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OPTIMIZING DRONE COVERAGE IN AGRICULTURE: AN OVERVIEW AND NEW APPROACHES

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Abstract*—This article investigates the problem of trajectory optimization for unmanned aerial vehicles during multispectral imaging of agricultural lands within the framework of precision agriculture concepts. The main problems related to complex field geometry, presence of natural and artificial obstacles, as well as limited battery capacity of drones are considered. A new hybrid route optimization method is proposed that integrates the ant colony optimization algorithm for global planning of zone traversal sequence with the binary gridding method for detailed local replanning within complex areas and obstacle avoidance. A key feature of the method is an adaptive mission recovery mechanism that allows the drone to dynamically return to the charging station, save mission state, and automatically continue operation from the last uncovered area. Simulation and comparative analysis results demonstrate that the developed approach significantly reduces total traveled route length and optimizes mission execution time compared to traditional methods, confirming its effectiveness for increasing autonomy and productivity of agricultural unmanned aerial vehicles.*

Keywords—Route optimization; unmanned aerial vehicles; precision agriculture; coverage planning; ant colony optimization; battery charge management; obstacle avoidance; autonomous navigation.

I. INTRODUCTION

Modern agricultural unmanned aerial vehicles (UAVs) are increasingly being used for crop monitoring, precision spraying, and data collection within the framework of precision agriculture concepts. One of the central tasks in this context is the autonomous control of drones during missions to cover agricultural territories. This task is complicated by a number of practical factors, primarily the geometric heterogeneity of fields, the presence of natural (trees, water bodies) and artificial (power lines, structures) obstacles, as well as the limited resources of the device itself – particularly, the limited battery capacity.

In conditions where a field has an arbitrary, often irregular shape, traditional coverage methods such as "line-by-line" (Boustrophedon) prove to be ineffective or lead to partial route duplication, coverage losses, or increased energy consumption. The problem is exacerbated if the field contains isolated areas or internal "islands" of obstacles that require adaptive routing and the ability to change flight trajectory in real time. As shown in research [13], route modeling that takes into account multiple processing areas and inaccessible zones allows for significant savings in mission time and energy.

The issue of ensuring autonomous mission execution by a single drone stands separately. In real conditions, the size of an agricultural object often exceeds the distance that a drone can cover on a single battery charge. This creates an additional requirement – to develop a mechanism for mission interruption with subsequent return of the UAV to the charging station, as well as the ability to automatically continue task execution from the point where the mission was interrupted. Such approaches currently remain insufficiently researched, despite their importance for single monitoring systems. As results presented in [11] show, even energy-efficient route planning without considering a recovery mechanism does not guarantee complete territory coverage within a single flight.

A comprehensive solution to the task of agricultural territory coverage by drone should combine intelligent route planning with adaptation to complex geometry and obstacles, energy efficiency, and a mechanism for saving and restoring mission state after interruptions related to battery resource limitations.

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II. Analysis of Recent Research and Publications

A visualization of a typical agricultural coverage task is presented in Fig. 1: the need for complete coverage of all territories, taking into account field boundaries and existing obstacles.

Metaheuristic algorithms remain among the leading solutions for autonomous planning of territory coverage by drones. In particular, a review by Sameer Agrawal et al. [1] compares algorithms such as ant colony optimization (ACO), particle swarm optimization (PSO), genetic algorithm (GA), differential evolution (DE), cuckoo search (CS), and Firefly in the context of agricultural tasks. It was established that ACO and PSO demonstrate the best adaptability to fields with complex geometry and numerous obstacles, but face limitations when scaling to large territories. The need for combined approaches that provide a balance between accuracy, energy efficiency, and resistance to environmental changes is becoming increasingly relevant.

In the field of intelligent methods, significant attention is drawn to the review by Iftekhar Anam et al. [2], which highlights the integration of drones and artificial intelligence for plant monitoring, weed and pest control. AI technologies proved useful for adaptive routing, reducing the need for human intervention. Similarly, Mar Ariza-Sentís et al. [9] demonstrated the effectiveness of the ACO algorithm for precise detection of grape clusters and planning coverage routes, which reduces mission time costs.

Issues of cooperation between multiple drones are considered in the works of Shijie Yang [3], Xinyu Liu [4], and Qianwen Shen [15]. In the first case, it concerns network interaction of drones during agricultural data collection, allowing coordinated trajectory planning taking into account collective goals. The second study applies Aquila Optimizer for flight synchronization, achieving high coverage density and object identification accuracy. The third proposes a new multi-objective bio-inspired optimizer for routing drone groups, capable of avoiding obstacles and reducing overall flight time.

A significant contribution to the development of planning algorithms has been made through the use of machine learning methods. In particular, Akshya J [5] investigated the application of deep neural networks optimized by the Adam method, which ensured error reduction and stabilization of drone trajectories. A similar direction is taken in the research by Doğan Güneş and Hideo Hasegawa [10], where machine learning was applied for precise and uniform spraying based on data obtained from the fields themselves.

At the level of obstacle avoidance strategies, the approach by Gamil Ahmed and Tarek Sheltami [6] is key, based on the concept of Receding Horizon Control. Such a model allows flexible response to changing environmental conditions and reduces collision risks. This approach harmoniously combines with the ideas from Sergio Vélez's work [7], where accounting for biophysical characteristics of lands (plantation height, cover density) allowed adapting routes to specific areas.

In the context of adaptation to complex territory geometry, the research by Wang-ying XU [8] is exemplary. The proposed binary gridding method ensured effective spraying of fields with irregular contours, demonstrating high accuracy and flexibility to terrain features. Also important is the work by Shiwei Chu and Wenxia Bao [14], which combined convolutional neural networks with swarm intelligence-based optimization for dynamic pest classification, confirming the effectiveness of AI for monitoring purposes in the agricultural sector.

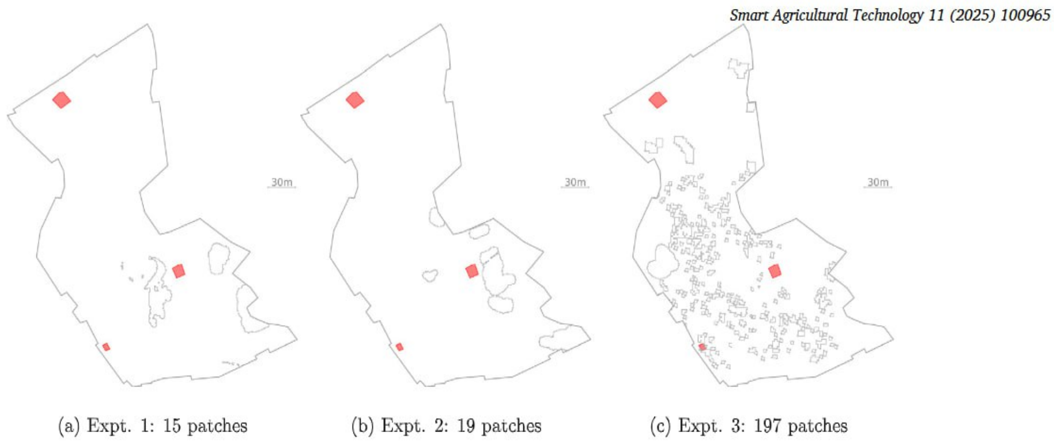

Fig. 1. Schematic problem formulation of agricultural territory coverage by drone taking into account multiple patches and obstacles [13]

Energy consumption issues are central in the works of Gamil Ahmed [11] and Mogens Plessen [13]. The first study analyzes the dependence of energy consumption on flight parameters, while the second combines the traveling salesman problem with area coverage, improving territory processing uniformity and reducing resource intensity. Finally, Adib Bin Rashid's approach [12] summarizes current trends through the integration of IoT and AI in agricultural platforms, emphasizing the importance of automation for achieving complete drone autonomy in field conditions.

Overall, analysis of existing approaches demonstrates the importance of combining metaheuristics, intelligent control, and energy-efficient strategies for solving routing tasks in agricultural environments. All these aspects directly support the problem statement within this article, particularly hybrid routing taking into account obstacles, remaining charge, and complex coverage geometry.

III. PROBLEM STATEMENT

Within the framework of the research, the task of building an intelligent method for optimizing the coverage route of agricultural territories using one autonomous unmanned aerial vehicle under conditions of complex spatial configuration of fields, presence of dynamic or static obstacles, as well as limited energy capacity of the battery system has been formulated. At the core of the task is the need to form such a flight plan that would not only guarantee complete coverage of the entire territory, but also ensure efficient use of battery resources with the possibility of saving and restoring mission execution after forced interruption.

In tasks of autonomous territory coverage by UAVs, the main goal is to ensure maximum complete, efficient, and energy-optimal coverage of a given area. This leads to the necessity of a multi-criteria problem formulation, where the following are simultaneously considered:

1) Minimization of route length L, which directly affects energy consumption and execution speed;

2) Minimization of mission time T, including flights, waiting, and charging;

3) Minimization of the number of returns to base N, which affects both efficiency (fewer stops) and equipment wear.

For unification of these three criteria, the weighted sum method is applied:

$$F = \alpha L + \beta T + \gamma N,$$

where F is a scalar functional of route efficiency that is subject to minimization. The weight coefficients α, β, γ reflect the operator's priorities or operational mission constraints.

From a technical point of view, the problem being solved is a variant of the combined Coverage Path Planning problem with energy resource constraints and spatial constraints that change over time.

Formally, the goal is reduced to minimizing a functional of the form

$$J = \alpha L + \beta T + \gamma N,$$

where L is the total length of the traveled route; T is the total mission execution time; N is the number of returns to the base station for charging; and α, β, γ are weight coefficients that reflect the relative importance of each criterion (route length, mission execution time, and number of returns to base respectively) and must sum to one ($\alpha + \beta + \gamma = 1$). For example, larger values of α favor minimizing route length, while an increased value of γ emphasizes reducing the number of returns for charging. Specific coefficient values are chosen depending on the characteristics of the agricultural task and operator priorities.

In addition to the main goal of minimizing route length and mission execution time, it is advisable to include a number of additional constraints in the routing task, caused by the physical and technical characteristics of drone flight. In particular, flight altitude, speed, as well as the influence of weather conditions should be considered.

Flight altitude $h(t)$ affects the quality of data collection, particularly image resolution, as well as the width of the territory coverage strip. With increasing altitude, detail decreases, but a larger area is covered in one pass. At the same time, flight altitude cannot exceed the permissible standards established for UAV flights. This constraint can be described by the inequality $h_{\min} \le h(t) \le h_{\max}$.

Flight speed $\upsilon(t)$ directly affects both the total mission execution time and the stability of collected data. Increasing speed potentially reduces flight duration, but may cause image blurring, especially in low light conditions or windy weather. Therefore, it is advisable to consider the limits: $\upsilon_{\min} \le \upsilon(t) \le \upsilon_{\max}$.

Weather conditions, especially wind, significantly affect energy consumption. The total energy consumption of an unmanned aerial vehicle at each moment in time is determined by the combination of two main components: the energy required to keep the drone in the air, and the energy spent directly on movement.

Hover power P_{hover} is advisable to consider constant for a specific drone model and depends on its weight, propeller configuration, aerodynamic efficiency coefficient, and atmospheric pressure. It is estimated through thrust parameters and the speed of the downward airflow created:

$$P_{\text{hover}} \approx \frac{T \cdot \upsilon_{\text{induced}}}{\eta},$$

where T is the thrust required to maintain in the air; $\upsilon_{\text{induced}}$ is the induced velocity; and η is the efficiency coefficient of the propeller system.

On the other hand, the power required to overcome resistance during motion P_{hover} $(h(t), \upsilon(t), w(t))$ corresponds to variable power losses during active drone movement in an environment with changing conditions. The dependence on velocity $\upsilon(t)$ is caused by the quadratic nature of aerodynamic resistance, which increases with the square of velocity:

$$F_{drag} \propto \upsilon^2, \; \Rightarrow P_{drag} \propto \upsilon^2,$$

However, in practical application, a simplified quadratic dependence $P \sim \upsilon^2$ is often used, which adequately approximates energy consumption at relatively low speeds of movement over agricultural areas. The dependence on altitude $h(t)$ reflects the influence of air density changes on propeller efficiency and overall energy consumption. As altitude increases, air density decreases, requiring greater effort to create the necessary thrust. Additionally, many models account for deterioration in battery performance with changes in temperature and pressure, which is also related to altitude.

Increasing wind speed $w(t)$ leads to increased movement resistance, which correspondingly increases energy consumption. In the case of headwind, it is necessary to compensate for its force with additional energy consumption, and in crosswind conditions – to stabilize flight through asymmetric loading on the propellers. Total energy consumption at each moment in time can be described as a function

$$P_{\text{total}}(t) = P_{\text{hover}} + P_{\text{travel}}\left(h(t), \upsilon(t), w(t)\right),$$

where P_{hover} is the energy consumption during hovering; and P_{travel} depends on the interaction between altitude, speed, and wind load. Such formalization allows for considering adaptive solutions regarding altitude and speed in response to changing environmental conditions.

The planning object is a closed area $A \subset R^2$ that describes the contour of an agricultural field obtained from vectorized dataset data, and a set of impassable obstacles $O = \{O_1, O_2, \ldots, O_k\} \subset A$, which are subareas with the condition $A \setminus U_i O_i = A_{\text{free}}$, that is, the area accessible for flight. Each route point must satisfy reachability conditions, range limitations, and remaining battery charge. If for the current position $p(t)$ and predicted trajectory $P = \{p_0, \ldots, p_n\}$, the inequality holds:

$$E(p_n) + \varepsilon > E_{\text{remaining}},$$

where $E(p_n)$ is the predicted energy consumption until the end of the sub-route, ε is the energy safety margin, and $E_{\text{remaining}}$ is the current battery charge, then a decision must be made to return to base with fixation of the current mission state.

Within the article, a hybrid structure of algorithmic solution is proposed, in which the global level of planning is implemented based on the ant colony optimization algorithm. Its task is to determine the optimal order of traversing the set of field sub-areas or patches that were obtained as a result of prior territory division. The algorithm forms a solution to the routing problem taking into account non-intersecting trajectories and minimizing total distance. For each sub-area, local route construction is performed based on binary grid division. In this grid topology, obstacles are modeled as inaccessible cells, and the route is planned as traversal of all accessible cells with guarantee of no coverage duplication.

A special role in the proposed approach is played by the flight energy model, which takes into account variable energy consumption depending on drone speed, direction of movement, wind load, and route configuration. Energy consumption is calculated at each simulation step using the formula:

$$E_i = \delta_t \left(P_{\text{hover}} + P_{\text{travel}}(\upsilon_i, \theta_i)\right),$$

where P_{hover} is the energy consumption during hovering, P_{travel} is the dynamic energy consumption during movement at speed υ_i at angle θ_i to the wind direction, δ_t is the simulation step duration.

The algorithmic system analyzes current and predicted energy consumption, and in case of threat of exceeding energy limits, initiates mission interruption and returns to the charging station. In this process, a mission state vector is formed that includes coordinates of the last uncovered grid element, sequential number of the sub-area, coverage status at grid level (bit mask), and actual remaining charge. After charging, the drone uses this data for automatic route resumption from the uncovered part.

The proposed problem formulation goes beyond classical coverage planning and includes contextual decision-making logic, dynamic resource consumption forecasting, modular trajectory reconstruction after stops, and multi-level adaptation to environmental changes. Such an approach opens possibilities for transition to fully autonomous agricultural missions that can function under conditions of large area, complex terrain, and limited operator support.

IV. Hybrid Routing Algorithm Formalization

The proposed route optimization method is based on a multi-level approach, where global planning of traversal sequence is performed using the ACO algorithm, and detailed local coverage is based on binary grid division.

To ensure energy-efficient autonomous coverage of large agricultural territories, it is advisable to divide the task into two levels: global route planning between individual sub-areas and local coverage of each of them. At the global level, the model assumes that the entire territory $A \subset R^2$ is divided into a set of compact subareas $P = \{P_1, P_2, ..., P_n\}$ based on spatial segmentation – for example, using clustering methods or regular tessellation division (Voronoi, gridding). Each sub-area is considered as a separate unit of local coverage and is defined as a compact closed set taking into account geometric constraints and obstacles in the field. To build an efficient flight route between sub-areas, each of them is represented through its geometric center or center of mass, which is denoted as C_i is the centroid of sub-area P_i. Thus, the global route is transformed into a task of building a path that connects these centroids with minimal total length, which can be considered as a variation of the traveling salesman problem (TSP).

The optimal representation of the set of sub-areas for traversal is denoted as S^*, and the optimality criterion is minimizing the total Euclidean distance between sequentially visited centroids. Formally, the task can be written in the form:

$$S^* = \arg \sum_{i=1}^{n-1} d(C_i, C_{i+1}),$$

where $\Pi(P)$ is the set of all possible permutations of sub-areas, and $d(C_i, C_{i+1})$ is the Euclidean distance between corresponding centroids. Such an approach allows formalizing global route planning as a combinatorial optimization problem, to which efficient heuristic methods are applied, particularly ant algorithms, genetic algorithms, or modified greedy search.

Within global route planning for traversing sub-areas of agricultural territory, it is advisable to use adaptive heuristic algorithms that allow efficiently finding near-optimal visit permutations with a large number of combinations. One of the most productive approaches in this context is the ACO algorithm, which imitates the collective behavior of social insects, particularly the ability of ants to find the shortest path between a food source and colony through the formation of pheromone trails.

In the context of the sub-area routing task, the pheromone information left by virtual agents (ants) reflects the success of choosing a certain path in previous algorithm iterations. Parallel to the pheromone, the current heuristic assessment of the feasibility of choosing one or another sub-area is also considered. For this purpose, the concept of heuristic desirability of transition from the current sub-area C_s to another C_j is introduced, which is usually inversely proportional to the Euclidean distance between them

$$\eta_{ij} = \frac{1}{d(C_s, C_j)},$$

where $d(C_s, C_j)$ is the Euclidean distance. Taking into account both pheromone concentration τ_{ij} and heuristic desirability η_{ij}, the probability of choosing the next sub-area is determined by a stochastic rule that balances between exploitation of known efficient paths (through pheromone) and exploration of new routes (through heuristics).

Formally, the probability of transition from the current sub-area C_s to sub-area C_j at each step of the ACO algorithm is determined by the formula:

$$p_{ij} = \frac{\left[\tau_{ij}\right]^{\alpha}\left[n_{ij}\right]^{\beta}}{\sum_{k \in N_i}\left[\tau_{ik}\right]^{\alpha}\left[n_{ik}\right]^{\beta}}, \qquad (1)$$

where parameters α and β control respectively the influence of the pheromone component and heuristic function. By changing these parameters, one can regulate the strategic balance between the intensity of pheromone reinforcement and greediness of current choice. In case of large α values, the probability of using already established routes increases, while larger β promotes choosing the shortest distances without considering history. Such a stochastic model allows effectively avoiding local minima and finding globally advantageous trajectories even with significant size of the permutation space.

For each sub-area, a grid representation is formed based on regular subdivision (binary gridding), where the coverage area is modeled as a set of cells. Obstacles are represented as inaccessible cells. The local route is calculated as traversal of all accessible cells with minimization of duplications and undercoverage.

The energy model takes into account energy consumption at each mission step. Current energy consumption is determined as:

$$P_{\text{total}}(t) = P_{\text{hover}} + \frac{1}{2}C_d\rho A\upsilon(t)^3 + \delta\big(w(t), h(t)\big),$$

where C_d is the drag coefficient, ρ is air density, A is the effective area of the drone, and the additional term δ models the influence of altitude and wind conditions. Under the condition that predicted consumption exceeds the remaining charge taking into account safety margin ε, mission interruption is performed:

$$E_{\text{remaining}} < E(p_n) + \varepsilon.$$

In case of return to the base station, a state vector is fixed that includes the current coordinate, sub-area index, grid coverage mask, and residual energy. After charging, the drone automatically resumes mission execution, using the saved information to build a partial sub-route.

The proposed algorithm combines global optimization planning with energy adaptation to environmental conditions, which allows ensuring autonomy and efficiency of agricultural mission execution.

To accomplish the set tasks, a hybrid method of agricultural coverage route optimization by drone was implemented, which takes into account the complex geometry of the area, presence of natural and artificial obstacles.

V. OPTIMAL TRAJECTORY SEARCH ALGORITHM

Within the proposed approach, the formation of the optimal trajectory of the autonomous unmanned aerial vehicle is based on a combination of combinatorial optimization of the bypass sequence with analytical modeling of local coverage taking into account resource constraints. For this purpose, the problem is considered on a set of sub-plots that form a covering set $P = \{P_1, P_2, \ldots, P_n\} \subset A$, where A is the geometric region of the agricultural plot. For each sub-plot, the center of mass $C_i \in R_2$ is determined, and the global bypass sequence is given by the permutation $S = (C_{\sigma(1)}, C_{\sigma(2)}, \ldots, C_{\sigma(n)})$, which minimizes the total path length. The optimality criterion is the functional:

$$J(S) = \sum_{k=1}^{n-1} d\left(C_{\sigma(k)}, C_{\sigma(k+1)}\right),$$

where $d\left(C_{\sigma(k)}, C_{\sigma(k+1)}\right)$ is the Euclidean distance between the centers of the subdivisions.

To accomplish the set tasks, a hybrid method of agricultural coverage route optimization by drone was implemented, which takes into account the complex geometry of the area, presence of natural and artificial obstacles, as well as battery resource limitations. The developed method combines the classical approach to the TSP with adaptive flight planning and recovery mechanisms, ensuring a high level of mission execution autonomy.

The agent's transition probability is determined by a stochastic rule based on pheromone information and heuristic attractiveness, which corresponds to the classical ACO formula and is already presented in equation (1). After passing the route, all agents update the pheromone matrix according to the rule:

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \sum_{m}^{k=1}\Delta\tau_{ij}^{(k)},\ \Delta\tau_{ij}^{(k)} = \begin{cases} \dfrac{Q}{L^{(k)}},\ \text{if}\ (i,j)\in S^{(k)} 0,\ \text{otherwise}, \end{cases}$$

where ρ is the pheromone evaporation rate; Q is the gain constant; $L^{(k)}$ is the route length of agent k. Such stochastic multi-agent computation is repeated until the criterion converges $J(S)$.

The optimized global sequence specifies the order of traversing the sub-areas, within which the trajectory is refined through a mesh topology. Each sub-area P_i is divided into a regular grid of cells with size Δx, Δy, and obstacles are displayed as unreachable nodes. Local trajectory Γ_i is a connected cycle that traverses all reachable cells once, i.e. the local traversal functionality is minimized $L(\Gamma_i)$ under the condition of full coverage:

$$\bigcup_{i=1}^{n}\Gamma_i = A \setminus U_k O_k,$$

where O_k are obstacle areas. To minimize the repetition of transitions, a greedy nearest point heuristic or a modified Boustrophedon rule adapted to the mesh topology is used.

The key aspect is the energy model of the trajectory. For each potential link of the trajectory, the energy consumption is estimated:

$$E_{ij} = P_{ij}\cdot t_{ij},$$

where P_{ij} is the power of the flight between nodes, defined as

$$P_{ij} = P_0 + C_D \cdot \frac{1}{2} \rho A \upsilon_{ij}^3,$$

where P_0 is the power to stay in the air; C_D is the drag coefficient; ρ is the air density; A is the effective projection area of the drone; υ_{ij} is the speed on the section. If the predicted amount of energy consumption for the current bypass exceeds the remaining charge, taking into account the safety margin ϵ, then the drone's return to the base station is initiated. The mission state vector stores the coordinate of the last cell, the coverage mask and the remaining battery life, which guarantees correct resumption of the bypass.

The constructed algorithm structure provides multi-level planning: global bypass of sub-plots optimizes the macro sequence, while the local scheme guarantees detailed coverage with obstacle avoidance, and the energy model allows you to dynamically adjust the mission execution taking into account limited resources. This formalizes the entire trajectory search cycle from the initialization of pheromone parameters and grid topology to flight resumption procedures after forced interruptions, which together increases the reliability of autonomous bypass of agricultural lands.

1) To accomplish the tasks, a hybrid method for optimizing the route of agricultural drone bypass was implemented, which takes into account the complex geometry of the plot, the presence of natural and artificial obstacles, as well as battery life limitations. The developed method combines the classical approach to the traveling salesman problem (TSP) with adaptive flight planning and recovery mechanisms, which provides a high level of mission autonomy.

2) The basis of the implementation is the integration of the metaheuristic algorithm ACO, which is used for global planning of the bypass order of a set of cultivated areas, with a local replanning procedure based on binary gridding.

3) The implementation of a hybrid approach to drone trajectory planning in agricultural conditions involves the sequential execution of a number of steps that combine global optimization of the bypass order of subplots with local planning of the coverage of each zone.

4) First, the target area is divided into a set of compact sub-plots, which can be obtained by spatial clustering or regular partitioning. For each sub-plot, a geometric center is calculated, which is then used as a reference point for the global route.

5) After constructing the set of centers, an ant optimization algorithm is initiated to determine the order of traversing the sub-plots. At this stage, the basic parameters of the algorithm are set, in particular the number of iterations, the number of agents, as well as the coefficients responsible for the weight of the pheromone trail, the influence of the heuristic function, and the rate of pheromone evaporation.

6) For each pair of sub-plots, a heuristic measure of the attractiveness of the transition is calculated, which is based on the inverse distance between the centers. At the same time, the initial level of pheromone concentration is set for all edges of the route.

7) During several iterations, virtual agents form routes, guided by a stochastic rule for choosing the next sub-plot. Based on the results obtained, the pheromone trails are updated taking into account the success of the corresponding path.

8) After completing a given number of iterations, the optimal route with the smallest total distance is selected.

9) At the next stage, local planning of the coverage of each individual subsection is performed using a binary grid partition. Each zone is divided into cells, the accessibility of which is determined based on the obstacle map.

10) The sequence of bypassing the cells is established using a heuristic rule that minimizes the number of uncovered areas and prevents duplication of the route.

11) Before starting to cover each subsection, the system checks the drone's charge level. If the current charge allows completing the processing of the zone, the drone begins the bypass. Otherwise, a return to the base station is initiated to replenish energy.

12) In the event of a return, the current state of the mission is saved, in particular the last processed cell. After resuming work, the route is resumed from the position at which execution was interrupted.

13) The algorithm is considered complete when all sub-areas are processed and the entire target area is covered according to the specified completeness criterion.

In the simulation, flight altitude parameters h = 40 m and speed v = 3 m/s were established, which correspond to the permissible limits defined in the problem statement. Energy consumption calculation was performed taking into account wind resistance at the level of w = 2 m/s.

The simplified logic of the proposed hybrid route optimization method for a single drone is presented in Fig. 2. The process begins with the global planning stage, where the ACO algorithm is used to determine the optimal order of traversing the set of processing zones. This is followed by transition to local planning, which is based on the binary gridding method. This stage allows detailed coverage of territories with complex shapes and consideration of existing obstacles by modeling them as impassable areas.

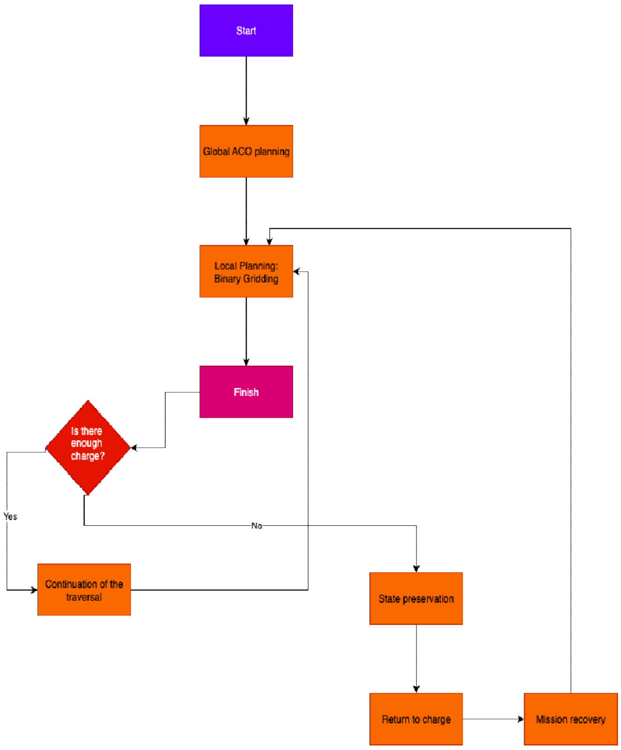

Fig. 2. Generalized logic of the hybrid method for agricultural coverage route optimization by drone

During mission execution, continuous monitoring of remaining battery charge is performed. If there is sufficient charge to continue traversal, the drone continues task execution in the current area. In case there is insufficient charge to complete the mission, the system decides to interrupt the mission and save its state. After this, the drone returns to the base station for recharging. After charge restoration, mission recovery occurs, and the drone automatically continues traversal from the last uncovered area. This cyclical process continues until complete coverage of the entire agricultural territory, after which the mission is considered complete.
Such a combination allows both effective planning of site visitation sequence and detailed coverage of territories with complex shapes, taking into account existing obstacles. For processing zones with irregular geometry, a mechanism for generating routes around obstacles was implemented, which are modeled as impassable areas in grid topology.

A critical element of the proposed method is consideration of remaining battery charge in the planning process. For this purpose, an adaptive energy consumption assessment module was implemented, which allows determining the appropriate moment for the drone to return to the base station for recharging. If it is detected that the remaining charge is insufficient to complete the mission, the system automatically interrupts the traversal, saves the task execution state, and initiates the return procedure to the launch point. After charge restoration, the drone continues mission execution from the last uncovered area, which is implemented by constructing a partial sub-route based on the saved traversal progress vector.

For modeling the operation of the proposed method and testing it under conditions close to real agricultural missions, the vector dataset EU Field Boundaries [16] was selected. This dataset contains automatically extracted boundaries of agricultural plots obtained based on Sentinel-2 satellite images for the period May-June 2022. In the dataset, each agricultural plot is represented as a vector polygon that corresponds to a spatially homogeneous land unit used for growing one type of crop.

The main reasons for choosing this particular dataset are its high accuracy (detailed field boundaries), relevance (2022), spatial diversity of plots (including fields with complex geometry), as well as broad coverage of agricultural regions of the European Union. Thanks to the vector data representation, direct integration of polygonal field boundaries into the mathematical modeling environment is possible, which allows formal verification of trajectory planning algorithm efficiency, identification of uncovered zones, and assessment of the need for drone return for recharging. Specifically, based on selected polygons, scenarios of single-drone traversal of plots with different configurations are modeled, with energy resource constraints and presence of obstacles.

A typical fragment of data obtained in the EU Field Boundaries dataset [16] is shown in Fig. 3. As can be seen, field boundaries are automatically extracted from satellite images with high accuracy, which allows their use for testing drone route optimization methods on plots with complex geometry.

Testing was conducted in a simulation modeling environment that allows controlling drone parameters (flight time on one charge, speed), characteristics of processed fields, and optimization algorithms.

At the first stage, a comparison of the developed hybrid method (hereinafter – HMO) with two baseline algorithms was conducted:

1) Simple Grid Coverage Path Planning (GCPP): The field is divided into a uniform grid, and the drone sequentially traverses each cell. This method guarantees complete coverage but does not account for field shape complexity and obstacle placement, which can lead to excessive route length.

2) Traveling Salesperson Problem (TSP) algorithm for field centroids: For a set of separate fields (without internal obstacles), an optimal order of their traversal is constructed by solving the TSP problem for the centroids of these fields. Within each field, simple grid traversal is applied. This method optimizes the sequence of field visits but does not account for detailed geometry and obstacles within each field, and also does not provide a mission recovery mechanism.

The following metrics were used for comparison:

1) Total Path Length (TPL): The total distance flown by the drone for complete territory coverage. A lower TPL value indicates a more efficient route.

2) Number of Battery Swaps (NBS): The number of times the drone had to interrupt the mission and return for charge replenishment. A lower NBS value indicates better energy efficiency of planning.

3) Mission Completion Time (MCT): The total time spent on complete territory coverage, including flight time and time spent on returns and charging (if any occurred).

The results of comparative analysis for a typical field with complex shape and presence of internal obstacles are presented in Table I.

As can be seen from Table I, the developed hybrid method optimization (HMO) demonstrates significantly smaller total traveled route length compared to baseline algorithms, which indicates a more efficient traversal strategy that takes into account field shape and obstacles. In the case of TSP for field centroids, although the order of traversing individual field parts was optimized, the necessity of returning to the charging station led to an increase in total mission execution time. HMO was able to completely cover the territory without the need for mission interruption, which positively affected the total execution time.

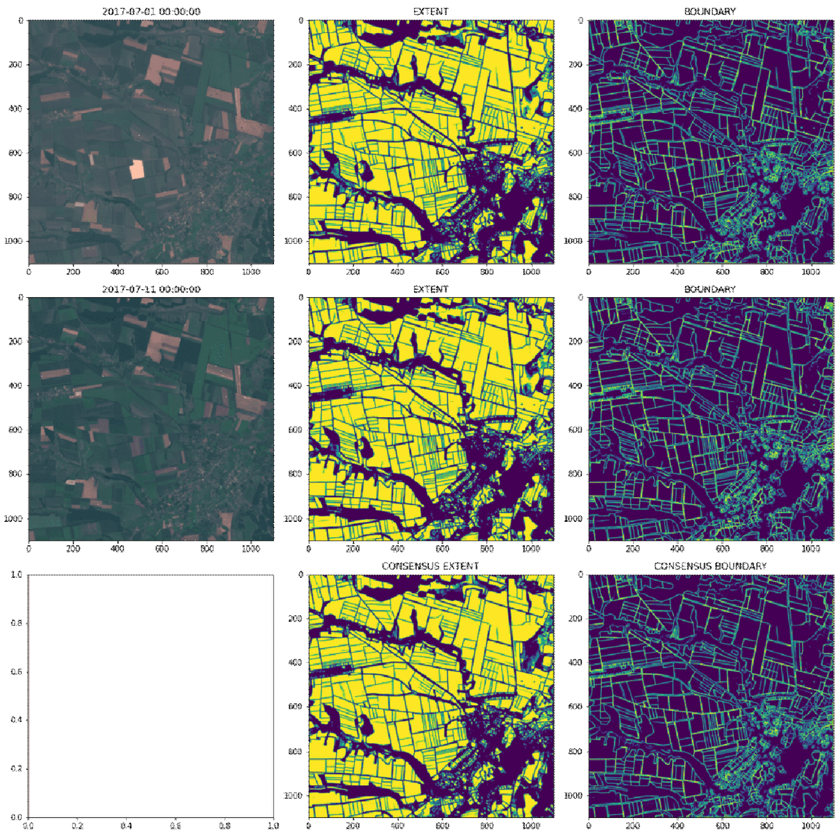

Fig. 3. Example of results of automatic agricultural field boundary extraction based on Sentinel-2 satellite images within the dataset *EU Field Boundaries* [16]

TABLE I. COMPARATIVE ANALYSIS RESULTS

Algorithm	Total Route Length (km)	Number of Returns	Execution Time (min)
Simple Grid Traversal (GCPP)	12.5	0	75.0
TSP for Field Centroids	10.8	1	82.3
Developed Hybrid Method (HMO)	9.3	0	60.5

For results visualization, a graph of the dependence of total route length on field area for different algorithms was constructed (Fig. 4).

As can be seen from Fig. 4, for fields of increasing area, the advantage of HMO by the criterion of total route length becomes more pronounced. This is related to the ability of ACO to effectively find the optimal order of traversing a large number of sub-zones, and binary gridding to optimize the trajectory within each complex-shaped area.

To study the influence of field geometry complexity and presence of obstacles on the performance of the developed method, a series of experiments was conducted with fields of different fractal dimensions and varying numbers and sizes of artificially added obstacles. The results showed that HMO demonstrates high resistance to increasing field configuration complexity and presence of obstacles. Thanks to the local replanning mechanism based on binary gridding, the algorithm effectively bypasses impassable zones while minimizing additional route length.

A comparison of the increase in the total HMO route length in percentage terms relative to simple grid traversal depending on the obstacle density in the field is presented in Fig. 5. Obstacle density was defined as the ratio of total obstacle area to the area of the entire field.

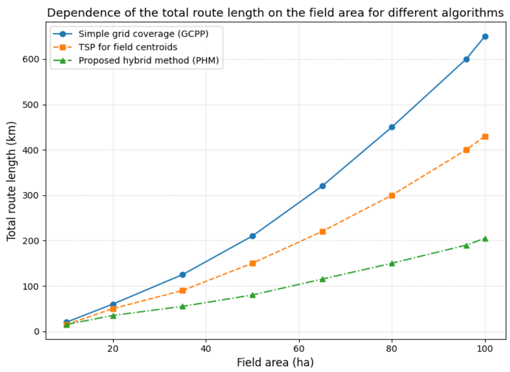

Fig. 4. Dependence of total route length on field area for different algorithms

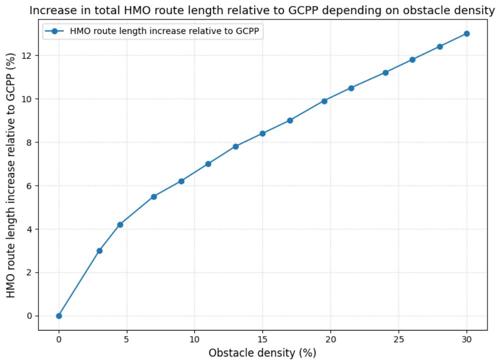

Fig. 5. Increase in total route length of HMO relative to GCPP depending on obstacle density

As can be seen from Fig. 5, even with significant obstacle density (for example, 15%), the increase in route length of HMO compared to simple grid traversal remains relatively small. This confirms the effectiveness of the developed obstacle avoidance mechanism.

To evaluate the effectiveness of the adaptive mission recovery mechanism, a series of simulation runs was conducted on large fields whose sizes exceeded the capabilities of continuous coverage with one drone battery charge. Drone parameters (battery capacity, energy consumption) were modeled based on characteristics of commercially available agricultural UAVs.

The results showed that HMO successfully determines optimal points for returning to the charging station while minimizing the number of necessary returns and total mission execution time. The algorithm considers both current remaining charge and predicted energy costs for further traversal, allowing informed decisions regarding the necessity of mission interruption.

Compared to the fixed flight time strategy before returning for charging, the adaptive mechanism of HMO demonstrated reduction in both the number of returns (on average by 15–20%) and total mission execution time (on average by 10–12%). This is explained by the algorithm's ability to dynamically adjust the return moment depending on the complexity of the processed area and current energy consumption.

The implemented method allows not only full autonomous route planning in agricultural environments with complex geometry, but also ensures flexible drone resource management, increasing efficiency and reliability of precision agriculture mission execution.

VI. Conclusion

It has been proven that the proposed approach, which integrates global planning based on the ACO algorithm with local replanning using binary gridding and an adaptive mission recovery mechanism, significantly increases the autonomy and productivity of agricultural UAVs.

Key results demonstrate that the method successfully overcomes challenges related to geometric heterogeneity of fields and presence of numerous obstacles. Implementation of dynamic energy resource monitoring and automatic mission interruption/recovery allows the drone to adapt to limited battery capacity while minimizing operational costs and downtime. Comparative analysis with traditional route planning algorithms confirmed that the developed hybrid approach provides reduction in total traveled path length and, accordingly, decrease in mission execution time. This optimization is particularly noticeable for large and complex-configuration agricultural lands, where traversal efficiency without considering landscape specifics significantly decreases.

The research emphasizes the potential of intelligent planning systems for expanding the capabilities of autonomous agricultural missions. The developed method creates a solid foundation for further research in the direction of multi-drone systems, which will allow scaling UAV application for covering significant territories. Prospects for further development include integration of planning algorithms with real-time sensor data for route adaptation to dynamic condition changes (for example, weather factors or detection of crop anomaly zones), as well as development of strategies for optimizing not only coverage but also efficiency of performing specific tasks such as precision spraying or data collection. This opens new possibilities for even greater automation and increased efficiency of drone use in precision agriculture.

REFERENCES

[1] Sameer Agrawal, Bhumeshwar K. Patle, and Sudarshan Sanap, "A systematic review on metaheuristic approaches for autonomous path planning of unmanned aerial vehicles," *Drone Systems and Applications*, vol. 12, 2024, pp. 1–28, ISSN 2564-4939, https://doi.org/10.1139/dsa-2023-0093.

[2] Iftekhar Anam, Naiem Arafat, Md Sadman Hafiz, et al., "A systematic review of UAV and AI integration for targeted disease detection, weed management, and pest control in precision agriculture," *Smart Agricultural Technology*, vol. 9, 100647, 2024. ISSN 2772-3755, https://doi.org/10.1016/j.atech.2024.100647.

[3] Shijie Yang, Jiateng Yuan, Zhipeng Zhang, et al., "Multi-UAV Collaborative Mission Planning Method for Self-Organized Sensor Data Acquisition," *Computers, Materials and Continua*, vol. 81, Issue 1, pp. 1529–1563, 2024, ISSN 1546-2218, https://doi.org/10.32604/cmc.2024.055402.

[4] Xinyu Liu, Longfei Wang, Yuxin Ma et al., "Collaborative Trajectory Planning for Stereoscopic Agricultural Multi-UAVs Driven by the Aquila Optimizer," *Computers, Materials and Continua*, vol. 82, Issue 1, pp. 1349–1376, 2025. ISSN 1546-2218, https://doi.org/10.32604/cmc.2024.058294.

[5] J. Akshya, G. Neelamegam, C. Sureshkumar et al., "Enhancing UAV Path Planning Efficiency through Adam-Optimized Deep Neural Networks for Area Coverage Missions," *Procedia Computer Science*, vol. 235, pp. 2–11, 2024. SSN 1877-0509, https://doi.org/10.1016/j.procs.2024.04.001.

[6] Gamil Ahmed and Tarek Sheltami, "Receding Horizon and Optimization-based Control for UAV path planning with Collision Avoidance," *Procedia Computer Science*, vol. 251, pp. 15–22, 2024. ISSN 1877-0509, https://doi.org/10.1016/j.procs.2024.11.079.

[7] Sergio Vélez, Gonzalo Mier, Mar Ariza-Sentís et al., "Integrated framework for multipurpose UAV Path Planning in hedgerow systems considering the biophysical environment," *Crop Protection*, vol. 187, 106992, 2025. ISSN 0261-2194, https://doi.org/10.1016/j.cropro.2024.106992.

[8] Wang-ying XU, Xiao-bing YU, and Xin-yu XUE, "A binary gridding path-planning method for plant-protecting UAVs on irregular fields," *Journal of Integrative Agriculture*, vol. 22, Issue 9, pp. 2796–2809, 2023. ISSN 2095-3119, https://doi.org/10.1016/j.jia.2023.02.029.

[9] Mar Ariza-Sentís, Sergio Vélez, and Hilmy Baja, "An aerial framework for Multi-View grape bunch detection and route Optimization using ACO," *Computers and Electronics in Agriculture*, vol. 221, 108972, 2024. ISSN 0168-1699, https://doi.org/10.1016/j.compag.2024.108972.

[10] Doğan Güneş and Hideo Hasegawa, "Optimizing UAV sprayer performance using field data and machine learning approaches," *Smart Agricultural Technology*, vol. 11, 101013, 2025. ISSN 2772-3755, https://doi.org/10.1016/j.atech.2025.101013.

[11] Gamil Ahmed, Tarek Sheltami, Ashraf Mahmoud et al., "Energy-Efficient UAVs Coverage Path Planning Approach," *CMES – Computer Modeling in Engineering and Sciences*, vol. 136, Issue 3, pp. 3239–3263, 2023. ISSN 1526-1492, https://doi.org/10.32604/cmes.2023.022860.

[12] Adib Bin Rashid, Ashfakul Karim Kausik, Anika Khandoker et al., "Integration of Artificial Intelligence and IoT with UAVs for Precision Agriculture," *Hybrid Advances*, vol. 10, 100458, 2025. ISSN 2773-207X, https://doi.org/10.1016/j.hybadv.2025.100458.

[13] Mogens Plessen, "Path planning for spot spraying with UAVs combining TSP and area coverages," *Smart Agricultural Technology*, vol. 11, 100965, 2025. ISSN 2772-3755, https://doi.org/10.1016/j.atech.2025.100965.

[14] Shiwei Chu and Wenxia Bao, "Dynamic Agricultural Pest Classification Using Enhanced SAO-CNN and Swarm Intelligence Optimization for UAVs," *International Journal of Cognitive Computing in Engineering*, vol. 6, pp. 588–602, December 2025.

ISSN 2666-3074, https://doi.org/10.1016/j.ijcce.2025.04.002.

[15] Qianwen Shen, Damin Zhang, Qing He et al., "A novel multi-objective dung beetle optimizer for Multi-UAV cooperative path planning," *Heliyon*, vol. 10, Issue 17, e37286, 2024. ISSN 2405-8440, https://doi.org/10.1016/j.heliyon.2024.e37286.

[16] B. Matej, "EU field boundaries," *Zenodo*. URL: https://doi.org/10.5281/zenodo.14229032

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В. М. Синєглазов, Р. С. Конюшенко. Оптимізація покриття території дронами у сільському господарстві: огляд та нові підходи

У статті досліджено проблему оптимізації траєкторії руху безпілотних літальних апаратів під час виконання мультиспектральної зйомки сільськогосподарських угідь у рамках концепції точного землеробства. Розглянуто основні проблеми, пов'язані зі складною геометрією полів, наявністю природних та штучних перешкод, а також обмеженою ємністю акумуляторів дронів. Запропоновано новий гібридний метод оптимізації маршруту, який інтегрує алгоритм мурашиних колоній для глобального планування послідовності обходу зон з методом двійкового сіткового поділу для детального локального перепланування всередині складних ділянок та обходу перешкод. Ключовою особливістю методу є адаптивний механізм відновлення місії, що дозволяє дрону динамічно повертатися на зарядну станцію, зберігати стан місії та автоматично продовжувати роботу з останньої непокритої ділянки. Результати моделювання та порівняльного аналізу демонструють, що розроблений підхід значно зменшує загальну довжину пройденого маршруту та оптимізує час виконання місії порівняно з традиційними методами, що підтверджує його ефективність для підвищення автономності та продуктивності аграрних безпілотних літальних апаратів.

Ключові слова: оптимізація маршруту; безпілотні літальні апарати; точне землеробство; планування покриття; алгоритм мурашиних колоній; керування зарядом аккумулятора; уникнення перешкод; автономна навігація.

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