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MULTI MOVING TARGET LOCALIZATION IN AGRICULTURAL FARMLANDS BY EMPLOYING OPTIMIZED COOPERATIVE UNMANNED AERIAL VEHICLE SWARM

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Abstract. The paper proposes an original method for employing optimised cooperative swarms of Unmanned Aerial Vehicles (UAVs) to localise multiple moving objects in agricultural farmlands. Crop Monitoring (CM), targeted fertilizer distribution, and Livestock Management (LM) are some of the Smart Farming (SF) applications of UAVs. However, the ever-changing nature of agricultural settings makes it challenging to set up UAV swarms. Detecting multiple evolving objectives in dynamic environments is complicated, and conventional methods are regularly optimized for single objectives, such as area or reduced Energy Consumption (EC), which is unsuitable. This research recommends a Multi-Objective Evolutionary Algorithm (MOEA) as a model for UAV swarms to balance task service, communication, and EC during the investigation. The approach paves the method for innovation in the agricultural sector by optimizing tasks in real-time, addressing unpredictable targets, boosting productivity, and reducing costs. The study's findings present optimism for smart farm management and accurate SF by improving UAV systems' response time and scalability.

Key words: UAV, Smart Farming, Energy Consumption, Crop Monitoring, Agricultural Technology, Precision Agriculture

1. Introduction and examples. A novel concept from the twenty-first century called "Smart Farming" (SF) focuses on productivity and Precision Agriculture (PA). The development of innovation in the SF sector has been driven primarily by modern-era technology, namely robotic devices and Unmanned Aerial Vehicles (UAVs). Considering that these inventions are a number of devices, they may improve ecologically friendly SF methods, which is how study participants have advocated for their use to enhance SM procedures and improve resource optimization [13]. Crop Yield (CY), Soil Health (SH) evaluation and robotic technology have all experienced significant advances due to UAVs and robotic equipment. In order to guarantee that every person around the globe has access to nutritious food, these developments are crucial. In light of their significant scientific functions, UAVs have become prevalent in the AS. UAV technology has radically altered the activity of Crop Monitoring (CM), herbicide applications, chemicals, and livestock monitoring (LM) [11]. As an outcome, SH checks have gotten better, and SF-CY has increased, which has made these improvements feasible for a more significant number of people [7].

With the ability to quickly encompass huge regions, UAVs can collect data with an index of accuracy and reliability that outperforms that of any farmers [9]. In order to help with real-time data storage for complete analysis and decision-making procedures (DMP), they recommend operating the framework permanently. Pest control using UAV proves more effective, consumes minimal chemical compounds, and has minimal impact on

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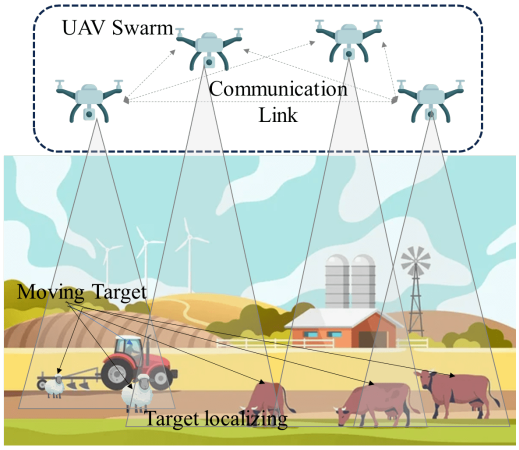

Fig. 1.1: MMT Environment

the natural environment [16]. In CM, they assist in finding errors and issues rapidly, and in LM, they maintain a check on the livestock to make sure they're in good health and provide as much as feasible.

SF has made significant progress, but the challenge of Multi-Moving Target (MMT) geolocation remains. This involves monitoring numerous moving objects across extensive farmlands, such as cattle and mobile SF devices. Accurately locating these targets is crucial for real-time monitoring, resource deployment, and workflow control. Current techniques focus on optimizing one task at a time, ignoring the connected nature of real-life situations and significant Energy Consumption (EC). Despite these challenges, the use of UAVs in SF remains essential. Figure 1.1 illustrates a conventional MMT setting. The present techniques could optimize Global Positioning System (GSP) coverage or energy efficiency, ignoring the connected nature of the real-life situation [8].

The unpredictable nature of SF necessitates a focus on the multi-target GSP problem, a key area of study for UAVs, as current technology fails to adapt to the varied and continuously evolving SF settings, leading to operational errors and rising costs. The study presents an innovative approach to MMT-GSP challenges in agricultural land using an optimized cooperative UAV swarm design. It uses an advanced Multi-Objective Evolutionary Algorithm (MOEA) to balance EC, transmission productivity, and area coverage. The Pareto-Optimality Theory (POT) ensures that no objective improves at the proportional cost of another, making UAVs more flexible and accurate in changing SF settings. This integrated approach opens new possibilities for SF.

This study article outlines the following: Chapter 2 starts with the existing literature analysis; Chapter 3 presents the framework hypothesis; Chapter 4 focuses on the planned tasks; Chapter 5 includes experimental research; and Chapter 6 concludes the research.

2. Literature Review. Employing UAVs for Multi-Target Tracking (MTT) is an enormous advance in the rapidly expanding AS. Numerous research studies have described numerous tactics and methods to enhance UAV systems' performance in challenging scenarios.

The paper [3] emphasizes an intelligent method that enhances tracking accuracy and incorporates collision prevention techniques in the UAV-based cooperative monitoring design. In place of solutions that use deep Q-networks, their strategy significantly improves tracking accuracy and reduces time. The study [10] demonstrates the practical application of inaccurate distance metrics to optimise UAV control actions and explores Deep Reinforcement Learning (DRL) implementation to manage UAVs while monitoring rescue workers in 3D regions.

The DRL method, which emphasizes reducing the Cramér-Rao lower bound (CRLB), can achieve precise monitoring at minimal operational costs. The authors of [14] invented a novel technique for selecting a path with a dynamic Artificial Potential Field (D-APF) and optimized it for multirotor UAVs that aim to capture objects in motion on ground levels. The above technique improves standard possible SF techniques in models and performs well in dynamic and dense conditions.

The paper [5] developed a novel technique known as Motion-encoded Particle Swarm Optimization (MPSO) to enhance the target detection features of UAVs. Because the swarm's behavioural and psychological attributes encompass the process of searching path, MPSO achieves more effective results than standard PSO and other metaheuristic algorithms in both theoretical and real-world scenarios. To improve UAV-DMP for more accurate target tracking, the study [6] implemented a comprehensive, all-encompassing Multi-Agent Reinforcement Learning (MARL) approach. The technique integrates data on spatial entropy, EC techniques, monitoring success rates, and EC with positive results [2].

Ultimately, the paper [15] highlights particular issues with MTT and provides innovative techniques to improve the circumstances. To deal with Multi-Agent Pursuit-Evasion (MAPE) problems, the study [4] proposes an adaptation of the Multi-Agent Deep Deterministic Policy Gradient (MADDP) method. Their role-based system expedites the process of monitoring invisible objects. However, the authors of [12] focuses their research on livestock monitoring, using an approach that optimizes detection and tracking by employing optical flow and low-confidence path filtering techniques. This technique works with YOLOv7 and DeepSORT algorithms [1].

3. System Model. The proposed UAV swarm-based cooperative tracking paradigm model incorporates three fundamental models: Task, Transmission, and Energy. These models must emerge in order to provide successful, suitable tracking and predictive path computation, all while maintaining EC and providing secure communication among the UAVs.

3.1. Task Model. The Task Model focuses on how the UAV gets allocated tracking duties and how these tasks are executed. Any UAV is liable for maintaining tracks on specific parts of the targeted region and tracking any targets that have been identified within that area of search. Assume $T = \{T_1, T_2, \ldots, T_n\}$ be the set of all targets to be monitored, and $Z = \{Z_1, Z_2, \ldots, Z_m\}$ be the set of zones divided by the UAV for monitoring. The allocation of tasks can be represented by a task allocation matrix A, where each element a_{ij} indicates the assignment of the target T_j to the zone Z_i, EQU (3.1)

$$A = [a_{ij}] \text{ where } a_{ij} = \begin{cases} 1, & \text{if target } T_j \text{ is in zone } Z_i \\ 0, & \text{otherwise} \end{cases} \tag{3.1}$$

The goal of the Task Model is to maximize the coverage and tracking accuracy while minimizing overlaps and gaps in monitoring, which can be represented by the optimization problem EQU (3.2) and EQU (3.3)

$$\max_A \sum_{i=1}^{m} \sum_{j=1}^{n} a_{ij} \cdot c\left(T_j, Z_i\right) \tag{3.2}$$

subject to

$$\begin{aligned} &\sum_{i=1}^{m} a_{ij} \leq 1, \forall j \\ &\sum_{j=1}^{n} a_{ij} \leq U_i^{\text{cap}}, \forall i \end{aligned} \tag{3.3}$$

where $c\left(T_j, Z_i\right)$ is the coverage score indicating the efficiency of tracking the target T_j in zone Z_i, and U_i^{cap} is the tracking capacity of UAV U_i.

3.2. Transmission Model. The Transmission Model concerns the data exchange between UAVs for collaborative detection, tracking, and path prediction of MMTs. Each UAV has communication modules to transmit and receive data to and from its neighbors. Let C_{ij} be the communication link between UAV U_i and UAVU_j, which is attributed to its bandwidth B_{ij}, latency L_{ij}, and reliability R_{ij}.

The data transmission rate between two UAVs can be depicted by Shannon's EQU (3.4):

$$R_{ij} = B_{ij} \cdot \log_2\left(1 + \frac{s_{ij}}{N_{ij}}\right) \tag{3.4}$$

where R_{ij} is the rate, B_{ij} is the bandwidth, S_{ij} is the signal power received from a UAV U_j by UAV U_i, and N_{ij} is the noise power in the communication channel between U_i and U_j.

The Transmission Model aims to maximize the overall network throughput while ensuring low latency and high reliability, EQU (3.5) by the optimization problem:

$$\text{Maximize} \sum_{i=1}^{m-1} \sum_{j=i+1}^{m} R_{ij} \tag{3.5}$$

subject to EQU (3.6) and EQU (3.7)

$$L_{ij} \leq L_{\max}, \forall i \neq j \tag{3.6}$$

$$R_{\min} \leq R_{ij} \leq R_{\max}, \forall i \neq j \tag{3.7}$$

where $L_{\max}$ is the maximum acceptable latency, $R_{\min}$ is the minimum required data rate, and $R_{\max}$ is the maximum achievable data rate on the communication channel.

3.3. Energy Model. The Energy Model addresses the EC aspects of the UAVs during the tracking mission. EC is crucial for prolonged operations and endurance of the UAV swarm. The EC for a UAV U_i includes the EC during the flight E_{flight_i}, sensing and processing E_{sense_i}, and communication E_{comm_i}. The energy model is represented as EQU (3.8)

$$E_{\text{total }_i} = E_{\text{flight }_i} + E_{\text{sense }_i} + E_{\text{comm }_i} \tag{3.8}$$

The objective is to minimize the total EC of the UAV while ensuring the completion of the tracking task, which can be posed as the following optimization problem: EQU (3.9) to EQU (3.13)

$$\text{Minimize} \sum_{i=1}^{m} E_{\text{total }_i} \tag{3.9}$$

subject to:

$$E_{\text{flight }_i} \leq E_{\text{flight }_{\max}}, \forall i \tag{3.10}$$

$$E_{\text{sense }_i} \leq E_{\text{sense }_{\max}}, \forall i \tag{3.11}$$

$$E_{\text{comm }_i} \leq E_{\text{comm }_{\max}}, \forall i \tag{3.12}$$

$$\mathbf{A} \cdot (\mathbf{E}_{\text{flight}} + \mathbf{E}_{\text{sense}} + \mathbf{E}_{\text{comm}}) \leq E_{\text{res}}, \forall i \tag{3.13}$$

where $E_{flight_{max}}$, $E_{sense_{max}}$, and $E_{comm_{max}}$ are the maximum EC allowances for flight, sensing, and communication, respectively, and E_{res} is the residual energy required for the UAV to return to the base or next task point.

4. Proposed Multi-Objective Optimization Problem (MOOP) Definition for UAV Optimization. The overarching goal of deploying a UAV for SF target tracking is to harness the collective capabilities of the UAV while adhering to the operational constraints of task efficiency, communication integrity, and EC. This method defines an MOOP that includes the mutually dependent objectives resulting from the UAVs' task allocation, transmission specifications, and EC. This addresses the design problem.

4.1. Problem Interdependencies. Several interrelated objectives, outlined below, emerge from the basic functional designs that set this challenge apart:

1. **Task Allocation and Energy Dynamics:** Each UAV's EC model immediately influences the scheduling of monitoring tasks. Minimising reused flight paths is one way to determine how effectively the assignment of tasks can help minimise EC.
2. **Communication and EC:** In order for an entire group to make real-time recommendations, the channel of communication must be secure and efficient. A boost in EC due to increased transmission powers is an accepted consequence of enhancing the level of communication.
3. **Task Execution and Communication Coherence:** Information sharing between the UAVs is required if they are to monitor and predict the location of their surveillance targets effectively. An interface design that enables minimal latency transmission of data at a high rate is necessary for this explanation.

4.2. Objective Function and Constraints. Rather than deciphering specific equations from the task, transmission process, and energy models, this work explains the multi-objective problem using an approach that emphasizes the interconnected nature of these models. The aim of this work is to construct an optimization architecture that considers all the following factors in a comprehensive approach:

- They achieve high task coverage and precise target localization.
- The task involves maintaining a robust and efficient communication network amongst UAVs.
- The goal is to minimize the overall EC across the UAV without compromising mission effectiveness.

Limits describe the features of the UAVs, the terrain, and the essential variables. The optimization aims to ensure that UAVs maintain their operational power restrictions, minimum communication channel requirements, and limited energy sources.

4.3. Decision Variables and Optimization Process. Finding an accurate prime vector 'X' is essential for optimizing the tasks of the UAV swarm. The key operational settings for the task, communication, and Energy Models have been included in this vector that is used. The decision vector is mathematically represented as EQU (4.1)

$$\mathrm{X} = x_1, x_2, \ldots, x_k \tag{4.1}$$

where each x_i within the vector, X represents a specific operational decision variable. These variables contain UAV-GPS allocations, transmission settings, and UAV flight paths.

The objective of this work optimization is to simultaneously minimize or maximize a set of functions defined as EQU (4.2)

$$\text{Minimize/Maximize} F(\mathrm{X}) = [f_1(\mathrm{X}), f_2(\mathrm{X}), \ldots, f_p(\mathrm{X})] \tag{4.2}$$

subject to the following constraints: EQU (4.3) and EQU (4.4)

$$G(\mathrm{X}) = [g_1(\mathrm{X}), g_2(\mathrm{X}), \ldots, g_q(\mathrm{X})] \leq 0 \tag{4.3}$$

$$H(\mathrm{X}) = [h_1(\mathrm{X}), h_2(\mathrm{X}), \ldots, h_r(\mathrm{X})] = 0 \tag{4.4}$$

In the above EQU (4.4), $F(\mathrm{X})$ is the vector of objective functions f_i, where each function aims at one distinct target, such as EC minimization or task coverage maximization. The vectors $G(\mathrm{X})$ and $H(\mathrm{X})$ denote the sets of variation and equality limit functions, respectively.

To solve this MOOP, this study employs a POT, where the Pareto front, Y, is defined as EQU (4.5)

$$Y = \{\mathbf{X} \mid \nexists \mathbf{X}' : F(\mathbf{X}') \leq F(\mathbf{X}), G(\mathbf{X}') \leq G(\mathbf{X}), H(\mathbf{X}') = H(\mathbf{X})\} \tag{4.5}$$

When no other feasible solution, X$'$, will enhance any objective without negatively impacting another, researchers claim that X is the Pareto optimal solution. Overall, the most effective solutions in the field of objectives make up the Pareto front Y. In order to discover the search space to find the set of Pareto-optimal keys, it is vital to use advanced optimization methods.

Coordinating UAV operations with the particular needs of SF monitoring tasks is the final objective of optimization. It attempts to provide different operational plans that manage the trade-offs between task efficiency (E_{task}), communication quality (Q_{comm}), and EC (E_{total}). The decision-makers then have an extensive set of selections.

4.4. MOEA Process for UAV Optimization for MMT Localization. The MOEA presents a high-level structure for navigating the complex field of solutions for the challenging task of MMT localization in rural SF land using an ensemble UAV swarm. Identifying a set of POTs that optimally balance task protection, communication efficiency, and EC is the primary goal of MOEA in this environment.

1. **Representation (Chromosomes):** An encoded result vector $\mathrm{X}=\left[\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, ..\mathrm{x}^{\mathrm{k}}\right], \mathrm{x3}, \ldots \mathrm{xk}]$ describes the set-up of the UAV and comprises decision variables $\left[\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, \ldots \mathrm{x}^{\mathrm{k}}\right]$ that are responsible depending on swarm features like location, altitude, and sensor direction. A chromosome X is an encoded solution vector representing the UAV swarm's configuration, consisting of decision variables $\left[\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, .\mathrm{x}^{\mathrm{k}}\right]$ where each variable represents a specific aspect of the swarm, such as location, altitude, and sensor orientation $\mathrm{X}=\left[\mathrm{x}_1, \mathrm{x}_2, \mathrm{x}_3, ..\mathrm{x}^{\mathrm{k}}\right]$.
2. **In the context of UAVs:** x_i could represent the i^{th} UAV's position and orientation in 3D space, $\left(x_{i,\text{pos}}, y_{i,\text{ pos}}, z_{i,\text{ pos}}, \theta_{i,\text{ ori}}, \phi_{i,\text{ ori}}\right)$, and its communication and energy parameters.
3. **Population Initialization:** Initial solutions $P_0=\left\{X_1, X_2, \ldots, X_N\right\}$ are generated within the feasible search space, respecting constraints such as flight zones and maximum energy capacity.
4. **Fitness Evaluation (Objective Functions):** Fitness evaluation is performed concerning the defined objectives:
   - **Objective 1 (Coverage):** $f_1(X)=\sum_{i=1}^m \sum_{j=1}^n a_{ij} \cdot c\left(T_j, Z_i\right)$ where a_{ij} indicates the importance of covering the target T_j by UAVZ_i, and c is a coverage function that might depend on the distance, angle of the sensors, and other environmental factors.
   - **Objective 2 (Communication):** $f_2(X)=\sum_{i=1}^{m-1} \sum_{j=i+1}^m R_{ij}\left(x_{i,\text{ com}}, x_{j,\text{ com}}\right)$ where R_{ij} is the communication reliability between UAVs i and j, depending on their communication settings $x_{i,\text{ com}}$ and $x_{j,\text{ com}}$.
   - **Objective 3 (EC):** $f_3(X)=\sum_{i=1}^m E_i\left(x_{i,\text{pos}}, x_{i,\text{ act}}\right)$ where E_i is the EC of UAV i, which depends on its position $x_{i,\text{ pos}}$ and the action taken $\chi_{i,\text{ act}}$.

   The MOEA process involves selecting the fittest individuals to act as parents for the next generation. Round selection and roulette wheel selection are two methods that can be employed. Then, these selected parents are subjected to genetic processes like mutation and crossover in order to have children, which boosts the population's variability and introduces novel features.
5. *Selection:* A case study of a predictable selection method employed by MOEA for UAV swarm optimization is Rank-based Selection. This method involves ranking the population according to their fitness values and selecting the top-ranking individuals with a higher probability. A rank $r\left(X_i\right)$ is assigned to every individual X_i, and the selection probability $P\left(X_i\right)$ is given by EQU (4.6).

$$P\left(X_i\right)=\frac{r\left(X_i\right)}{\sum_{j=1}^N r\left(X_j\right)} \tag{4.6}$$

   The individuals with higher ranks (lower rank) have higher chances of being selected.
6. *Crossover:* The crossover operation is a recombination process where two parent chromosomes exchange segments to produce offspring. A commonly used crossover operator in MOEA is the Single-Point Crossover. Two parent chromosomes X^{p1} and X^{p2} are selected, and a crossover point cp is chosen randomly along the length of the chromosomes. The offspring X^{o1} and X^{o2} are then created as follows: EQU (4.7) and EQU (4.8)

$$X^{o1}=\left(x_1^{p1}, \ldots, x_{cp}^{p1}, x_{cp+1}^{p2}, \ldots, x_k^{p2}\right) \tag{4.7}$$

$$X^{o2}=\left(x_1^{p2}, \ldots, x_{cp}^{p2}, x_{cp+1}^{p1}, \ldots, x_k^{p1}\right) \tag{4.8}$$

where k is the number of genes in the chromosome.

7. *Mutation:* Mutation introduces variation into the population by randomly altering the offspring's genes. For UAV swarm optimization, a Gaussian Mutation is used, where the value of the mutated gene x_i' is given by EQU (4.9)

$$x_i' = x_i + N\left(0, \sigma^2\right) \tag{4.9}$$

Here, x_i is the original gene value, $N\left(0, \sigma^2\right)$ is a Gaussian distribution with mean 0 and standard deviation σ, which controls the extent of the mutation. The value of σ is often decreased over generations to reduce the search space as the algorithm converges.

8. *Constraint Handling:* If the MOEA intends to develop feasible UAV operation options, controlling restrictions is a prerequisite. These drawbacks include restrictions on payload capacity, no-fly regions, and the lifespan of batteries. The application of a penalty function is a usual approach to risk control. This function adjusts the fitness value of a solution according to how much it breaches the controls. This concept can be illustrated through the following mathematical expression EQU (4.10)

$$F'(X) = F(X) - P(X) \tag{4.10}$$

where:
- $F(X)$ is the original fitness value of the solution X.
- $P(X)$ is the penalty incurred by the solution X.
- $F'(X)$ is the penalized fitness value.

The penalty function $P(X)$ is a sum of individual penalties for each constraint, as given by EQU (4.11)

$$P(X) = \sum_{i=1}^{C} p_i \cdot v_i(X) \tag{4.11}$$

where:
- C is the constraint count.
- p_i is the penalty factor for the i-th constraint.
- $v_i(X)$ is a violation measure for the i-th constraint, which is zero if the condition is not violated and positive if it is.

9. **Survivor Selection:** Survivor selection determines which individuals from the current population P_t and the offspring O_t will pass to the next generation P_{t+1}. A common method used with MOEA is Elitist Selection, where a segment of the top-performing individuals from the present population is assured of the monitor. The remaining spots in the new population are filled based on the fitness values after considering penalties. This can be formulated as EQU (4.12)

$$P_{t+1} = E\left(P_t\right) \cup S\left(F'\left(P_t \cup O_t\right), \left|P_t\right| - \left|E\left(P_t\right)\right|\right) \tag{4.12}$$

where:
- $E\left(P_t\right)$ is the elitist set in the current population P_t.
- $S\left(F'(A), N\right)$ is the function that selects N individuals from set A based on their penalized fitness $F'(A)$.

The elitist selection ensures that high-quality solutions are preserved from generation to generation, thereby preventing the loss of the best-found solutions due to genetic drift or poor crossover/mutation outcomes.

10. **Convergence Toward Pareto Optimality:** In a multi-objective optimization scenario, the aim is not just to find a single optimal solution but rather a set of solutions representing the best possible trade-offs among the objectives, known as the Pareto front. As the evolutionary process proceeds, the MOEA aims to converge toward this Pareto front. This investigation assesses the Pareto optimality of solutions based on dominance criteria, considering a solution X to dominate another solution Y if it is at least equivalent to Y in all objectives and distinctly superior in at least one objective.

The crowding distance method in the Non-dominated Sorting Genetic Algorithm II (NSGA-II) can help predict accuracy while preserving population variation, providing each solution with a diversity measure based on its proximity to its neighbours in the objective space d(X). This is crucial to prevent the genetic algorithm from selecting a single approach, thereby maintaining its diversity. EQU (4.13) provides the expression for crowding distance.

$$d(X)=\sum_{i=1}^{O}\left(f_i\left(X^{\text{next}}\right)-f_i\left(X^{\text{prev}}\right)\right) \tag{4.13}$$

where:

- O is the number of objectives.
- $f_i(X)$ is the value of the i-th objective function.
- X^{next} and X^{prev} are the solutions adjacent to X in the sorted list of the population for each objective.

Each iteration of the MOEA performs a non-dominated selection to group the solutions into discrete identities based on the dominance parameters. This research assigns a fitness value to each front, usually inversely proportional to its rank. The 1st rank (nondominated solutions) represents the current estimate of the Pareto front.

Metrics like the hypervolume indicator or the inverted generational distance typically assess convergence by measuring how close the current solutions are to the true Pareto front. The MOEA iteratively updates the population using the selection, crossover, mutation, and survival selection processes to improve these metrics and move closer to the true Pareto front.

The loop expression can describe the iterative process:

Step 1. While (not termination condition)
Step 2. Perform non-dominated sorting of $P_t \cup O_t$
Step 3. Update crowding distances $d(X)$ for each solution X
Step 4. Select parents from P_t based on fitness and $d(X)$
Step 5. Apply crossover and mutation to create O_{t+1}
Step 6. Evaluate $F'\left(O_{t+1}\right)$ and apply constraint handling
Step 7. Set P_{t+1} as the best solutions from $P_t \cup$
Step 8. O_{t+1} based on non-dominance and $d(X)$
Step 9. End While

The iterative optimization cycle continues until a stopping criterion is satisfied. A pre-established number of evolutionary processes, a sufficiently small change in the Pareto front indicating convergence, or a consistent lack of progression in the Pareto front's performance indicators can dictate this. This experiment explicitly ties the performance indicators to these research objectives: task coverage, communication network robustness, and energy efficiency. Also, this paper carefully monitors the iterative process to ensure that the Pareto front improvements align with the goals of effective surveillance and target tracking while managing the UAVs' EC and maintaining communication integrity. The following algorithm presents the steps involved in the MOEA-UAV swarm optimization.

In MOOP, metrics such as Pareto dominance, Pareto front coverage, and Pareto spread are important because they help measure the trade-offs between competing goals and evaluate the variety of Pareto front solutions. By evaluating a solution's superiority over another across a range of goals, Pareto dominance is a tool for finding non-dominated solutions. Pareto front coverage measures how accurately the Pareto front depicts the trade-off space and how thorough the solutions are. By examining the distribution and dispersion of options along the Pareto front, Pareto spread allows us to recognize the ideal solution environment in its complete form by emphasizing the range and spacing of the optimal solutions.

5. Experimental Analysis. The present investigation assessed the recommended MOEA by reproducing UAV swarm operations for agricultural monitoring using a TensorFlow-based simulator. In order to simulate the challenging task of following moving objects in extensive, unrestricted farmlands, researchers set up a virtual natural environment and deployed four UAVs on predetermined routes to collect data. This study built

Algorithm 1 MOEA for UAV Optimization

Inputs:

- m : Number of UAVs in the swarm.
- n : Number of targets to cover.
- N : Population size.
- MaxGen; Maximum number of iterations.
- σ_{init} : Initial standard deviation for mutation.
- σ_{final} : Final standard deviation for mutation.
- P_t : Current population at generation t.
- O_t : Offspring population at generation t.

Outputs:

- P^* : The optimized UAV swarm configurations.

1. **Initialization:**
   (a) Set generation count $t = 0$.
   (b) Initialize population P_0 with N random but feasible solutions respecting operational constraints.
   (c) Evaluate the initial population P_0 using the fitness functions f_1, f_2, and f_3.
   (d) Set $\sigma = \sigma_{\text{init}}$.
2. **Evolutionary Loop:**
   (a) While ($t <$ MaxGen) and (not convergence criteria met):
      i. Perform non-dominated sorting on $P_t \cup O_t$ to classify solutions into fronts based on dominance.
      ii. Calculate crowding distances $d(X)$ for each solution X.
      iii. Select parents from P_t based on fitness and $d(X)$.
      iv. Apply crossover and mutation to create $O_{(t+1)}$.
         - **For crossover:** Select parents X^{p1}, X^{p2} and perform Single-Point Crossover.
         - **For mutation:** Apply Gaussian Mutation to offspring, $x_i' = x_i + N\left(0, \sigma^2\right)$.
      v. Evaluate $F'\left(O_{(t+1)}\right)$ for the offspring and apply constraint handling.
      vi. Update σ by decreasing it gradually towards σ_{final} .
      vii. Perform selection for the next generation.
         - Combine and sort P_t and $O_{(t+1)}$ based on non-dominance and $d(X)$.
         - Select the best N solutions to form $P_{(t+1)}$.
      viii. $t = t + 1$.
3. **Elitism and Final Selection**
   (a) Perform a final non-dominated sort on P_t.
   (b) Select the elite set $E\left(P_t\right)$ ensuring the best solutions are preserved.
   (c) Update the final population P^* with non-dominated solutions representing the Pareto front.
4. **Termination**
   (a) The algorithm terminates when the stopping criteria are met:
      - Maximum generations MaxGen reached.
      - Convergence is assessed by changes in the Pareto front or performance indicators.
   (b) Return the final set P^* of Pareto-optimal solutions for UAV swarm configurations.

this work-tracking model on real flight paths and GPS-cached data from mobile targets, checking them for hypothetical intrusive risks to ensure maximum accuracy. This paper scheduled the deployment of the MOEA model in this computer simulation to enhance the operational features of the UAV swarm, including its EC, monitoring service, and aircraft performance, among other attributes.

Something that is part of the testing process for the MOEA used for UAV control pricing is looking at how well it can adapt to changes in the outside environment, the way things are moving, and uncertainty. The results of this experiment demonstrate that the procedure is practical in many situations. The use of security

Table 5.1: Key parameters for UAV simulation in the MOEA framework

Parameter	**Specification**
Minimum separation distance	4 m
Count of invasive targets	2
Total UAVs in simulation	4
Data link bandwidth range	[40 MHz, 90 MHz]
Communication power per UAV	35 dm
Average UAV cruising speed	70 km/h
Typical target movement speed	65 km/h
Target tracking route length	550 m
Data payload size limit	120 Mbytes
The operational limit for target capture	0.7 s

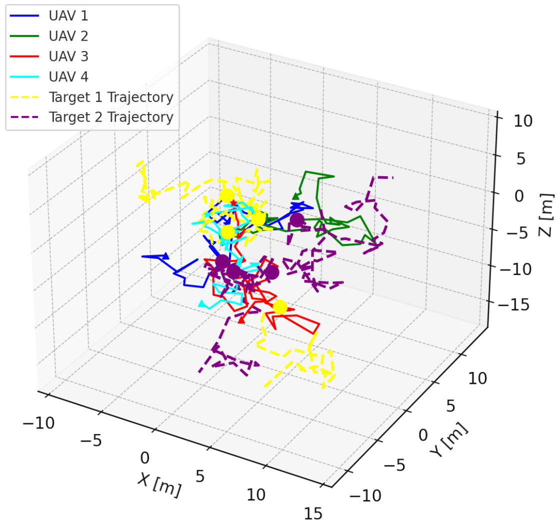

Fig. 5.1: Path graph for four UAVs and two moving target

metrics includes how secure a solution is in unpredictable situations, how well it adapts to new statistics, and how well it manages unpredictability in its task and environment. A study of the degree to which an approach maintains its functionality and the types of solutions it propositions. This study can determine the reliability of an approach by studying its ability to maintain functionality and the types of solutions it finds with changes in input settings or operating conditions. Acnes, including dynamic settings and inherent risks, it is essential to assess the algorithm from a reliability perspective. Table 5.1 provides the primary metrics, which are categorized as follows:

Figure 5.1 shows the 3D paths of the four UAVs, and Figure 5.2 shows the localization error as determined by the Mean Squared Error (MSE). Throughout one hundred iterations, the most significant performance metric was MSE. The MSE evaluates how well the UAV swarm can identify multiple targets, an essential part of operational efficiency that requires accuracy. This paper continuously monitored and evaluated each model's ability to minimize this error as the experiment progressed through its iterations.

Reliable enhancement in performance over 100 iterations is what sets the proposed framework for UAV swarm optimization. In contrast to ACO, PSO, and GA, which show variability to a certain extent and delayed convergence, the proposed framework begins with a low error rate that decreases consistently, demonstrating significant optimization and learning features. After the 20$^{\text{th}}$ era, when the proposed design begins to func-

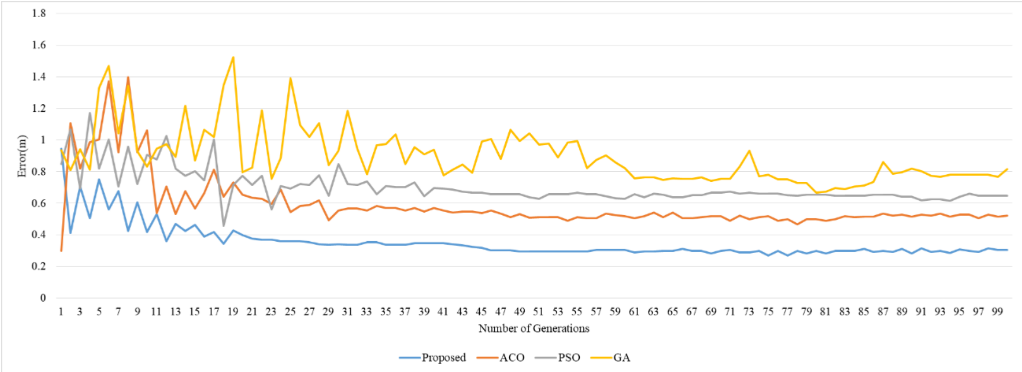

Fig. 5.2: Error comparison for 100 iterations

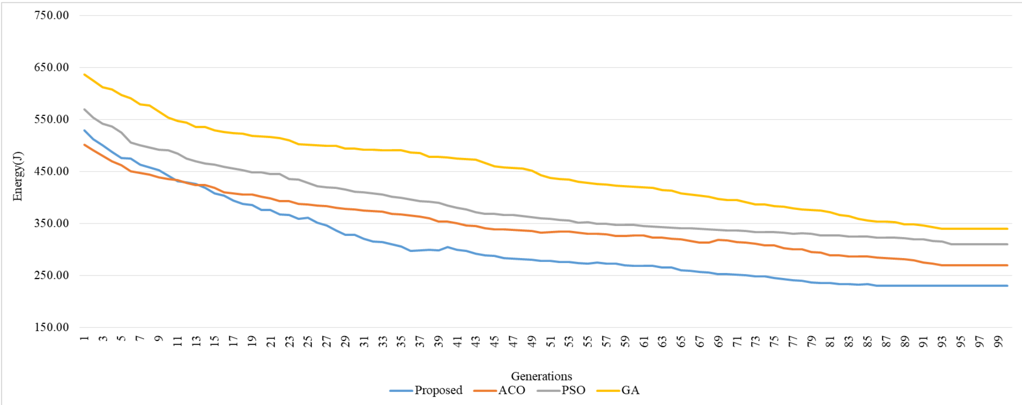

Fig. 5.3: EC analysis

tion regularly with other models, the pattern becomes increasingly evident. Accuracy is a key attribute for agricultural applications, and the proposed framework appears to successfully enhance its GPS accuracy, as demonstrated by the constant drop in error. Theoretically, it is more reliable and effective for UAV swarm-based multi-target GPS in SF, and the recommended approach maintains a lower error rate and less unpredictability in performance by its final iteration when compared to the other models. The recommended model's converging sequence indicates it is highly optimized, as it changes rapidly to the task and sustains performance over time. The proposed framework is appropriate for addressing the complicated challenges of SM environments requiring accuracy and adaptability due to its reliability and lower, more predictable error path.

Figure 5.3 presents a graph of the average aggregate unit EC over 100 iterations for four distinct algorithm choices. Starting at the lowest point and maintaining a minimal EC impact across any era, it is readily apparent that the proposed MOEA regularly dominates in energy efficiency. The next step, PSO, consistently consumes more energy than MOEA while maintaining comparable performance. Although ACO and PSO begin on similar ground levels, the former's rapid EC decrease over iterations indicates that ACO is less efficient in optimization. After increasing time, the GA generally concludes that there is more EC than any other algorithm, starting with the highest consumption. The proposed MOEA may be a better, more cost-effective, and better for the environment way to coordinate UAV swarm operations in this case. It is better than other known algorithms with over 100 iterations in terms of EC in the whole system.

Figure 5.4 compares the performance of the suggested MOEA to that of ACO, PSO, and GA regarding the total number of physical conflicts that ensued over 100 iterations. The obvious downward path of the proposed

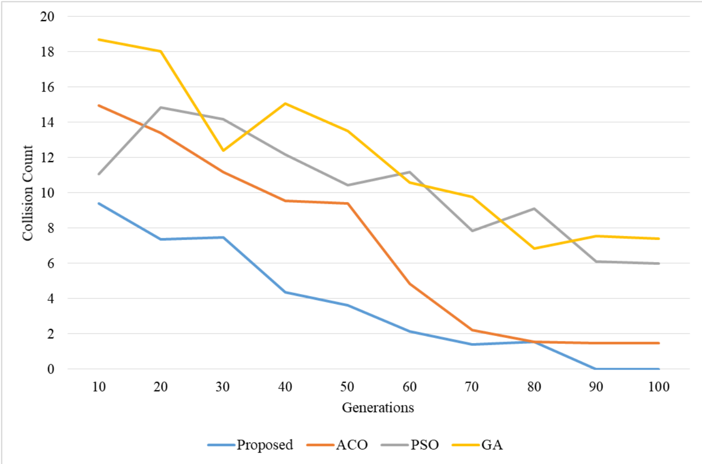

Fig. 5.4: Collision analysis for multiple iterations

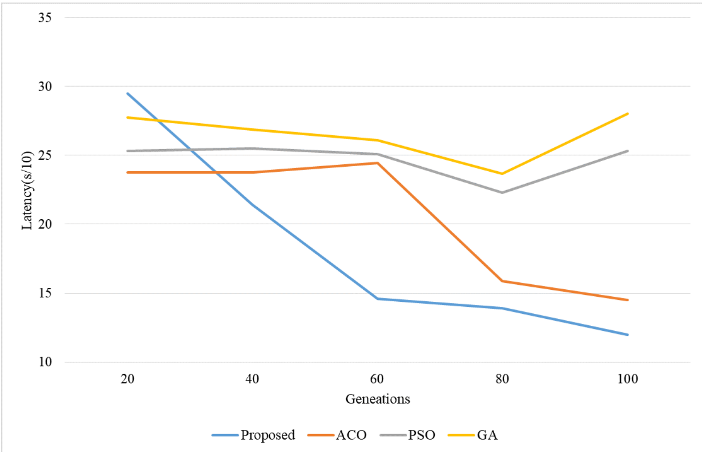

Fig. 5.5: Latency analysis for the compared models

MOEA, starting at 9 in the 10th iteration and successfully decreasing to zero in the 90th, demonstrates an optimization in preventing physical collisions. Conversely, the ACO begins at a higher level, approximately 15, and gradually decreases until it detects collisions at the 100th iteration. After starting in the middle of the group, PSO decreases until it maintains above five in the last generation, demonstrating success in avoiding collisions. GA exhibits the least effective performance among the examined methods, starting with the highest collision rate at over 18 and ending with a rate of approximately 7, even though it reduces by more than half towards the end. Findings illustrate how the proposed MOEA can improve UAV swarm operations and minimize collisions, making the system reliable and secure in future iterations.

Figure 5.5 provides the data on system performance delay for the proposed MOEA across 100th iterations compared to ACO, PSO, and GA models. With a delay reduction from 29.49 in the 20th iteration to 11.97 in the 100th, the proposed MOEA significantly improves execution speed with each successive generation. While ACO's latency is initially less than the proposed system at the 20th iteration, it increases in performance, only decreasing to 14.50 by the 100th iteration. PSO starts at 25.30 and continues similarly throughout the iterations, indicating a plateau in delay reduction, whereas GA shows lower-quality results. From iteration 27.73 to the 100th iteration, when GA's latency reaches 28.03 (which indicates a drop in performance), they are typically the highest. The data shows that by the 100^{th} iteration, the proposed MOEA has the fastest execution speed compared to the other models. It also keeps changing, which shows how well and quickly it works to reduce system latency.

MOEAs require plenty of computing power to maintain a balance in UAV swarm EC, communication effectiveness, and task service. O(N.D.) for setup, O(N.E.) for fitness review, O(M.N2) for selection, and O(N.D.) for genetic functions like crossover and mutation all contribute to the total time complexity. This study can employ the following analysis to determine the overall cost period: The formula for calculating the total period of cost is O(G.N2.M+G.N.D.E), where G represents the total number of iterations. The primary explanation for the level of complexity of memory management is the storage of data for the entire population (O (N.D.)) and fitness metrics (O (N.M.)). Real-world mobile applications could potentially leverage device speed and concurrent processing to alleviate these demands. To effectively manage large-scale UAV-swarm installations, we need to conduct research and apply the findings by modifying the algorithm for specific problem scenarios.

6. Conclusion. The research accurately localizes multiple moving targets in Smart Farming (SF) environments by introducing an optimized pre-emptive Unmanned Aerial Vehicle (UAV) swarm model. The Multi-Objective Evolutionary Algorithm (MOEA) enhances the framework's capacity to adapt to dynamic circumstances by improving its communication, task service, and energy consumption features. Using UAV swarms in SF requires the implementation of a holistic approach with multiple objectives. The developed blueprint, a significant advancement in SM techniques, aims to optimize the behaviour of UAV swarms in both static and dynamic environments. This MOEA-optimized UAV swarm system has the potential to significantly improve the productivity, effectiveness, and sustainability of SF services.

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