Optimization Techniques for Multi Cooperative Systems MCTR 1021
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SWARM ROBOTS FOR DYNAMIC FIREFIGHTING (ADAPTIVE COVERAGE CONTROL)

By

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This is to certify that:

(i) the report comprises only our original work toward the course project,

(ii) due acknowledgment has been made in the text to all other material used

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Chapter 1

Introduction

1.1 Overview of the Topic

Swarm robots for dynamic firefighting represent a cutting-edge application of multi-robot systems, where a team of autonomous robots collaborates to contain and monitor spreading fires in real-time. This approach, known as adaptive coverage control, involves robots dynamically adjusting their positions to maintain optimal coverage of the fire boundary while minimizing travel distance and ensuring balanced energy consumption across the team. In a two-dimensional environment with obstacles and an evolving fire region, the challenge lies in formulating an optimization problem that accounts for decision variables such as robot positions and velocities, objective functions like boundary coverage and energy balance, and constraints including velocity limits and collision avoidance. This project aims to develop a simulation-based framework to address these issues, ultimately enhancing fire containment strategies. Building on this foundation, the following sections will review relevant literature to contextualize recent advancements.

1.2 Literature Review

Swarm robots for dynamic firefighting involve deploying a team of autonomous robots to monitor and contain spreading fires in real-time. This requires adaptive coverage control, where robots adjust their positions to cover evolving fire boundaries while minimizing travel distance and balancing energy consumption. As outlined in the problem formulation, this is a multi-objective optimization problem involving decision variables (robot positions and velocities), objective functions (e.g., minimizing uncovered boundary, travel distance, and energy imbalance), and constraints (e.g., velocity limits, collision avoidance, and energy capacity).

The literature review below draws from recent articles (2018–2025) that apply meta-heuristic algorithms to similar problems. These algorithms help solve the complex, non-linear optimization challenges in swarm robotics by exploring large solution spaces efficiently. The review highlights how these works address dynamic environments, compares their approaches to the given formulation, and identifies benchmarks and metrics for evaluating the project's results.

Chapter 2

Condensed Literature Review: Swarm Robots for Dynamic Firefighting

2.1 Overview

Recent work (2018–2025) applies metaheuristics to multi-robot coverage, path planning, and information acquisition—problems that mirror our dynamic firefront tracking task. Across these studies, algorithms balance exploration vs. exploitation to search large, non-convex spaces, with evaluation typically reported via coverage ratio, path length/smoothness, collision penalties, and convergence time.

ACO for swarm coordination. [1] surveys pheromone-driven Ant Colony Optimization for discrete pathfinding/coverage (e.g., TSP), showing how evaporation and heuristic biasing stabilize convergence and provide strong combinatorial seeds for multi-robot routes.

SA for ergodic coverage. [2] uses Simulated Annealing to tune target distributions for ergodic control so that team trajectories proportionally sample high-information regions—directly relevant to maintaining coverage on an evolving fire boundary under uncertainty.

Hybrid Firefighter Optimization. [3] introduces a hybrid population-based scheme mixing GA/PSO/SA ideas to improve local-optima escape and robustness—useful for non-stationary, cluttered wildfire scenarios.

PSO family for motion quality. PSO with Sine/Lévy perturbations yields shorter, smoother, collision-aware paths in cluttered maps [4], while a PSO–GA hybrid improves global search and stagnation resistance for multi-UAV coverage [5].

Implications for our formulation. The literature supports our multi-objective cost $J = \alpha_1 J_{\text{cov}} + \alpha_2 J_{\text{dist}} + \alpha_3 J_{\text{bal}}$: ACO and SA-ergodic inform *coverage* metrics; PSO and PSO-hybrids target *distance/smoothness* (and collisions); hybrids like FFO motivate robust search.

Accordingly, we compare GA/PSO/SA (noting hybrid variants) on shared benchmarks using boundary-coverage deficit, total path length, collision/smoothness penalties, and convergence time.

2.2 Article Summaries

1. Ant Colony Optimization for Swarm Robotics [1]

Objective: To optimize swarm robotic group control, focusing on the Traveling Salesman Problem (TSP) as a representative combinatorial problem, where microrobots coordinate for optimal pathfinding and task execution.

Objective Function: Minimize total path length (optimal tour) for path coverage with constraints:

$$\min_{(i,j)\in \text{tour}} \sum d_{ij}$$

- d_{ij} is the distance (or cost) between city/node i and city/node j,
- ”tour” refers to the sequence of visited nodes forming a complete route.

Constraints:

- Maximum iterations for the algorithm
- Graph sizes vary (20 to 200 vertices)
- Number of ants (5 to 400)
- Parameters regulating pheromone intensity and evaporation

Optimization Algorithm: Ant Colony Optimization (ACO) metaheuristic inspired by ant foraging behavior. Uses pheromone trails to probabilistically guide search agents (ants) toward the best routes. Evaporation factor prevents premature convergence to suboptimal paths. Iterative probabilistic exploration with positive feedback mechanisms for solution improvement.

Accomplishments:

- Scalable to varying graph sizes and numbers of ants without loss of solution quality.
- Able to find near-optimal solutions efficiently for combinatorial pathfinding problems.
- Demonstrated importance of fine-tuning parameters (Q, p) to balance exploration and exploitation.
- Probabilistic pheromone evaporation helped to avoid local minima.
- Computational experiments showed consistent convergence with varying graph configurations.

Shortcomings:

- Algorithm convergence rate is not predictable.
- Limited to relatively small to medium-sized problems due to computational cost for larger graphs.
- No explicit consideration of real-time dynamics or environmental uncertainty.
- Mainly evaluated on static problem instances, which may limit applicability to dynamic firefighting scenarios.
- Energy consumption and multi-objective trade-offs, such as coverage vs. speed, are not explicitly modeled.

Results: Achieved reliable path coverage with iteration counts typically between 75 and 300. Execution times increased with problem size (number of vertices), e.g., 20 vertices took about 23 seconds, while 200 vertices took over 168 seconds. Effective selection of pheromone parameters Q and p significantly influenced solution quality and search efficiency. Outperformed traditional combinatorial methods in time-to-solution for tested cases.

Relevance : Provides a strong foundation for swarm robot coordination using metaheuristic search. Illustrates key parameter tuning needed for adaptive coverage control. Though tested on static graphs, principles are adaptable for dynamic environments with extensions. Useful performance metrics include solution quality (path length), computational time, and number of iterations to convergence.

2. SA for Multi-Robot Ergodic Information Acquisition [2]

Goal: Allocate robot trajectories proportional to spatial information density. **Information Metric:**

$$E = -\sum_i p_i \log p_i$$

where p_i represents the probability of information presence in region i. **Method:** SA tunes the ergodic target distribution while robots execute ergodic control laws. **Outcome:** Smooth and robust trajectories under uncertainty; scalable for large teams.

Accomplishments:

- Provides a dynamic adaptation mechanism that shifts from uniform exploration to focused sampling.
- Avoids local minima through SA's stochastic search process.
- Ensures ergodic coverage by linking entropy to the optimization objective.
- Scales efficiently to multi-robot teams through distributed trajectory updates.

Shortcomings:

- Computational complexity increases significantly in large or complex environments.
- Performance is highly sensitive to the annealing schedule and discretization resolution.
- Focuses primarily on information acquisition without addressing energy use or obstacle avoidance.

3. Firefighter Optimization (FFO) Hybrid Metaheuristic [3]

Goal: Solve complex high-dimensional optimization problems by balancing exploration and exploitation inspired by real firefighter collaboration tactics.

Objective Function: Problem-specific; generally any $f(x)$ to be minimized over agent positions $x \in \mathbb{R}^n$ within defined bounds.

Algorithm: Population-based hybrid metaheuristic combining Genetic Algorithm (GA) crossover and mutation, Particle Swarm Optimization (PSO)-inspired social learning, and Simulated Annealing (SA) temperature-controlled local search. Agents represent candidate solutions. Adaptive step size, perturbations, and cooling schedules dynamically adjust search behavior. Stagnation escape via guided perturbations toward best solutions.

Accomplishments:

- Hybrid design exploits complementary strengths of GA, PSO, and SA.
- Adaptive mechanisms improve convergence and solution quality.
- Efficient search demonstrated on functions across dimensions and complexities.
- Provides trajectory and fitness history useful for deep analysis.

Shortcomings:

- Moderate to high computational cost depending on parameter tuning and problem size.
- Performance sensitive to parameter settings (mutation rate, cooling schedule).
- General-purpose algorithm requiring custom problem-specific objective design.
- Consistency across runs requires multiple executions due to stochastic nature.

Optimization Algorithms Compared:

- Ant Colony Optimization (ACO)
- Bat Algorithm (BA)
- Biogeography-Based Optimization (BBO)

- Flower Pollination Algorithm (FPA)
- Genetic Algorithm (GA)
- Grey Wolf Optimizer (GWO)
- Harmony Search (HS)
- Particle Swarm Optimization (PSO)
- Simulated Annealing (SA)
- Tabu Search (TS)
- Whale Optimization Algorithm (WOA)
- Cuckoo Search (CS)
- Firefly Algorithm (FA)

Results: Competitive or superior performance against 13 popular metaheuristic algorithms on 24 benchmark functions. Achieves better fitness values, convergence speed, and exploration balance. Shows robustness in escaping local optima and avoids stagnation.

Relevance: This study presents a novel hybrid metaheuristic inspired by real firefighter collaboration, designed to solve complex high-dimensional optimization problems with strong exploration-exploitation balance.
Its adaptive, hybrid approach offers robust, efficient optimization relevant for dynamic swarm robotic firefighting and resource allocation tasks.

4. PSO + Sine/Cosine for Path Planning (2025) [4]

Objective Function:

$$F = w_1 L + w_2 S + w_3 C$$

where:

- L = path length,
- S = smoothness cost,
- C = collision penalty,
- w_i = corresponding weights.

Enhancement: PSO velocity updates are perturbed by sinusoidal oscillations to escape local minima. **Outcome:** Generated shorter, smoother, and collision-free paths, suitable for cluttered and dynamic environments.

Accomplishments:

- Enhanced PSO with sinusoidal perturbations improves exploration and reduces the chance of premature convergence.
- Generated shorter, smoother, and collision-free paths suitable for cluttered environments.
- Improved path quality compared to standard PSO without significant computational cost.
- Demonstrates adaptability to dynamic scenarios.

Shortcomings:

- Performance remains sensitive to parameter tuning such as inertia weight and oscillation parameters.
- Lacks explicit consideration of multi-robot coordination or energy constraints.
- Scalability to very large environments or robot teams was not thoroughly evaluated.

5. Hybrid PSO–GA for Multi-Robot Coverage [5]

Concept: Integrate PSO's exploitation and GA's exploration via crossover and mutation operations. **Advantages:** Improved global search, reduced stagnation, and enhanced coverage efficiency. **Limitation:** Increased computational complexity and parameter tuning effort.

Accomplishments:

- Outperforms standalone PSO and GA approaches in both convergence speed and solution quality.
- Achieves improved global search capability while maintaining efficient local exploitation.
- Demonstrates scalability across various numbers of UAVs and waypoint densities.
- Effectively mitigates individual weaknesses of PSO (local minima) and GA (slow convergence).

Shortcomings:

- Computational complexity increases steeply with problem size, limiting real-time use.
- Requires careful parameter tuning (mutation rate, crossover strategy, PSO weights).
- Energy use, communication overhead, and collision avoidance are not explicitly modeled.
- Waypoint-based modeling may oversimplify continuous, obstacle-rich environments.

2.3 Comparative Discussion

Table 2.1: Comparative Summary of Reviewed Studies

Aspect	**ACO** [1]	**SA-Ergodic** [2]	**FFO** [3]	**PSO-Hybrid** [4]	**GA** [5]
Domain	Application	Info acquisition	Optimization	Path planning	Coverage
Decision Variables	tour	Distributions	Agents	Waypoints	Waypoints
Objective	Pathfinding	Entropy	Minimization	Length/smoothness	Coverage
Metaheuristic	Pheromone-based	SA	Hybrid	PSO+GA/Sine-Cosine	Hybrid

Key Observations:

- SA excels in discrete combinatorial optimization and uncertainty handling.
- PSO is effective for continuous trajectory optimization.
- GA enhances diversity and avoids premature convergence when hybridized.
- Frontier-based swarming offers simplicity and robustness but lacks multi-objective adaptability.
- FFO hybrid combines GA, PSO, and SA strengths, providing robustness, escape from local optima, and adaptive search control.
- FFO shows competitive performance on multiple benchmark functions, demonstrating scalability and solution quality.
- Effective at combinatorial path optimization with probabilistic pheromone evaporation to avoid local minima.
- Performance heavily depends on tuning pheromone parameters for balance of exploration and exploitation.
- Outperforms standalone PSO and GA in convergence speed and solution quality.
- Scalable to varying numbers of UAVs and waypoint densities.

2.4 Identified Gaps

- Limited focus on **dynamic boundary tracking** (e.g., moving firefronts).
- Inadequate consideration of **energy fairness** and **workload balance**.
- Lack of real-time adaptation under evolving environmental conditions.

- Absence of a unified **GA–PSO–SA benchmark** under identical conditions.
- Current metaheuristics often do not combine multiple search paradigms adaptively as FFO does.
- Limited practical applications of hybrid algorithms such as FFO in swarm firefighting contexts.
- Limited real-time adaptation for dynamic or uncertain environments.
- Neglects energy consumption and multi-objective trade-offs like coverage versus speed
- Computational cost grows sharply with problem size, limiting real-time use.
- Requires careful parameter tuning for effective performance.

2.5 Relevance to the Current Project

This research addresses the above limitations by focusing on **dynamic fire boundary coverage** using cooperative swarm robots. The proposed study introduces a multi-objective framework balancing:

- energy efficiency,
- boundary-tracking accuracy,
- obstacle avoidance,
- and communication connectivity.
- Robust adaptive optimization inspired by Firefighter Optimization hybrid metaheuristic principles.
- Provides foundational principles for decentralized swarm coordination using metaheuristics.
- Parameter tuning insights are valuable for developing adaptive coverage control in dynamic firefighting.
- Demonstrates the benefits of hybrid metaheuristic approaches for multi-robot coverage.
- Highlights challenges in computational complexity and multi-objective control.

A comparative evaluation of GA, PSO, and SA on shared benchmarks will yield valuable insights into their relative effectiveness in highly dynamic firefighting scenarios.

Chapter 3

Methodology

3.0.1 Problem Formulation

The objective of this project is to design a simulation-based framework in which a swarm of robots cooperatively contain a dynamically spreading fire. Each robot must adapt its position to maintain continuous coverage of the fire boundary while minimizing total travel distance and balancing energy consumption across the team.

The environment is modeled as a two-dimensional workspace $\mathcal{W} \subset \mathbb{R}^2$ containing obstacles $\mathcal{O} \subset \mathcal{W}$ and a dynamic fire region $\mathcal{F}(t)$ whose boundary $\Gamma(t) = \partial\mathcal{F}(t)$ evolves over time. The fire boundary is discretized into M_k sampled points $s_j^k \in \Gamma(t_k)$ at each time step $t_k = k\Delta t$.

Robot Model. A team of N robots is deployed in the workspace. Each robot i has position $x_i(t) = [x_i(t), y_i(t)]^\top$ and control input $u_i(t)$ corresponding to its velocity. The discrete-time motion model is given by

$$x_i^{k+1} = x_i^k + \Delta t\, u_i^k, \qquad i = 1, \ldots, N, \quad k = 0, \ldots, T-1 \tag{3.1}$$

subject to a maximum velocity constraint $\|u_i^k\| \leq v_{\max}$.

Coverage Model. Each robot provides fire coverage to nearby boundary points within its sensing range r_s. The coverage strength of robot i on boundary point s_j^k is modeled as

$$p_{ij}^k = \exp\left(-\frac{\|s_j^k - x_i^k\|^2}{2\sigma^2}\right), \tag{3.2}$$

where σ controls the rate of coverage decay with distance. The combined team coverage at each point is

$$C_j^k = 1 - \prod_{i=1}^{N} \left(1 - p_{ij}^k\right). \tag{3.3}$$

Decision Variables. The optimization problem determines the set of positions and velocities for all robots over time:

$$\mathbf{X} = \{x_i^k\}, \qquad \mathbf{U} = \{u_i^k\}, \quad \forall i = 1..N,\ k = 0..T-1.$$

Objective Functions. The problem is formulated as a multi-objective optimization problem with three goals:

(a) **Boundary Coverage:** Minimize uncovered portions of the fire boundary:

$$J_{\text{cov}} = \sum_{k=0}^{T} \sum_{j=1}^{M_k} w_j^k [1 - C_j^k]. \tag{3.4}$$

This term ensures continuous fire boundary coverage, minimizing unmonitored regions and improving containment efficiency.

(b) **Travel Distance:** Reduce total path length traveled by all robots:

$$J_{\text{dist}} = \sum_{i=1}^{N} \sum_{k=0}^{T-1} \|x_i^{k+1} - x_i^k\|. \tag{3.5}$$

This term reduces unnecessary motion and response time, enabling faster repositioning around the spreading firefront.

(c) **Energy Balance:** Distribute energy consumption evenly among all agents:

$$J_{\text{bal}} = \text{Var}\left(\sum_{k=0}^{T-1} \|u_i^k\|^2\right). \tag{3.6}$$

This term balances energy use among all robots, preventing early depletion and maintaining overall swarm endurance.

The overall multi-objective cost function is expressed as a weighted sum:

$$\min_{\mathbf{X},\mathbf{U}} \ J = \alpha_1 J_{\text{cov}} + \alpha_2 J_{\text{dist}} + \alpha_3 J_{\text{bal}}, \tag{3.7}$$

where $\alpha_1, \alpha_2, \alpha_3 > 0$ are the relative weights.

The optimization problem is subject to the following physical and operational constraints, which ensure realistic swarm movement and safe operation:

Constraints. The optimization problem is subject to the following physical and operational constraints:

Constraint (1): Motion model	$x_i^{k+1} = x_i^k + \Delta t\, u_i^k,$	(3.8)
Constraint (2): Velocity limit	$\|u_i^k\| \leq v_{\max},$	(3.9)
Constraint (3): Collision avoidance	$\|x_i^k - x_\ell^k\| \geq d_{\min}, \qquad \forall i \neq \ell,$	(3.10)
Constraint (4): Communication connectivity	$\exists\, \ell \neq i : \|x_i^k - x_\ell^k\| \leq r_c,$	(3.11)
Constraint (5): Energy limit	$\sum_{k=0}^{T-1} \|u_i^k\|^2 \Delta t \leq E_i^{\max},$	(3.12)
Constraint (6): Workspace constraint	$x_i^k \in \mathcal{W} \setminus \mathcal{O}.$	(3.13)

Assumptions.

- The fire boundary $\Gamma(t)$ is estimated or known at each time step.
- Robots operate under single-integrator kinematics.
- Obstacles are static and known in advance.
- Sensing and communication ranges are circular with radii r_s and r_c respectively.
- Initial robot positions x_i^0 satisfy connectivity and workspace constraints.

Relation to Project Goals. This formulation achieves the project's core objectives:

- Minimizing J_{dist} reduces total travel distance and unnecessary motion.
- Minimizing J_{cov} ensures complete boundary coverage for effective fire containment.
- Minimizing J_{bal} balances energy usage, maintaining system endurance and fairness among robots.

The resulting optimization framework can be solved using metaheuristic algorithms such as Genetic Algorithm (GA), Simulated Annealing (SA), or Particle Swarm Optimization (PSO). In the implemented code, the fitness value J is computed as the weighted sum of J_{cov}, J_{dist}, and J_{bal} for given decision variables X and U, enabling metaheuristic optimization of the swarm configuration.

Bibliography

[1] T. A. Vakaliuk, R. P. Kukharchuk, O. V. Zaika, and A. V. Riabko. Optimization of swarm robotics algorithms. *Radio Electronics, Computer Science, Control*, 2022.

[2] Benjamin Wong, Aaron Weber, Mohamed M. Safwat, Santosh Devasia, and Ashis G. Banerjee. Simulated annealing for multi-robot ergodic information acquisition using graph-based discretization, 2025.

[3] M. Z. Naser and A. Z. Naser. The firefighter algorithm: A hybrid metaheuristic for optimization problems. *arXiv preprint arXiv:2406.00528*, 2024.

[4] Zhiwei Yang et al. Improved particle swarm optimization algorithm for mobile robot path planning, 2024.

[5] Hassan Haghighi, Seyed Hossein Sadati, S.M. Mehdi Dehghan, and Jalal Karimi. Hybrid form of particle swarm optimization and genetic algorithm for optimal path planning in coverage mission by cooperated unmanned aerial vehicles. *Journal of Aerospace Technology and Management*, 12, 2020.