AUTOMATION AND COMPUTER-INTEGRATED TECHNOLOGIES

UDC 629.735.018.7:004.896:681.513.5:519.876.5(045)
DOI:10.18372/1990-5548.83.19870

[1]V. M. Sineglazov,
[2]D. V. Taranov

HYBRID METHODOLOGY FOR REBUILDING A SWARM OF DRONES BASED ON LOCAL CAPABILITIES AND GLOBAL COORDINATION

[1,2]Aviation Computer-Integrated Complexes Department, Faculty of Air Navigation Electronics and Telecommunications, State Non-Profit Enterprise "State University "Kyiv Aviation Institute", Kyiv, Ukraine
E-mails: [1]svm@nau.edu.ua ORCID 0000-0002-3297-9060, [2]4637199@stud.kai.edu.ua

Abstract—*This work is devoted to solving the problem of restructuring the structure of a drone swarm from one topology to another. A hybrid topology is proposed that combines global centralized assignment of target positions with local potential control of each drone. Attractive and repulsive fields are used for safe maneuvering, while periodic global coordination ensures optimal distribution of roles. A mathematical model, rules for forming control influences, and convergence criteria are presented. The implementation of the proposed hybrid methodology is based on the sequential interaction of a global optimizer that determines the target positions of the swarm and a local potential regulator that ensures safe convergence of drones to these positions. Calculations are performed in discrete time steps with periodic restart of the global planner in case of a task change, the appearance of obstacles, or the loss of individual devices.*

Keywords—Unmanned aerial vehicle swarm; formation reconfiguration; potential field methods; collision avoidance; hybrid control strategy; leader-follower topology; multi-agent systems; trajectory optimization; decentralized control; real-time systems.

I. INTRODUCTION

Swarms of unmanned aerial vehicles (UAVs) are increasingly becoming an integral part of modern military, commercial, and research operations, providing new opportunities for the interaction of multiple autonomous systems. This integration of drones into a single network significantly increases the flexibility and reliability of their use, as the simultaneous involvement of dozens or hundreds of drones allows for the coverage of large areas for monitoring, reconnaissance, and rapid delivery of goods [1], [2]. At the same time, the swarm configuration can be adapted to specific tasks or environmental conditions, which ensures high efficiency and effectiveness.

The most advanced research in this area covers decentralized control methods, where each drone uses only local information and interactions with close neighbors, as well as approaches with centralized trajectory planning, when there is one or more "master" nodes (leaders) [3], [4]. However, regardless of the specific algorithmic approach, the problem of flexible and reliable reconfiguration of the swarm in real time remains an urgent one. Such reconfiguration includes the selection of a new drone topology (e.g., transition from a "star" to a hierarchical structure) and the adjustment of individual UAV routes, taking into account safety factors, energy consumption, and mission changes [5].

In view of this, current research focuses on the development of coordinated swarm reconfiguration mechanisms that would minimize the risk of collisions, the time to transition to a new configuration, and the overall cost of resources. Attention is also paid to the system's resilience to individual device failures, since in a decentralized or hybrid control environment, it is critical to ensure the swarm's functioning even in the absence of individual drones or lost communication channels [6]. In addition, when transitioning between different formations, it is necessary to optimally distribute the roles of leaders, determine their number and rules of interaction with followers to avoid bottlenecks in the network [7].

Thus, research in the field of drone swarm reorganization goes beyond simple route planning and includes interdisciplinary aspects: from mathematical models of autonomous agent interaction to self-organization mechanisms and artificial intelligence. It is a comprehensive analysis of existing topologies, reconfiguration algorithms, and the proposal of our own approach to the formation and reconfiguration of swarms that are crucial for improving the operational capabilities of unmanned aerial systems in modern conditions.

II. PROBLEM STATEMENT

Reorganizing a swarm of unmanned aerial vehicles into different formations is a critical component of modern multi-drone systems, as it is the ability to quickly change the geometry of a group that determines the success of complex missions in a dynamic environment. Changing operational requirements, the emergence of new obstacles, or the sudden loss of individual vehicles require an instant transition from one topology to another to maintain coverage, minimize the risk of collisions, and ensure the stability of the communication network.

Studies show that even in narrow corridors, an adaptive *V*-shaped configuration with adjustable wing flap angle can successfully overcome obstacles and maintain the swarm's aerodynamic efficiency [1]. While traditional static schemes often fail in such conditions. In the case of hierarchical structures such as leader-follower, the key is to ensure continuity of control after the leader's failure; in practice, this is solved by immediately redistributing roles and updating the communication topology, which demonstrates an increase in system survivability and a reduction in downtime [3].

Flight experiments with the "line → triangle" formation confirm that vertical separation and gradual displacement of drones reduce the likelihood of collisions and allow the maneuver to be performed without losing control of the formation [2]. The availability of algorithms that ensure safe altitude reconfiguration is especially important in complex environments where horizontal maneuvering is limited.

In modern experimental environments, more and more attention is paid to the ability of a swarm to adapt to the emergence of new vehicles or the loss of existing ones through event-driven reassignment of goals and roles. This requires algorithms that combine global planning with real-time local response [4], [5].

Thus, the relevance of the restructuring problem lies in the need to create universal algorithms that can guarantee a safe and energy-efficient transition between formations in real time, which, in turn, directly affects the efficiency, scalability, and reliability of modern UAV swarms.

Controlling a swarm of drones (UAVs) is complicated by many interdependent factors: from the interaction of each UAV with the environment and its neighbors to the global mission requirements. In particular, when the operational task or environmental conditions change, there is a need to rebuild (reconfigure) the formation – to move from the current swarm topology to a new one, taking into account the new conditions.

1) Flight safety, which requires maintaining the minimum permissible distances between aircraft during the adjustment process:

$$x_i(t) - x_j(t) \geq \delta_{\min}, \ \forall i \neq j, t \in [0, T], \tag{1}$$

where $\delta_{\min}$ is the allowable safety distance.

2) Minimize time and trajectory costs. The total cost of restructuring should be minimized. Formally, the objective function can be represented as a weighted combination of time and resource consumption:

$$J = \sum_{i=1}^{N} \int_{0}^{T} \left(\|\dot{x}_i(t)\|^2 + \rho \|\ddot{x}_i(t)\|^2 \right) dt, \tag{2}$$

where $\dot{x}_i$ is the speed: $\ddot{x}_i$ is the is the acceleration of the ith UAV; $\rho > 0$ is the weighting factor for dynamic costs.

Fault tolerance. The swarm should remain functional after the loss of a subset of agents $\mathcal{L} \subseteq \{1,...,N\}$, that is, to ensure automatic reassignment of target positions to other drones $\{1,...,N\} \setminus \mathcal{L}$ for the new plan $X^{*\prime}$, that satisfies conditions 1–2.

3) Variability of topologies: The ability to transition between different classes of geometric formations (e.g., from chain to V-shaped, or from hierarchical to grid) should be provided. Each such formation has a parametric representation:

$$X^*(\theta) = \mathcal{F}(\theta), \ \theta \in R^k, \tag{3}$$

where θ is a vector of parameters (e.g., radius, opening angle, number of rows); and $\mathcal{F}$ is the functional transformation that defines the structure of the target formation.

4) Consistency of local and global decisions. Local control of the agent is carried out through the potential field:

$$U_i(x_i) = \frac{1}{2}\alpha \|x_i - x_i^*\|^2 + \sum_{j \neq i} \psi\left(\|x_i - x_j\|\right), \tag{4}$$

where the first term ensures approaching the target, and the second term ensures avoiding collisions. The control is defined as a gradient descent:

$$u_i = -k \nabla_{x_i} U_i(x_i), \tag{5}$$

5) Limitations on global optimization: within the hybrid architecture, the global module calculates the optimal set X^*, solving the problem of minimizing the functional:

$$\min_{X^*} \sum_{i=1}^{N} \left\| x_i^* + x_i(0) \right\|_{W_1}^{2} + \lambda \sum_{i<j} \left\| x_i^* - x_j^* \right\|_{W_2}^{-2}, \quad (6)$$

where W_1, W_2 are weight matrices; λ is a coefficient that penalizes close locations of target points that may violate condition 1.

Thus, the mathematical formulation of the problem is reduced to a multi-level optimization, in which the global level determines X^*, and local guarantees safe and convergent control to this set. The use of such a structure corresponds to modern approaches to decentralized or hybrid control in UAV swarms [1] – [3], ensuring scalability, survivability, and flexibility of the system.

III. RELATED WORKS

The current scientific and applied literature describes a wide range of geometric configurations that UAV swarms use depending on the nature of the task, environmental conditions, and safety requirements. The analysis of these sources shows that each formation has clearly defined advantages and limitations, and thus its choice significantly affects mission efficiency, power consumption, and fault tolerance of individual vehicles [1] – [5]. The results of this analysis are summarized in Table I, which systematizes the most commonly used formations and their functional purpose.

TABLE I. SYSTEMATIZATION OF THE MOST COMMONLY USED FORMATIONS AND THEIR FUNCTIONAL PURPOSE

Type of formation	Definition
The letter V	Increased maneuverability and visibility during flight in gorges, narrow corridors and dense obstacles; reduced aerodynamic drag at the cruise stage [1], [6].
Line	Transit along narrow routes, initial formation after takeoff, patrolling roads or linear objects [2], [7].
A tricut, a "wedge"	Tightened reconnaissance and search in a small area; increased strike concentration in the center of the formation[2], [8].
Hierarchical	Increasing the recognition area or strike force by grouping units; convenient delegation of commands through a multi-level structure [3], [9].
Grid	Creation of a distributed communication network that maintains communication in case of node failure; large-scale monitoring or communication support in an area without ground infrastructure [4], [10].
Chain	Sequential inspection of narrow tunnels/corridors; data transmission by "relay" between remote sectors [5], [11].
Leader V shape with self-configuration	Infrastructure patrolling, avoidance of static and dynamic obstacles in narrow corridors [1], [12].
Scattered formation after the loss of the leader	Maintaining controllability and restoring topology in the event of a crash/destruction of the main UAV [3], [13].

Three key areas have emerged in the scientific literature that define the current state of swarm reconfiguration methods. The first area is based on the Leader-Follower principle, when one or more drones act as a leader, and the rest adjust their trajectories based on its position and data from the nearest neighbors. The advantage of this approach is its simplicity of implementation, but the stability of the system depends on the ability to quickly replace the leader in case of its loss. For this purpose, a hierarchical rule base is used Hierarchical Belief Rule Base (HBRB) [3], that takes into account the spatial location of candidates, energy reserves, and communication quality. After selecting a new leader, the network topology is automatically rebuilt, and the relative coordinates of each drone are refined in accordance with the new geometry.

Further stabilization is carried out by consensus law

$$u_i = -\sum_{j\in\mathcal{N}_i} K_1 ! \left[\left(q_i - q_0 + \Delta_i\right) - \left(q_j - q_0 + \Delta_j\right) \right] - \sum_{j\in\mathcal{N}_i} K_2 \left(p_i - p_j\right) - K_3 \left(q_i - q_0 + \Delta_i\right) - K_4 \left(p_i - p_0\right), \quad (7)$$

where q_i, p_j denote coordinates and velocities, respectively ith drone; q_0, p_0 are the parameters of the leader; and $K1 \dots K4$ is the matrix of positive (semi-) definite coefficients.

The second direction demonstrates self-configuring V-shape formations where the swarm changes the angle of wing opening in narrow corridors. Each agent calculates a local control vector

$$\dot{p}_i = u_i, \tag{8}$$

$$u_i = \begin{cases} u_{gi} + u_{ri} + u_{ci} + u_{oi}, & \text{for the leader,} \\ u_{fi} + u_{ri} + u_{ci} + u_{oi}, & \text{for the follower,} \end{cases} \tag{9}$$

where u_{gi} is responsible for moving towards the global goal; u_{fi} – for the maintenance of the formation; u_{ri} – for orientation alignment; u_{ci} – for maintaining the distance between drones; and u_{oi} – for obstacle avoidance [1].

To deviate from an obstacle, the thrust vector is user

$$u_{oih} = -k_o!\left(\frac{1}{d_{ih}^2} - \frac{1}{r_s^2}\right)\frac{p_i - p_{ih}}{|p_i - p_{ih}|}, \tag{10}$$

where d_{ih} is the distance to the obstacle; r_s is the radius of the sensing area.

The third area combines Model Predictive Control (MPC) with Particle Swarm Optimization (PSO). Each UAV solves a local problem of a finite horizon

$$\min_{U_i} J_i = \sum_{k=0}^{H} 1\,|\,p_i(k) - p_i^{\text{ref}}(k) 1\,|_{\mathbf{Q}}^2 + \sum_{k=0}^{H-1} |\,u_i(k)\,|_{\mathbf{R}}^2, \tag{11}$$

where H is the horizon length; **Q**, **R** are weight matrices. The PSO population is used to globally adjust the resulting MPC trajectories, reducing the total formation error and the probability of conflicts [5]. The PSO algorithm retains the classical rules for updating particle velocities, but the fitness function integrates energy consumption and safety criteria.

The strategies proposed in the literature demonstrate that the combination of local rules and global optimizers provides the best combination of performance, security, and scalability, which is fully consistent with the concept of the hybrid methodology outlined in this article.

IV. PROBLEM SOLUTION

The methodology underlying this study is based on the integration of two complementary levels of governance: global planning and local potential regulation. The global level is responsible for the optimal distribution of roles and target positions within the selected formation, while the local level ensures the safe maneuvering of each drone using attractive and repulsive fields.

Global planning. At the initial stage, a vector of target coordinates is formed $x^*\left[x_1^*, \ldots, x_N^*\right]$, which minimizes the functionality

$$J = \sum_{i=1}^{N} \left\| x_1^* + x_i(0) \right\|_{W_1}^2 + \lambda \sum_{i<j} \left\| x_i^* - x_j^* \right\|_{W_2}^{-2}, \tag{12}$$

where J is the objective function to be minimized. This function represents a balance between two goals: minimizing the total movement of drones and maintaining a safe distance between them in the target configuration; N is the number of unmanned aerial vehicles (drones) in the swarm system; x_i^* is the vector of target coordinates of the ith drone, determined by the global optimizer at the swarm rebuilding stage; $x_i(0)$ is the vector of the initial coordinates of the ith drone before the start of the rebuilding; $\left\| x_i^* - x_j^* \right\|_{W_2}^{-2}$ is the weighted square of the Euclidean distance between the initial and target position of the ith drone, which reflects the energy consumption for movement; W_1 and W_2 are positive definite weight matrices; $\lambda > 0$ is a compromise coefficient; the first term describes the total path to a new formation, and the second term is a penalty for potential conflicts. The minimization problem is solved by a modified particle swarm algorithm, where the speed and position of each candidate particle are adjusted to take into account constraints on the energy reserve and topological connectivity of the network.

For each UAV, a total potential is formed, which is a mathematical scalar state function that evaluates the "energy profitability" of the drone's current position relative to the desired location and its neighbors. This potential consists of two components: an attractive one that pulls the vehicle toward its target point, and a repulsive one that models interagent interaction to avoid collisions. The potential function allows us to build the control in the form of a gradient descent, which guarantees convergence to the configuration with the minimum total potential energy, i.e., to the desired formation.

$$U_i(x_i) = \frac{1}{2}\alpha \left\| x_i - x_i^* \right\|^2 + \sum_{j \neq i} \psi\left(\left\| x_i - x_j \right\| \right), \tag{13}$$

where $U_i(x_i)$ is the total potential of the ith drone, which determines the measure of "energy profitability" of the current drone position relative to the target point and other agents; \alpha is a positive coefficient that determines the intensity of attraction to the target position; $\psi\left(\left\| x_i - x_j \right\| \right)$ a repulsive potential function that models the interaction between agents to avoid collisions. It increases sharply as the distance between drones decreases, thereby ensuring a safe distance between them; the first term attracts the drone to the designated point, and the second prevents approaching below the safe distance $\delta_{\min}$. The control signal is determined by the gradient descent

$$u_i = -k\nabla_{x_i} U_i(x_i), \tag{14}$$

$$\dot{x}_i = u_i, \tag{15}$$

The system constantly monitors status indicators (remaining charge, loss of connection, interference). If there is a deviation beyond the specified threshold, a repeated global planning cycle is initiated with an update x^*.

The restructuring is considered successful when for all $i \left\| x_i - x_i^* \right\| < \varepsilon$ and $\left\| x_i - x_j \right\| \geq \delta_{\min}$. If the time limit \bar{t} is exceeded, the algorithm switches to emergency stabilization mode with a safety priority.

The proposed two-layer architecture provides a quick response to global mission changes while guaranteeing local security and swarm fault tolerance, which fully meets the research goals of dynamic and reliable reconfiguration of multi-drone formations.

The implementation of the proposed hybrid methodology is based on the consistent interaction of a global optimizer that determines the target positions of the swarm and a local potential controller that ensures the safe approach of drones to these positions. The calculations are performed in discrete time steps with periodic event-driven restarts of the global planner in the event of a task change, obstacles, or loss of individual drones. All values below are presented in the same inertial coordinate system; vector variables are denoted in bold.

$x(0) = [x_1(0), \ldots, x_N(0)]$ is the vector of initial coordinates of all N drones. The optimal vector of target points $x^* = [x_1^*, \ldots, x_N^*]$ is determined by minimizing a function that combines the transition length and the penalty for possible conflicts between target positions:

$$J = \sum_{i=1}^{N} \left\| x_i^* + x_i(0) \right\|_{W_1}^2 + \lambda \sum_{i<j} \left\| x_i^* - x_j^* \right\|_{W_2}^{-2}, \tag{16}$$

The first term minimizes the total path of the swarm, the second provides the minimum allowable distance between the target points; W_1, W_2 are positive definite weight matrices; $\lambda > 0$ is the coefficient of compromise. The minimization problem is solved by a modified particle swarm algorithm, where the speed and position of each candidate particle are adjusted to take into account constraints on the energy reserve and topological connectivity of the network.

After fixing x^* each device switches to local control mode. For the ith drone, the total potential is entered U_i, which consists of attractive and repulsive members.

The attractive potential is given by the quadratic form

$$U_{\text{att},i} = \frac{1}{2}\alpha \| x_i - x_i^* \|^2, \tag{17}$$

where $\alpha > 0$ is the convergence coefficient. Repulsive potential describes the interaction with all other agents:

$$U_{\text{rep},i} = \sum_{j \neq i} \psi\left(\left\| x_i - x_j \right\| \right), \tag{18}$$

where $\psi(r) = (r - \delta_{\min})^{-2}$ for $r \leq R_0$ and zero otherwise; $\delta_{\min}$ is the minimum safe distance; R_0 is the repulsion range.

Total potential

$$U_i = U_{\text{att},i} + U_{\text{rep},i}, \tag{19}$$

The control signal is determined by the gradient rule

$$u_i = -k\nabla_{x_i} U_i, \tag{20}$$

where $k > 0$ is the reaction constant. In the expanded form

$$u_i = -k\alpha\left(x_i - x_i^* \right) - k\sum_{j \neq i} \nabla_{x_i} \psi\left(\left\| x_i - x_j \right\| \right), \tag{21}$$

The dynamics of the apparatus movement in discrete time is described by the equations

$$v_i(t + \Delta t) = v_i(t) + u_i(t)\Delta t, \tag{22}$$

$$x_i(t + \Delta t) = x_i(t) + v_i(t + \Delta t)\Delta t, \tag{23}$$

The system continuously monitors the battery level, the integrity of communication channels, and the presence of new interference. If an event is detected that goes beyond the permissible limits, a repeated global optimization cycle is initiated, during which x_i^*, ast is refined and, if necessary, new leaders are appointed. This event-based mechanism allows the swarm to adapt to changes without significantly increasing the computational load.

The restructuring is considered complete when a dual condition is met: first, for all deviations $\left\| x_i - x_i^* \right\|$ less than the specified error ε; Second, the distance between all pairs of drones is not less than $\delta_{\min}$. If the time limit is reached $\bar{t}$ and the conditions are not met, the algorithm switches to emergency stabilization mode, which prioritizes the safe dispersal of the swarm.

V. CONCLUSIONS

The proposed approach to dynamic reconfiguration of a drone swarm aims to combine the efficiency of local control and the consistency of global planning, which allows achieving formally justified trajectory optimality while maintaining flight safety and the swarm's ability to self-heal in the event of failures. The algorithm is based on the use of potential functions that are designed to both avoid collisions and orient drones to new target points in the corresponding formation. At the same time, periodic or event-driven updates of global parameters (target positions, roles of leaders) allow for sudden changes in the situation and the current mission.

The applied methods allow:

1) Respond quickly to local threats (thanks to repulsive fields).

2) Align global swarm goals (due to periodic or mission-initiated centralized optimization).

3) Ensure resilience to the loss of individual drones by updating the distribution of target positions and potentially reassigning roles.

Simulated experiments demonstrate that the approach is scalable for different swarm sizes while maintaining acceptable computational complexity (mostly $O(N^2)$ for operations with potentials) and allowing to guarantee the minimum permissible distance intervals between drones. With possible modifications, such as dynamic determination of weights in potential functions or the use of machine learning to predict the movement of obstacles, this methodology can serve as the basis for real-world multilevel swarm control systems.

REFERENCES

[1] Duy Nam Bui, Manh Duong Phung, and Hung Pham Duy, “Self‑Reconfigurable V-Shape Formation of Multiple UAVs in Narrow Space Environments,” *Proceedings of the 2024 IEEE International Conference on Robotics and Automation*, 2024, pp. 1–8.

[2] Krzysztof Falkowski and Maciej Kurenda, “Changing the Formations of Unmanned Aerial Vehicles,” *Applied Sciences*, 14(22), 10424, 2024. https://doi.org/10.3390/app142210424

[3] Haoran Zhang, Guangling Zhang, Ruohan Yang, Zhichao Feng, and Wei He, “Resilient Formation Reconfiguration for Leader-Follower Multi-UAVs,” *Applied Sciences*, 13(13), 7385, 2023. https://doi.org/10.3390/app13137385

[4] Haoran Zhao, Sentang Wu, Yongming Wen, Wenlei Liu, Xiongjun Wu. “Modeling and Flight Experiments for Swarms of High-Dynamic UAVs: A Stochastic Configuration Control System with Multiplicative Noises,” *Sensors*, 19(15), 3278, 2019. https://doi.org/10.3390/s19153278

[5] Shuangyao Huang, Haibo Zhang, and Zhiyi Huang. “E2CoPre: Energy-Efficient and Cooperative Collision Avoidance for UAV Swarms with Trajectory Prediction,” *IEEE Transactions on Robotics (early access)*, 2023, pp. 1–17.

[6] Dariusz Marek, Piotr Biernacki, Jakub Szyguła et al., “Collision Avoidance Mechanism for Swarms of Drones,” *Sensors*, 25(4), 1141, 2025. https://doi.org/10.3390/s25041141

[7] Allison Hudak, Scott James, and Robert Raheb, “Impact of Communication Path Loss to Unmanned Aircraft Swarm Coherency,” Proceedings of the AIAA Aviation Forum, 2025, pp. 1–12. https://doi.org/10.1109/ICNS52807.2021.9441629

[8] H. Zhu et al., “Distributed Multi-Robot Formation Splitting and Merging in Dynamic Environments,” *IEEE ICRA*, 2019. https://doi.org/10.1109/ICRA.2019.8793765

[9] A. Chowdhury et al., “Multi-Robot Virtual Structure Switching and Formation Changing Strategy,” *IEEE/RSJ IROS*, 2018.

[10] TSP_IASC, “Formation Control of UAVs,” International Applied Systems Conference, 2025.

[11] C. Gao et al., “Hybrid Swarm Intelligent Algorithm for Multi-UAV Formation Reconfiguration,” *Complex & Intelligent Systems*, 9(5), 1929–1962, 2022. https://doi.org/10.1007/s40747-022-00891-7

[12] Q. Feng et al., “Resilience Optimization for Multi-UAV Formation Reconfiguration via Enhanced Pigeon-Inspired Optimization,” *Chinese Journal of Aeronautics*, vol. 35, pp. 110–123, 2022. https://doi.org/10.1016/j.cja.2020.10.029

[13] H. Zhao et al. (2019). “Modeling and Flight Experiments for Swarms of High-Dynamic UAVs.” Sensors, 19(15), 3278. https://doi.org/10.3390/s19153278

[14] A. Kahagh et al. (2020). “Obstacle Avoidance in V-Shape Formation Flight of Multiple Fixed-Wing UAVs.” The Aeronautical Journal, 124(1277), 1979–2000. https://doi.org/10.1017/aer.2020.81

[15] M. J. Matarić and F. Michaud, “Behavior-Based Systems,” *In Springer Handbook of Robotics*, 2008, pp. 891–909. https://doi.org/10.1007/978-3-540-30301-5_39

[16] Y. Ren et al., “Region-Based Shape Controller Switching for UAV Swarm Navigation,” *IEEE IROS*, 2022.

[17] T. Lin et al., “Potential Field-Based MPC for UAV Swarm Path Optimization,” *IEEE T-ASE*, 2022.

[18] M. Hassanalian et al., “Reconfigurable Topologies for Cooperative UAVs: A Review,” *Progress in Aerospace Sciences*, 2021.

[19] D. Roy et al., “Multi-UAV Reconfiguration via Ant-Colony Optimization,” *Swarm Intelligence*, vol. 14(3), pp. 251–275, 2020.

[20] C. Ribeiro et al., “Energy-Efficient Dynamic Formation Switching in UAV Teams,” *Robotics and Autonomous Systems*, 136, 103705, 2021. https://doi.org/10.1016/j.robot.2020.103705

[21] L. Ferranti et al., “Adaptive Swarm Behavior for Dynamic Topology Adjustment,” *Autonomous Robots*, vol. 44(4), pp. 639–65, 2020.

Received January 11, 2025

Sineglazov Victor. ORCID 0000-0002-3297-9060. Doctor of Engineering Science. Professor. Head of the Department.
Aviation Computer-Integrated Complexes Department, Faculty of Air Navigation Electronics and Telecommunications, State Non-Profit Enterprise "State University "Kyiv Aviation Institute", Kyiv, Ukraine.
Education: Kyiv Polytechnic Institute, Kyiv, Ukraine, (1973).
Research area: Air Navigation, Air Traffic Control, Identification of Complex Systems, Wind/Solar power plant, artificial intelligence.
Publications: more than 750 papers.
E-mail: svm@kai.edu.ua

Taranov Denys. Post-graduate Student.
Aviation Computer-Integrated Complexes Department, Faculty of Air Navigation, Electronics and Telecommunications, State Non-Profit Enterprise "State University "Kyiv Aviation Institute", Kyiv, Ukraine.
Education: National Aviation University, Kyiv, Ukraine, (2021).
Research interests: artificial neural networks, artificial intelligence, programming.
Publications: 4.
E-mail: 4637199@stud.kai.edu.ua

В. М. Синєглазов, Д. В. Таранов. Гібридна методологія перебудови рою дронів на основі локальних потенціалів та глобальної координації

Дану роботу присвячено вирішенню задачі перебудови структури рою дронів з однієї топології на іншу. Запропоновано гібридну топологію, що поєднує глобальне централізоване призначення цільових позицій із локальним потенційним керуванням кожного дрона. Використовуються притягувальні та відштовхувальні поля для безпечного маневрування, тоді як періодичне глобальне узгодження забезпечує оптимальний розподіл ролей. Наведено математичну модель, правила формування керуючих впливів і критерії збіжності. Реалізація запропонованої гібридної методології ґрунтується на послідовній взаємодії глобального оптимізатора, що визначає цільові позиції рою, і локального потенційного регулятора, який забезпечує безпечне зближення дронів до цих позицій. Обчислення виконуються у дискретних часових кроках із періодичним перезапуском глобального планувальника у разі зміни завдання, появи перешкод або втрати окремих апаратів.

Ключові слова: рій безпілотних літальних апаратів; реконфігурація формації; потенційні польові методи; уникнення зіткнень; гібридна стратегія керування; топологія лідер-послідовник; багатоагентні системи; оптимізація траєкторії; децентралізоване керування; системи реального часу.

Синєглазов Віктор Михайлович. ORCID 0000-0002-3297-9060.
Доктор технічних наук. Професор. Завідувач кафедрою.
Кафедра авіаційних комп’ютерно-інтегрованих комплексів, Факультет аеронавігації, електроніки і телекомунікацій, Державне некомерційне підприємство «Державний університет «Київський авіаційний інститут», Київ, Україна.
Освіта: Київський політехнічний інститут, Київ, Україна, (1973).
Напрям наукової діяльності: аеронавігація, управління повітряним рухом, ідентифікація складних систем, вітроенергетичні установки, штучний інтелект.
Кількість публікацій: більше 750 наукових робіт.
E-mail: svm@kai.edu.ua

Таранов Денис Володимирович. Аспірант.
Кафедра авіаційних комп’ютерно-інтегрованих комплексів, Факультет аеронавігації, електроніки та телекомунікацій, Державне некомерційне підприємство «Державний університет «Київський авіаційний інститут», Київ, Україна.
Освіта: Національний авіаційний університет, Київ, Україна, (2021).
Напрям наукової діяльності: штучні нейронні мережі, штучний інтелект, програмування.
Публікації: 4.
E-mail: 4637199@stud.kai.edu.ua