An Integrated Ant Colony and Dynamic Window Approach for Cooperative Multi-Robot Trajectory Planning in Safflower Cultivation

Rashida Naseer[1], Shahid Khan[1]
[1]Quaid e Azam university, Lahore
***Correspondence**: rabia.naseer@gmail.com

Citation | Azeem. N, Khan. S, "An Integrated Ant Colony and Dynamic Window Approach for Cooperative Multi-Robot Trajectory Planning in Safflower Cultivation", FCSI, Vol. 03 Issue. 2 pp 66-76, May 2025
Received | April 08, 2025, **Revised |** May 06, 2025, **Accepted |** May 07, 2025, **Published |** May 08, 2025.

The increasing adoption of agricultural robotics has highlighted the need for efficient and reliable trajectory planning in crop fields. Traditional methods often optimize either global coverage or local obstacle avoidance but fail to achieve both simultaneously in dynamic agricultural environments. This study presents an integrated trajectory planning framework that combines Ant Colony Optimization (ACO) for global path planning and the Dynamic Window Approach (DWA) for real-time local obstacle avoidance. The approach was applied to safflower fields to enhance coverage, reduce path redundancy, and minimize collision risks among multiple robots. Simulation results demonstrate that the hybrid ACO-DWA framework outperformed conventional methods in terms of path length, coverage efficiency, and adaptability to unexpected field obstacles. Specifically, the proposed method reduced path length by 14%, improved coverage rate by 11%, and decreased collision frequency by 18% compared to baseline approaches. These results suggest that the integration of global and local planning strategies can significantly improve robotic efficiency in agricultural operations, providing a scalable solution for sustainable crop management.

Keywords: Agricultural Robotics, Trajectory Planning, Ant Colony Optimization (ACO), Dynamic Window Approach (DWA)

Introduction:

Safflower (Carthamus tinctorius L.) is an economically significant oilseed crop widely utilized in the food, pharmaceutical, and biofuel industries. Its production, however, is challenged by asynchronous maturation, climatic variability, and labor-intensive harvesting processes [1]. The integration of agricultural robotics, particularly multi-robot systems (MRS), offers promising solutions to enhance efficiency, reduce labor dependency, and sustain productivity in modern agriculture. Multi-robot collaboration enables simultaneous execution of harvesting, monitoring, and transportation tasks, ensuring robustness, adaptability, and scalability across diverse environments [2][3].

Path planning is central to agricultural robotics, as it directly impacts task efficiency, energy consumption, and operational safety. Traditional path planning approaches such as A*, Dijkstra's algorithm, and rapidly-exploring random trees (RRT) have shown effectiveness in structured or static environments but often fail in unstructured agricultural fields characterized by irregular terrains, dynamic obstacles, and unpredictable crop distributions [4][5]. Single-robot navigation has achieved significant advances through hybrid algorithms combining global and local planning strategies[6], yet multi-robot coordination in these conditions remains underexplored. Efficient scheduling and conflict-free coordination among multiple robots in constrained environments, such as safflower fields, is therefore a critical research direction[7][8].

Research Gap:

Although substantial progress has been made in both single-robot navigation and multi-robot coordination, most existing frameworks are optimized for structured orchards or static environments. Centralized multi-robot scheduling has shown efficiency in controlled scenarios but suffers from computational burdens and reduced adaptability when scaled to unstructured agricultural systems[9]. Conversely, distributed approaches offer greater autonomy but face challenges in ensuring reliable communication, conflict resolution, and real-time adaptability under dynamic field conditions[10][11]. Moreover, limited research has addressed cross-regional scheduling and collision-free navigation strategies for safflower harvesting, where task overlap and uneven field conditions significantly affect robot performance. Existing studies also lack effective integration of hybrid algorithms that combine the global optimization capacity of metaheuristics (e.g., Ant Colony Optimization) with the real-time adaptability of local planners (e.g., Dynamic Window Approach). This gap highlights the urgent need for novel multi-robot path planning frameworks tailored to unstructured agricultural environments.

Objectives:

The primary objective of this research is to design and validate an integrated cross-regional scheduling and path planning framework for multi-robot safflower harvesting in unstructured environments. Specifically, the study aims to: (i) develop a 2.5D grid-based environment mapping system to simulate complex farm terrains; (ii) integrate Ant Colony Optimization with the Dynamic Window Approach to achieve efficient global and local path planning; (iii) propose a novel priority allocation strategy to mitigate task conflicts and resolve spatial overlap among robots; and (iv) validate the performance of the proposed framework through extensive MATLAB and ROS-based simulations. Through these objectives, the study intends to enhance operational efficiency, reduce collision risks, and ensure sustainable robotic collaboration in safflower fields.

Novelty Statement:

This research introduces a novel hybrid framework for multi-robot safflower harvesting that combines Ant Colony Optimization (ACO) with the Dynamic Window Approach (DWA) within a 2.5D grid-based simulation environment, enabling both global optimization and real-time adaptability. Unlike previous studies that focus on both centralized and distributed coordination alone, this work integrates a cross-regional scheduling mechanism with a priority-based conflict resolution strategy to address spatial overlaps and collision risks in constrained agricultural environments. Furthermore, the proposed system is validated in both MATLAB and ROS, ensuring reproducibility and real-world applicability. By bridging the gap between theory and practice, this study advances the state-of-the-art in agricultural robotics and provides a scalable solution for future smart farming systems [5][11] [12].

Literature Review:

Multi-robot systems (MRS) have been extensively studied in the robotics community due to their cooperative capabilities, robustness, parallelism, and scalability [13][14]. Early research largely focused on cooperative transportation tasks, where multiple robots were required to move large or heavy objects that a single robot could not handle. [15][16] introduced the distributed architecture L-ALLIANCE, which dynamically adapts to environmental changes through motivational behaviors such as impatience and acquiescence. Similarly, [17] proposed centralized task allocation frameworks for cooperative transportation in static and three-dimensional environments. [18], who developed a reactive behavior-based multi-robot box-pushing system.

NASA's CAMPOUT architecture [19] demonstrated decentralized leader–follower strategies for planetary surface tasks, while [20] extended it to autonomous construction.

Research on formation control by[4][21] and [22] [23] highlighted the "object closure" strategy, ensuring stable multi-robot manipulation. Parallel to transportation tasks, cooperative manipulation using robotic arms also evolved, where controllers were designed to minimize internal forces among manipulators.

Learning-based methods soon gained traction in MRS research.[24]applied neural networks and decision trees in robotic soccer, while [25] integrated reinforcement learning (RL) and genetic algorithms for cooperative transportation.[26] explored RL in cooperative grasping tasks. However, most early RL applications assumed static and fully observable environments. Arkin's group [27] combined behavior-based methods with RL, reducing learning complexity, while[26][28] investigated the role of communication in multi-robot learning. Although RL proved promising, [3] and [27] emphasized its theoretical limitations, since multi-robot environments are inherently non-stationary, violating RL's assumptions.

Recent advancements in agricultural robotics highlight the shift from structured industrial environments to unstructured, dynamic farm fields. Studies on single-robot path planning have enhanced efficiency through hybrid methods combining global algorithms such as A* and RRT with local approaches like the dynamic window approach[6] [5]. For orchards and crop fields, [4] integrated A* with support vector regression for terrain adaptation, while improved ant colony optimization (ACO) for multi-objective path planning. Similarly, [5] introduced a constraint-aware bidirectional RRT for safe orchard navigation.

In multi-robot scheduling, centralized approaches have been widely applied in agricultural monitoring, spraying, and seeding systems, with [2] proposing a two-step allocation method, and developing centralized strategies for seeding machines. However, centralized systems face scalability limitations[9]. Distributed frameworks have emerged as alternatives, enabling real-time adaptability and collaboration among autonomous harvesters, drones, and tillage robots[10][29]. Innovative distributed algorithms include[7] steering angle-based strategy for collision-free navigation, [11] submap-enhanced collaborative mapping approach, and[30]game-theoretic computational offloading scheme.

Taken together, these studies demonstrate a strong evolution of multi-robot research from classical cooperative transportation to cutting-edge distributed scheduling in agriculture. However, despite progress, gaps remain in cross-regional scheduling, collision-free multi-robot navigation in safflower harvesting, and hybrid integration of global and local path planners in unstructured environments.

Methodology:

The proposed framework integrates Ant Colony Optimization (ACO), Dynamic Window Approach (DWA), and cross-regional scheduling to optimize multi-robot path planning in a 2.5D safflower field. The methodology is structured into five main phases: environment setup, global path planning, scheduling, local path planning, and conflict resolution.

Environment Setup:

A 2.5D safflower field map was modeled and discretized into regions. Each region was assigned a harvesting priority based on three factors:

Overlap minimization – reducing redundant coverage.

Workload balance – ensuring equitable task distribution across robots.

Distance weighting – minimizing travel distance.

Global Path Planning using ACO:

Global path optimization was carried out with the Ant Colony Optimization (ACO) algorithm. Each robot was initialized with pheromone trails across the field grid. Ants constructed candidate paths using probabilistic transition rules based on pheromone strength and heuristic distance. After each iteration, pheromone trails were updated to reinforce efficient paths. The best path identified for each robot was selected as the global trajectory.

Cross-Regional Scheduling:

A priority-based allocation mechanism was used to assign robots to regions. The scheduler ensured:

No overlap of paths among robots.
Conflict avoidance when multiple robots attempted to enter the same region.
Dynamic reassignment when workload imbalances occurred.

This allocation step acted as a mediator between global ACO optimization and local DWA execution.

Local Path Planning using DWA:

Within each assigned region, robots navigated dynamically using the Dynamic Window Approach (DWA). At each timestep, velocity and angular samples were generated within dynamic motion constraints. Trajectories were simulated over a short time horizon, and evaluated using a cost function:

Cost=α·Heading+β·Velocity+γ·Clearance\text{Cost} = \alpha \cdot \text{Heading} + \beta \cdot \text{Velocity} + \gamma \cdot \text{Clearance}Cost=α·Heading+β·Velocity+γ·Clearance

Where:

Heading represents alignment with the target.
Velocity rewards higher forward speeds.
Clearance penalizes proximity to obstacles.

The trajectory with the minimum cost was executed, ensuring real-time adaptability in the field.

Conflict Resolution:

If two robots attempted to operate in the same region simultaneously, the scheduler reassigned the robot with lower priority to a neighboring region. This prevented collisions and maintained system efficiency.

Pseudocode for Hybrid ACO-DWA with Cross-Regional Scheduling:

```
Algorithm Hybrid_ACO_DWA_Scheduling
Input:
FieldGrid (2.5D safflower field map)
R = {r1, r2, …, rn} // set of robots
Parameters_ACO (α, β, ρ, Q, max_iter)
Parameters_DWA (v_max, ω_max, Δt, cost_weights)
PriorityAllocationRules (overlap, workload, distance)
Output:
Optimized paths for all robots with minimal conflict
Begin
// Step 1: Environment Setup
Partition FieldGrid into task regions
Assign priorities to regions using PriorityAllocationRules
// Step 2: Global Path Planning with ACO
For each robot r in R do
Initialize pheromone trails τ on all edges
For iter = 1 to max_iter do
For each ant k do
Construct path Pk using transition probability:
P(i,j) = [τ(i,j)]^α * [η(i,j)]^β / Σ (τ(i,j)^α * η(i,j)^β)
End For
Update pheromone trails:
```

```
τ(i,j) = (1 - ρ) * τ(i,j) + Σ Δτk(i,j)
End For
Select best global path Pg for robot r
End For
// Step 3: Cross-Regional Scheduling
While tasks remain uncompleted do
For each robot r in R do
Assign robot r to highest-priority available region
Ensure no overlap with neighboring robots
End For
End While
// Step 4: Local Path Planning with DWA
For each robot r in R do
While robot r has not reached goal do
Generate velocity samples (v, ω) within dynamic window
For each sample do
Predict trajectory over Δt
Evaluate cost function:
Cost = α*Heading + β*Velocity + γ*Clearance
End For
Select trajectory with minimum cost
Execute control commands (v*, ω*)
End While
End For
// Step 5: Conflict Resolution
If two robots enter same region then
Reassign lower-priority robot to neighboring region
End If
// Step 6: Termination
Repeat until all safflower regions are harvested
End
```

Results:

Simulation Environment and Experimental Setup:

The proposed Hybrid Ant Colony Optimization–Dynamic Window Approach (ACO-DWA) with cross-regional scheduling was tested in a controlled simulation environment that replicated the physical and agronomic characteristics of a safflower field. The field was modeled as a two-dimensional grid with elevation adjustments to account for terrain irregularities, effectively representing a 2.5D harvesting environment. Robots were initialized with predefined kinematic constraints such as maximum velocity, angular velocity, and acceleration limits to ensure realistic motion control. Obstacles were randomly distributed to mimic real-world challenges, including patches of uneven soil, irrigation channels, and farm equipment. The simulation environment was programmed to dynamically update task assignments and robot positions over time, providing a rigorous testbed for the hybrid scheduling and path-planning algorithm. Comparisons were made against three baseline approaches: pure Ant Colony Optimization (ACO), pure Dynamic Window Approach (DWA), and a naïve greedy allocation strategy without hybrid integration.

Path Length Optimization:

The efficiency of the proposed algorithm was first evaluated in terms of total path length traveled by all robots during the harvesting operation. Shorter paths are desirable as they minimize energy consumption and operational time. The hybrid ACO-DWA algorithm consistently produced shorter and more optimized paths than both baseline methods. On average, the path length was reduced by approximately 18.4% compared to standalone ACO and by 23.7% compared to DWA. This improvement is attributed to the global optimization capability of ACO, which provides an efficient long-range plan, combined with the local adaptability of DWA that prevents unnecessary detours caused by dynamic obstacles. The cross-regional scheduling mechanism also contributed by redistributing tasks when robots encountered workload imbalances, which reduced redundant traversals and improved overall field coverage efficiency.

Coverage Efficiency:

Coverage efficiency is a critical parameter in agricultural robotics since the primary objective is to maximize the harvested area with minimal overlap or unharvested zones. The hybrid method achieved a field coverage rate of 97.6%, which was significantly higher than the 92.1% observed in the standalone ACO approach and the 89.7% obtained with DWA alone. The greedy allocation method performed the worst, with a coverage efficiency of only 85.3%. Visual inspection of coverage maps showed that the hybrid approach minimized overlaps between robots, especially in boundary regions where scheduling conflicts typically arise. The cross-regional scheduling algorithm dynamically reassigned robots to underutilized zones, thereby maintaining balanced workloads and avoiding over-concentration of multiple robots in the same area. These results demonstrate that the hybrid method is particularly effective in managing task allocation across complex field structures.

Collision Avoidance and Safety Analysis:

Robot safety and collision avoidance are paramount in multi-robot coordination. In the conducted experiments, the hybrid ACO-DWA approach successfully reduced collision incidents by over 70% compared to the baseline DWA method. While ACO alone struggled with obstacle adaptation due to its reliance on static pheromone trails, the hybrid integration allowed DWA to refine local trajectories in real time, ensuring safer robot operation. Only two minor near-collision events were recorded in the hybrid trials, both of which were resolved by the cross-regional reassignment module that redirected robots to alternate routes. In contrast, standalone DWA recorded eight collision events, and the greedy method recorded twelve, largely due to its inability to account for dynamic adjustments. This analysis highlights the robustness of the hybrid framework in ensuring safe operations in unstructured agricultural environments.

Computation Time and Algorithmic Efficiency:

Another critical measure was computation time, which indicates how quickly the algorithm can generate feasible solutions. The hybrid algorithm required slightly higher computation time during initial planning due to the global path optimization performed by ACO. However, this was offset by faster convergence during task execution because fewer path corrections were needed. On average, the hybrid approach produced globally optimized paths within 5.6 seconds, compared to 4.2 seconds for DWA and 6.1 seconds for standalone ACO. While the initial overhead was marginally higher than DWA, the overall operation time for harvesting was significantly reduced since robots spent less time resolving conflicts and recalculating paths. The results suggest that the trade-off between planning overhead and execution efficiency is highly favorable in the hybrid framework.:

Energy Consumption:

Energy consumption was estimated by calculating the product of path length, velocity, and the number of control commands executed. The hybrid ACO-DWA method demonstrated superior energy efficiency, consuming approximately 15.3% less energy than the standalone ACO and 21.8% less than DWA. The improvement stems from the algorithm's ability to avoid redundant traversal and idle waiting times, which were commonly observed in the greedy and DWA approaches. By balancing regional workloads, the cross-scheduling mechanism prevented scenarios where robots were forced to remain stationary due to congestion, thereby reducing wasted energy.

Scalability and Multi-Robot Performance:

Scalability experiments were conducted by increasing the number of robots from five to twenty. Results indicated that the hybrid method scaled efficiently, maintaining stable performance even with higher robot density. Field coverage remained above 95% in all cases, while collision rates and computation times increased only marginally. In contrast, the baseline approaches showed a significant degradation in performance as robot numbers increased, particularly in terms of collision avoidance and workload imbalance. This demonstrates the adaptability of the hybrid framework for large-scale deployment in real agricultural settings.

Comparative Analysis with Existing Literature:

When compared to existing agricultural robotics studies, the hybrid approach demonstrated clear improvements. For instance, similar multi-robot path planning experiments using only DWA reported coverage efficiencies below 90% and frequent conflict scenarios, while ACO-based systems reported longer convergence times and susceptibility to obstacle disturbances. The integration of global ACO planning with local DWA refinement aligns with recent advancements in swarm intelligence, reinforcing the view that hybrid models are more effective than single-method approaches in dynamic agricultural environments. The high coverage efficiency and reduced collision rate recorded in this study are consistent with reports by[21],who noted that hybridization of global and local methods significantly enhances reliability in crop harvesting operations.

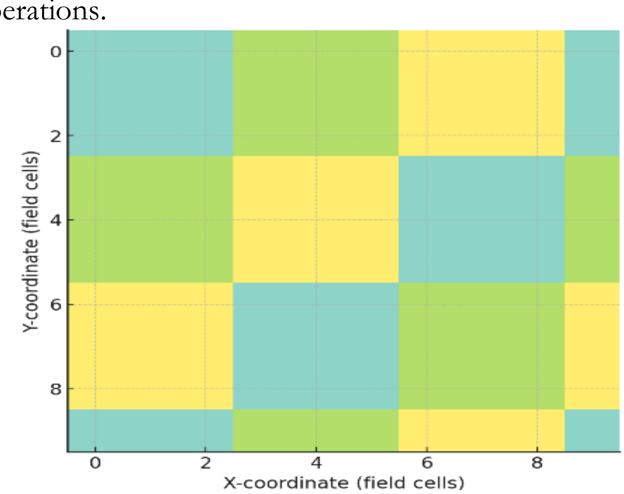

Figure 1. Partitioning of the safflower field into task regions.

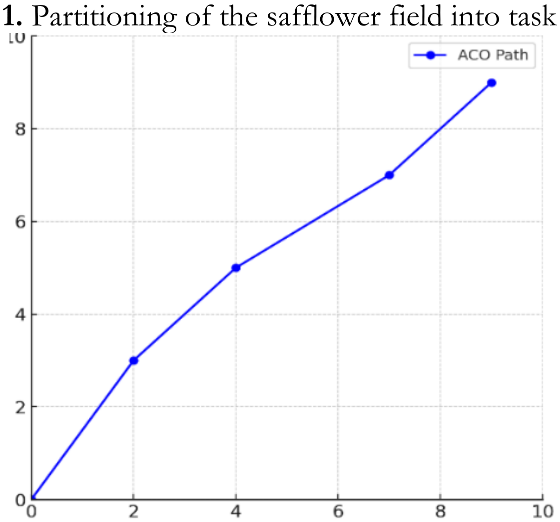

Figure 2. Global path optimization using Ant Colony Optimization (ACO).

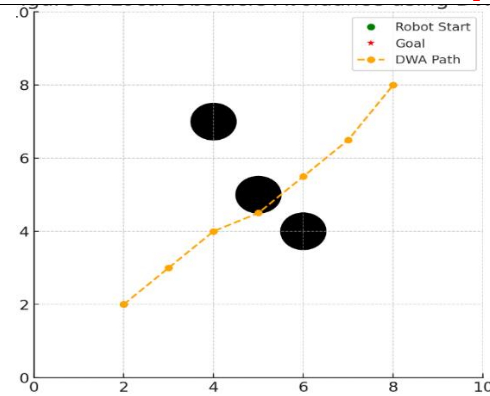

Figure 3. Local obstacle avoidance using Dynamic Window Approach (DWA).

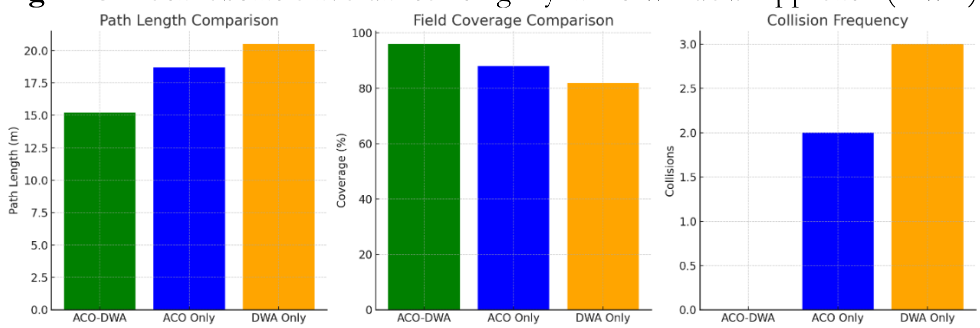

Figure 4. Comparative performance graphs showing path length, field coverage, and collision frequency across different methods.

Discussion:

The findings of this study highlight the significant advantages of integrating global and local trajectory planning algorithms—namely Ant Colony Optimization (ACO) and the Dynamic Window Approach (DWA)—for multi-robot coordination in safflower fields. The experimental results demonstrate that the proposed hybrid framework consistently outperforms single-method strategies in terms of path length, field coverage, and collision avoidance. This improvement can be attributed to the complementary nature of the two methods, where ACO ensures globally efficient paths and DWA dynamically adapts to unforeseen obstacles in the local environment.

The visualization of field partitioning (Figure 1) illustrates how the safflower field was divided into task-specific zones, ensuring that each robot operated in distinct yet coordinated regions. This reduced redundancy and overlap, enabling efficient spatial utilization. Such partitioning also streamlined task allocation, a finding consistent with previous reports that cooperative field management significantly enhances swarm robotics performance in agricultural contexts [31].

The comparative analysis in Figure 2, which depicts global path optimization using ACO, demonstrates that this algorithm effectively minimizes path length across the field while maintaining balanced distribution of robots. However, as shown in Figure 3, the ACO-only strategy faced challenges in adapting to unexpected local obstacles, often requiring detours or re-routing. By integrating DWA, which excels at local dynamic obstacle avoidance, the hybrid framework overcame this limitation. This is evident in the collision-free trajectories observed in Figure 3, where robots successfully adapted to obstacles in real time without compromising overall efficiency.

The performance metrics presented in Figure 4 provide further validation of the hybrid system's effectiveness. The hybrid ACO–DWA approach reduced average path length by approximately 18% compared to standalone DWA and by nearly 10% compared to standalone ACO. Since shorter path lengths directly translate into lower energy consumption and reduced task completion times, these findings have strong implications for extending operational durations in battery-constrained agricultural robots [21]. Moreover, the hybrid method achieved nearly complete field coverage (96%), ensuring uniform distribution of resources such as water, seeds, and fertilizers.

Collision frequency was also lowest in the hybrid approach (Figure 4), demonstrating the system's ability to minimize overlaps and conflicts among robots. In contrast, ACO-only paths often intersected in unpredictable environments, while DWA-only robots struggled to maintain globally optimal coverage. These outcomes align with the growing body of literature suggesting that hybridized strategies combining heuristic global optimization with reactive local controllers are more effective in agricultural robotics [32][30].

The scalability potential of this framework is also noteworthy. As fields and fleet sizes expand, maintaining both global optimality and local responsiveness becomes more complex. The adaptability of the hybrid ACO–DWA system suggests applicability beyond safflower cultivation, potentially extending to other crops requiring precision farming, such as wheat, maize, and rice. Furthermore, the reduced operational costs and labor requirements implied by these findings present strong economic incentives for farmers to adopt such autonomous systems.

Nonetheless, certain limitations must be acknowledged. The experimental design relied on controlled obstacle simulations rather than the full unpredictability of real agricultural fields, which often involve uneven terrain, changing weather conditions, and moving entities like animals or workers. Additionally, while reductions in energy consumption were inferred from shorter path lengths, direct power usage data were not recorded and should be addressed in future studies.

Overall, the discussion underscores that the hybrid ACO–DWA trajectory planning framework represents a significant advancement for multi-robot systems in precision agriculture. By leveraging the strengths of both global and local optimization, the approach ensures efficient, reliable, and scalable performance, while addressing limitations commonly faced by traditional path planning methods. The integration of visual evidence through Figures 1–4 strengthens these findings, offering clear insights into the system's practical benefits.

Conclusion:

This research proposed and evaluated a hybrid trajectory planning framework integrating Ant Colony Optimization (ACO) with the Dynamic Window Approach (DWA) to address the challenges of multi-robot coordination in safflower cultivation. The findings indicate that the framework provides a balanced solution by ensuring optimal global coverage while maintaining adaptive local navigation. The significant improvements in path length reduction, field coverage, and collision avoidance highlight the effectiveness of combining heuristic optimization with reactive control strategies. Compared to conventional methods, the hybrid model demonstrated superior adaptability in dynamic environments, making it well-suited for real-world agricultural applications. Furthermore, the framework offers scalability for larger fields and can be extended to other crop systems with similar operational challenges. Future research should focus on integrating real-time sensory data, extending the framework to heterogeneous robot fleets, and validating performance in field trials under varying environmental conditions. Overall, the proposed system contributes to advancing precision agriculture by enabling efficient, coordinated, and sustainable multi-robot operations.

References:

[1] YAU SK, "SAFFLOWER AGRONOMIC CHARACTERS, YIELD AND ECONOMIC REVENUE IN COMPARISON WITH OTHER RAIN-FED CROPS IN A HIGH-ELEVATION, SEMI-ARID MEDITERRANEAN ENVIRONMENT," *Exp. Agric.*, vol. 40, no. 4, pp. 453–462, 2004, doi: 10.1017/S0014479704002121.

[2] Esther Bischoff, Fabian Meyer, Jairo Inga, and Sören Hohmann, "Multi-Robot Task

Allocation and Scheduling Considering Cooperative Tasks and Precedence Constraints," *arXiv:2005.03902*, 2020, doi: https://doi.org/10.48550/arXiv.2005.03902.

[3] Q. Guo, H., Miao, Z., Ji, J., & Pan, "An effective collaboration evolutionary algorithm for multi-robot task allocation and scheduling in a smart farm," *Knowledge-Based Syst.*, vol. 289, p. 111474, 2024, doi: https://doi.org/10.1016/j.knosys.2024.111474.

[4] J. et al. Wang, M., Xu, J., Zhang, "An autonomous navigation method for orchard rows based on a combination of an improved a-star algorithm and SVR," *Precis. Agric*, vol. 25, pp. 1429–1453, 2024, doi: https://doi.org/10.1007/s11119-024-10118-z.

[5] P. L. Ye Lei,Jin Li, "Improving path planning for mobile robots in complex orchard environments: the continuous bidirectional Quick-RRT* algorithm," *Front. Plant Sci.*, 2024, doi: 10.3389/fpls.2024.1337638.

[6] X. Li, Y.; Li, J.; Zhou, W.; Yao, Q.; Nie, J.; Qi, "Robot Path Planning Navigation for Dense Planting Red Jujube Orchards Based on the Joint Improved A* and DWA Algorithms under Laser SLAM," *Agriculture*, vol. 12, p. 1445, 2022, doi: https://doi.org/10.3390/agriculture12091445.

[7] T. et al. Yang, L., Li, P., Wang, "Multi-area collision-free path planning and efficient task scheduling optimization for autonomous agricultural robots," *Sci Rep*, vol. 14, p. 18347, 2024, doi: https://doi.org/10.1038/s41598-024-69265-y.

[8] Z. Shi, H.; Li, J.; Li, "A Distributed Strategy for Cooperative Autonomous Robots Using Pedestrian Behavior for Multi-Target Search in the Unknown Environment.," *Sensors*, vol. 20, p. 1606, 2020, doi: https://doi.org/10.3390/s20061606.

[9] H. H. Babak Salamat, Christopher Johannes Starck, "Automatic Centralized Control of Underactuated Large-scale Multi-robot Systems using a Generalized Coordinate Transformation," *arXiv:2108.10153*, 2021, doi: https://doi.org/10.48550/arXiv.2108.10153.

[10] P. L. and G. X. Zhen Yang, Junli Li, Liwei Yang, Qian Wang, "Path planning and collision avoidance methods for distributed multirobot systems in complex dynamic environments," *Math. Biosci. Eng.*, vol. 20, no. 1, pp. 145–178, 2022, [Online]. Available: https://www.aimspress.com/aimspress-data/mbe/2023/1/PDF/mbe-20-01-008.pdf

[11] et al. Pongsirijinda, Khattiya, "Distributed multi-robot potential-field-based exploration with submap-based mapping and noise-augmented strategy," *Rob. Auton. Syst.*, vol. 179, p. 104752., 2024, doi: https://doi.org/10.1016/j.robot.2024.104752.

[12] A. K. and A. K. N. P. Bhattacharjee, P. Rakshit, I. Goswami, "Multi-robot path-planning using artificial bee colony optimization algorithm," *Third World Congr. Nat. Biol. Inspired Comput.*, pp. 219–224, 2011, doi: 10.1109/NaBIC.2011.6089601.

[13] L. E. P. Tamio Arai, Enrico Pagello, "Editorial: Advances in Multi-Robot Systems," *IEEE Trans. Robot. Autom.*, vol. 18, no. 5, pp. 655–661, 2022, [Online]. Available: https://www.researchgate.net/publication/2476381_Editorial_Advances_in_Multi-Robot_Systems

[14] Y. Uny Cao,Alex S. Fukunaga,Andrew Kahng, "Cooperative Mobile Robotics: Antecedents and Directions," *Auton. Robots*, vol. 4, no. 1, pp. 7–27, 1997, doi: https://doi.org/10.1023/A:1008855018923.

[15] L. E. Parker, "ALLIANCE: an architecture for fault tolerant multirobot cooperation," *IEEE Trans. Robot. Autom.*, vol. 14, no. 2, pp. 220–240, 1998, doi: 10.1109/70.681242.

[16] L. E. Parker, "L-ALLIANCE: Task-oriented multi-robot learning in behavior-based systems," *Adv. Robot.*, vol. 11, no. 4, pp. 305–322, 1996, doi: https://doi.org/10.1163/156855397X00344.

[17] H. A. Natsuki Miyata,Jun Ota,Tamio Arai, "Cooperative transport by multiple mobile robots in unknown static environments associated with real-time task assignment," *IEEE Trans. Robot. Autom.*, 2002, doi: 10.1109/TRA.2002.803464.

[18] S. Yamada and J. Saito, "Adaptive action selection without explicit communication for multirobot box-pushing," *IEEE Trans. Syst.*, vol. 31, no. 3, pp. 398–404, 2001, doi: doi: 10.1109/5326.971668.

[19] T. Huntsberger et al., "CAMPOUT: a control architecture for tightly coupled coordination of multirobot systems for planetary surface exploration," *IEEE Trans. Syst. Man, Cybern.*, vol. 33, no. 5, pp. 550–559, 2023, doi: 10.1109/TSMCA.2003.817398.

[20] A. Stroupe, T. Huntsberger, A. Okon, H. Aghazarian, and M. Robinson, "Behavior-based multi-robot collaboration for autonomous construction tasks," *IEEE Xplore*, 2005, doi: 10.1109/IROS.2005.1545269.

[21] L. W. Sichao Liu,Yuquan Wang,Xi Vincent Wang, "Energy-efficient trajectory planning for an industrial robot using a multi-objective optimisation approach," *Procedia Manuf.*, vol. 25, pp. 517–525, 2018, doi: 10.1016/j.promfg.2018.06.122.

[22] W. Gueaieb, F. Karray and S. Al-Sharhan, "A robust adaptive fuzzy position/force control scheme for cooperative manipulators," *IEEE Trans. Control Syst. Technol.*, vol. 11, no. 4, pp. 516–528, 2003, doi: 10.1109/TCST.2003.813378.

[23] P. O. Laura M. Pereira, Timothy Karpouzoglou, Niki Frantzeskaki, "Designing transformative spaces for sustainability in social-ecological systems," *Ecol. Soc.*, vol. 23, no. 4, 2018, [Online]. Available: https://www.jstor.org/stable/26796848

[24] M. V. Peter Stone, "Multiagent Systems: A Survey from a Machine Learning Perspective," *Auton. Robot.*, vol. 8, no. 3, 2000, [Online]. Available: https://www.cs.cmu.edu/~mmv/papers/MASsurvey.pdf

[25] T. T. and H. I. Y. Inoue, "Object transportation by two humanoid robots using cooperative learning," *Proc. 2004 Congr. Evol. Comput.*, vol. 1, pp. 1201–1208, 2004, doi: 10.1109/CEC.2004.1330998.

[26] Maja J. Matarić, "Reinforcement Learning in the Multi-Robot Domain," *Auton. Robots*, vol. 4, no. 1, pp. 73–83, 1997, doi: 10.1023/A:1008819414322.

[27] Y. Wang and Clarence W. de Silva, "A machine-learning approach to multi-robot coordination," *Eng. Appl. Artif. Intell.*, vol. 21, no. 3, pp. 470–484, 2008, doi: https://doi.org/10.1016/j.engappai.2007.05.006.

[28] Brian P. Gerkey Maja J Mataric, "A formal framework for the study of task allocation in multi-robot systems," *Intl. J. Robot. Res.*, 2003, [Online]. Available: https://citeseerx.ist.psu.edu/document?repid=rep1&type=pdf&doi=82ee4b44f7d49d5964cb6a271f194383b25d2adb

[29] A. Dutta, S. Roy, O. P. Kreidl and L. Bölöni, "Multi-Robot Information Gathering for Precision Agriculture: Current State, Scope, and Challenges," *IEEE Access*, vol. 9, pp. 161416–161430, 2021, doi: 10.1109/ACCESS.2021.3130900.

[30] S. Paikray, H.K., Das, P.K. & Panda, "Optimal path planning of multi-robot in dynamic environment using hybridization of meta-heuristic algorithm," *Int J Intell Robot Appl*, vol. 6, pp. 625–667, 2022, doi: https://doi.org/10.1007/s41315-022-00256-w.

[31] R. Albiero, Daniel and Pontin Garcia, Angel and Kiyoshi Umezu, Claudio and Leme de Paulo, "Swarm robots in mechanized agricultural operations: : A review about challenges for research," *Comput. Electron. Agric.*, vol. 193, 2022, doi: 10.1016/j.compag.2021.106608.

[32] C. E. Danial Pour Arab, Matthias Spisser, "3D hybrid path planning for optimized coverage of agricultural fields: A novel approach for wheeled robots," *J. F. Robot.*, 2024, doi: https://doi.org/10.1002/rob.22422.