resource.png', dpi=150, bbox_inches='tight'); plt.close()
```

Fig. 10. Surrounding environment's countermeasure resource impact analysis code block

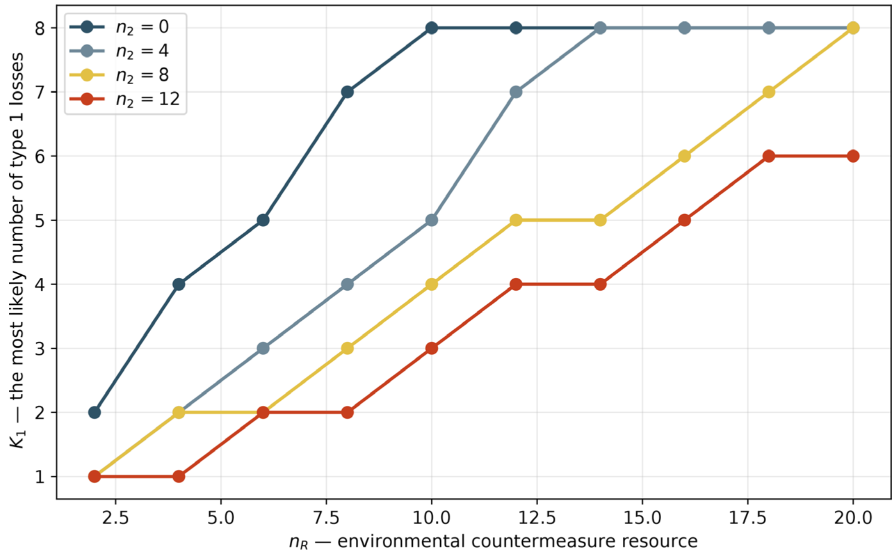

Fig. 11. Dependence of the most probable number of losses on the countermeasure resource at different n_2 values

Analysis of our results reveals that at small values, even a small number of auxiliary UAVs makes it possible to ensure a low level of losses of the main platforms. The higher the intensity of the counteraction, the less benefit is brought by increasing the number of additional UAVs. The counteraction from surrounding environment is one of the key factors that affect the viability of the system as a whole and the losses of individual elements.

6. Discussion of results based on investigating the model of multi-criteria optimization of the composition of a heterogeneous fleet of unmanned aerial vehicles

In our work, an analytical hypergeometric model was combined with a Monte Carlo simulation model. A feature of the proposed approach is the ability to obtain the results of scenarios with the same and different probabilities and compare them. In available studies [7], the geometric structure of the UAV fleet is optimized by the measure of importance, and in [5] the reliability of the fleet is assessed based on structural functions. Both studies have a fixed configuration in advance and do not set the task of choosing a composition. In contrast, in our work, the composition of the UAV fleet is the object of optimization according to two criteria – (1) and (2), which are contradictory to each other. This affects the nature of the curve results in Fig. 7, where with an increase in auxiliary vehicles, the most likely number of losses of the main vehicles of the fleet decreases.

An analysis of the basic hypergeometric model was carried out in the case of the same probability of loss of both types of devices, described by formula (3). Unlike [8], in which the hypergeometric distribution is represented in a general form, here it is adapted to the process of losses in the fleet as a selection of devices without returning from the general composition. This connects the number of main and auxiliary devices and the countermeasure resource with the most probable number of losses of the main UAVs. The Monte Carlo method [6] is taken as a basis in the general statement and adapted for a specific algorithm. This algorithm reproduces the sequence of events by recalculating the total composition of the UAV fleet at each iteration. A comparison of the probability distribution of losses with the empirical one obtained from the Monte Carlo method is illustrated in Fig. 5. The discrepancy between such distributions was at the level of 0.49%, which indicates the methodological correctness of our model.

Regarding the Pareto-optimal set, indicators for a separate device or fleet are given in [2, 3]. However, in our model of a heterogeneous UAV fleet, auxiliary vehicles play the role of preserving the main elements of the fleet, which affects the form of the sensitivity analysis shown in Fig. 9. The constructed Pareto-optimal set (Fig. 7) has a decreasing nature: an increase in the number of auxiliary vehicles reduces the most likely number of losses of the main ones.

Sensitivity analysis (Fig. 9) was conducted for three scenarios of the ratio of the probabilities of loss of devices – a scenario with significantly more stable auxiliary devices, a scenario with a moderate difference between the probabilities of loss, and a scenario with the same probabilities of loss of devices of both types. The analysis revealed that the greater the relative stability of auxiliary devices (that is, the lower the probability of their loss compared to the main ones), the greater their number is required for the same reduction in the most probable number of losses of main devices. The scenario with equal probabilities gives the best result at the smallest number of auxiliary devices; however, equality of probabilities of loss means the same type of devices and the loss of the very idea of a heterogeneous fleet; the most characteristic scenario for fleets with pronounced specialization is the scenario with significantly more stable auxiliary devices. This is explained by the fact that more stable auxiliary devices are less likely to absorb the impact from surrounding environment, therefore, more of them are required to redirect losses from the main group.

The influence of the resource of environment's countermeasure on the number of losses of fleet elements was studied. It is shown that with a small resource of environment's countermeasure, even a small number of auxiliary devices ensures a low level of losses of the main ones, while with increasing intensity of counteraction, the increase in benefit from adding auxiliary devices decreases.

Our study is limited to kinetic countermeasures, which lead to the loss of individual aircraft by air defense means, when each countermeasure event with a certain probability leads to the loss of one element of the fleet. Modern UAV countermeasure systems are combined, combined into a single system of the local and/or regional level. However, the proposed model does not cover countermeasures using radio electronic suppression (REP), optical-electronic suppression, electromagnetic damage, and combined cover. Such countermeasures affect mainly the entire group of UAV fleets and are not reduced to independent events of the loss of individual fleet vehicles. Accordingly, our results apply only to the case of kinetic countermeasures, leaving room for investigating its other types. The validation of the simulation model was carried out with a fixed random number generator, using the built-in Python function: np.random.seed(42). The number of iterations for Monte Carlo was chosen to be 50,000, as a compromise between statistical accuracy and computational time.

The disadvantage of this study is the simplified description of the external impact. The model does not take into account the possible dependence between the events of the external impact. The $K_2 = x_2$ criterion is a simplified estimate of resource costs and does not take into account the cost of the system as a whole. Also, the model is static because, after n_R events, the result of losses is registered, without taking into account the time dynamics.

Further studies should be aimed at expanding the types of elements in the UAV fleet. In addition to the main and auxiliary ones, additional groups can be distinguished. They could also consider introducing the time dynamics of losses.

7. Conclusions

1. The architecture of a heterogeneous UAV fleet model has been proposed, consisting of three functional modules – generation of random counteraction scenarios, modeling of aircraft losses, and statistical processing of results. To assess the effectiveness of the fleet composition, two criteria were used – the most probable number of losses of the main aircraft and the number of auxiliary aircraft. Since the number of aircraft is a discrete value, the space of permissible solutions is also discrete, and the result of optimization is a set of Pareto-optimal configurations, each of which provides its own balance between the level of security of the main platforms and the complexity of the system structure. Initial data were generated for the case of equal vulnerability of the aircraft (these are 10 main and 8 auxiliary aircraft, and the number of iterations is 50,000).

2. The mathematical (analytic hypergeometric) and simulation (Monte Carlo) loss models have been constructed. In contrast to the general representation of the hypergeometric distribution and the general Monte Carlo procedure, both models are adapted to the loss process as a selection of vehicles without replacement, which directly connects the composition of the fleet with the distribution of the number of losses of the main machines. A block diagram of the Monte Carlo simulation algorithm is proposed.

3. The simulation model was verified by comparing its results with the analytical hypergeometric distribution for the case of equal vulnerability. The maximum absolute difference between the empirical and analytical probabilities did not exceed 0.49% for $N = 50{,}000$ iterations, which confirms the correctness of the model implementation. Due to this, the simulation model was reasonably applied to the general case of different probabilities, for which the analytical solution is significantly complicated.

4. A Pareto-optimal set of fleet configurations has been constructed in the space of two criteria – the most probable number of losses of main units and the number of auxiliary units. The set is of a decreasing nature: in the absence of auxiliary units, the most probable number of losses of main units is 8, and with an increase in their number, this number decreases – in the presence of 18 auxiliary units, it is 2. Thus, an increase in the number of auxiliary units reduces the most probable number of losses of main units, forming a decreasing Pareto front.

5. A sensitivity analysis of the model was conducted for different scenarios of the ratio of probabilities of losses of elements of the main and auxiliary groups of the fleet. Among these scenarios, a scenario was selected in which auxiliary units are significantly more stable; a scenario with a moderate difference between probabilities; a scenario in which the probabilities are equal. Analysis of the results revealed that the greater the relative stability of auxiliary units, the more of them are required in the fleet to achieve a reduction in the most probable number of losses of main units. In particular, to reduce the most probable number of losses of main units to 2 in a scenario with equal probabilities, 13 auxiliary units are sufficient. While with a moderate difference between probabilities – 18, and with significantly more stable auxiliary units – 20.

6. Countermeasure resource is one of the key factors that affect the viability of the system as a whole and the losses of individual elements. With a countermeasure resource value of 10 events, increasing the number of auxiliary devices from 0 to 12 reduces the most likely number of main losses from 8 to 3. While with a resource value of 20 events, the same value of the number of auxiliary devices reduces it only from 8 to 6. Thus, our study of the impact of countermeasure resource from surrounding environment showed that the higher the intensity of the countermeasure, the less benefit is brought by increasing the number of additional UAVs. The results are applicable for preliminary justification of the composition of heterogeneous UAV groups and assessment of their survivability under conditions of random external influence.

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 and the results reported in this paper.

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Data availability

The data will be provided upon reasonable request.

Use of artificial intelligence

The authors declare the use of artificial intelligence tools: Claude Opus 4.7 version 2026; ChatGPT (GPT-5.5 Thinking, OpenAI, 2026), number 5.0.1.

The artificial intelligence tool was used in chapters "Introduction", "Literature review and problem statement", "Discussion", "Conclusions".

The artificial intelligence tool was used for editing and grammar checking. The results provided by the artificial intelligence tool were verified by manual testing on actual texts of the authors' scientific publications.

Results from the artificial intelligence tool reduced the impact of human grammatical errors when drawing conclusions for the study.

The total amount of AI assistance did not exceed 25% of the research work.

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Authors' contributions

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