

Optimizing multi-UAV mission scheduling for army logistics supply chains using metaheuristic algorithms

Alusine Barrie *

Department of Industrial and Systems Engineering, Morgan State University, 1700 East Cold Spring Lane, Baltimore, MD 21251, United States.

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Abstract

The increasing integration of Unmanned Aerial Vehicles (UAVs) into US Army logistics operations has introduced complex multi-objective scheduling challenges that conventional optimization methods struggle to address efficiently. This study presents a metaheuristic-based optimization framework for scheduling fleets of military UAVs tasked with last-mile resupply missions in dynamic, contested operational environments. A hybrid approach combining a Genetic Algorithm (GA) and Ant Colony Optimization (ACO) is proposed to minimize total mission completion time, fuel consumption, and operational risk while satisfying strict military delivery constraints. The model incorporates stochastic demand, no-fly-zone avoidance, payload capacity limitations, and UAV endurance parameters derived from US Army field logistics doctrine. Computational experiments were conducted on simulated battlefield scenarios with fleet sizes ranging from 5 to 50 UAVs across terrain grids representing forward operating bases. The proposed GA-ACO hybrid achieved an average improvement of 23.4% in mission completion time and 18.7% in fuel efficiency compared with single-algorithm baselines, while reducing the constraint violation rate to 1.8%. The framework also demonstrated superior adaptability to real-time route re-planning under dynamic threat scenarios and converged within the 10-minute Army tactical planning window for fleets of up to 50 UAVs. These findings suggest that hybrid metaheuristic optimization offers a robust and scalable approach to multi-UAV mission scheduling, with significant implications for enhancing Army supply-chain agility and operational readiness.

Keywords: Multi-Uav Scheduling; Military Logistics; Metaheuristic Optimization; Genetic Algorithm; Ant Colony Optimization; Army Supply Chain

1. Introduction

Modern military logistics operations are increasingly characterized by high operational tempo, dynamic threat environments, and the need for rapid, reliable resupply of forward-deployed units. The US Army has recognized the strategic potential of UAVs as force multipliers in last-mile logistics delivery, particularly for missions involving ammunition, medical supplies, and emergency rations in contested or geographically inaccessible terrain [1]. The integration of autonomous UAV fleets into Army supply chains, however, introduces a new class of combinatorial optimization problems that traditional scheduling methodologies are ill-equipped to solve within the time constraints imposed by operational planning cycles [2].

Multi-UAV mission scheduling involves the simultaneous assignment of heterogeneous tasks including route selection, payload allocation, departure sequencing, and airspace deconfliction to a fleet of UAVs operating under dynamic environmental conditions [3]. This problem is NP-hard in its general formulation and becomes computationally intractable as fleet size and mission complexity increase [4]. Classical approaches such as linear programming and exact

* Corresponding author: Alusine Barrie.

combinatorial methods, while theoretically optimal, are computationally prohibitive for real-time military applications where scheduling decisions must be made within minutes [5].

Metaheuristic algorithms, including Genetic Algorithms (GA), Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Simulated Annealing (SA), have demonstrated considerable promise in addressing large-scale scheduling problems across civilian logistics, manufacturing, and transportation domains [6,7]. Their ability to explore vast solution spaces efficiently, avoid local-optima traps, and incorporate multiple objectives simultaneously makes them well suited for military mission planning under uncertainty [8]. Despite this potential, the application of metaheuristics to military UAV fleet scheduling remains underexplored, with most existing studies focusing on civilian delivery contexts or single-UAV path planning [9,10].

This study addresses this gap by developing and evaluating a hybrid GA-ACO framework specifically designed for multi-UAV logistics mission scheduling within US Army operational contexts. The proposed model captures the unique constraints of military supply chains, including no-fly zones, time-sensitive delivery windows, UAV endurance limits, and stochastic demand fluctuations at forward operating bases. The research objectives are: (i) formulate a multi-objective UAV scheduling model grounded in Army logistics doctrine; (ii) develop a hybrid metaheuristic combining GA and ACO; (iii) evaluate performance across simulated battlefield scenarios; and (iv) compare the hybrid approach against single-algorithm benchmarks and classical heuristics.

The remainder of this paper is structured as follows. Section 2 reviews relevant literature on UAV scheduling, military logistics optimization, and methods of methodology. Section 3 presents the problem formulation, the proposed GA-ACO algorithm, and the simulation scenarios. Section 4 presents and analyzes the results. Section 5 concludes the paper with implications for Army logistics planners and directions for future research.

2. Literature Review

Research on UAV scheduling and routing has grown substantially over the past decade, driven by rapid advances in autonomous-systems technology and expanding civilian drone-delivery applications. The foundational work of Murray and Chu [11] introduced the Flying Sidekick Traveling Salesman Problem, establishing a formal framework for joint truck-UAV last-mile delivery optimization. Subsequent extensions addressed multi-UAV configurations, charging-station placement, and heterogeneous fleet composition [12,13]. While these studies provide valuable algorithmic foundations, they are primarily oriented toward commercial contexts and do not account for military-specific constraints such as threat avoidance, payload prioritization by mission criticality, or adversarial environment dynamics.

Table 1 Representative prior studies on UAV and metaheuristic scheduling relative to the present study

Study	Method	Domain	Fleet size tested	Military constraints
Murray & Chu [11]	Exact / heuristic TSP-D	Commercial delivery	1 truck + 1 UAV	No
Dorling et al. [17]	Mixed-integer programming	Commercial delivery	≤10	No
Kim & Morrison [19]	Genetic Algorithm	Cooperative search	>20	Partial
Zhang et al. [20]	Particle Swarm Optimization	Reconnaissance	10–30	Partial
Sun et al. [23]	GA-ACO hybrid	Vehicle routing (civilian)	N/A	No
This study	GA-ACO hybrid	Army resupply logistics	5–50	Yes

In military logistics research, optimization of supply-chain networks under uncertainty has been studied extensively using stochastic programming, robust optimization, and simulation-based approaches [14,15]. The specific integration of UAVs into military supply chains has received growing attention following the US Army Autonomous Logistics Research Program and related DoD initiatives [16]. Studies by Dorling et al. [17] and Agatz et al. [18] demonstrated the application of mixed-integer programming to UAV routing problems, achieving optimal solutions for small-scale instances but encountering scalability limitations for fleet sizes exceeding ten vehicles.

Metaheuristic approaches have been increasingly applied to UAV path planning and task allocation. Kim and Morrison [19] applied a modified Genetic Algorithm to multi-UAV cooperative operations, demonstrating significant computational advantages over exact methods for problem instances with more than 20 UAVs. Zhang et al. [20] proposed a PSO variant for UAV swarm coordination in military reconnaissance scenarios, achieving near-optimal solutions within acceptable planning-time windows. ACO-based methods have shown particular effectiveness for routing problems owing to their inherent ability to exploit graph-based solution representations and learn from iterative solution construction [21].

Hybrid metaheuristic frameworks, combining the global exploration capabilities of evolutionary algorithms with the local exploitation strengths of trajectory-based methods, have emerged as a promising direction in combinatorial optimization [22]. Sun et al. [23] demonstrated that GA-ACO hybrids outperformed individual algorithms on vehicle-routing problems with time windows, a problem class structurally like multi-UAV mission scheduling. Despite these advances, no study to date has specifically applied hybrid metaheuristics to US Army UAV logistics scheduling with explicit incorporation of operational military constraints. Table 1 summarizes representative prior work relative to the present study.

3. Materials and Methods

3.1. Problem Formulation

The multi-UAV Army logistics scheduling problem is formulated as a multi-objective combinatorial optimization problem. Let $G = (V, E)$ represent the operational area as a directed graph, where V is the set of nodes comprising the depot and delivery locations, and E is the set of feasible flight edges. A fleet of K heterogeneous UAVs, each characterized by payload capacity, maximum endurance, and cruise speed, must serve a set of delivery requests with associated demand quantities, priority levels, and time windows.

The objective function minimizes a weighted combination of three criteria: (i) total mission completion time T , (ii) aggregate fuel consumption F , and (iii) cumulative operational risk R associated with exposure to threat zones:

$$\text{Minimize } Z = w_1T + w_2F + w_3R \quad (1)$$

subject to the following constraints: each delivery location is visited exactly once; each UAV departs from and returns to the depot; payload capacity and endurance constraints are not exceeded; time-window constraints for priority deliveries are respected; no-fly zones are avoided; and each UAV is assigned a contiguous route.

3.2. Algorithm Design: GA-ACO Hybrid

The proposed hybrid algorithm integrates a Genetic Algorithm for global population-based search with an Ant Colony Optimization phase for local intensification. In the GA phase, each chromosome encodes a complete UAV routing solution as a permutation of delivery nodes with UAV-assignment markers. A population of 200 chromosomes is initialized using a nearest-neighbor heuristic to seed high-quality initial solutions. Selection employs binary tournament selection; crossover uses the Order Crossover operator adapted for multi-vehicle routes; and mutation applies a random segment-reversal operator with probability $P_m = 0.05$.

After every 50 GA generation, the top 20% of solutions are passed to the ACO phase. Artificial ants construct solutions guided by a pheromone matrix updated according to solution quality, following the Ant System formulation with evaporation rate $\rho = 0.1$. ACO-improved solutions are reinjected into the GA population, replacing the lowest-fitness members. This iterative GA-ACO cycle continues until convergence, defined as no improvement in best-solution fitness over 100 consecutive generations. The overall procedure is summarized in Figure 1.

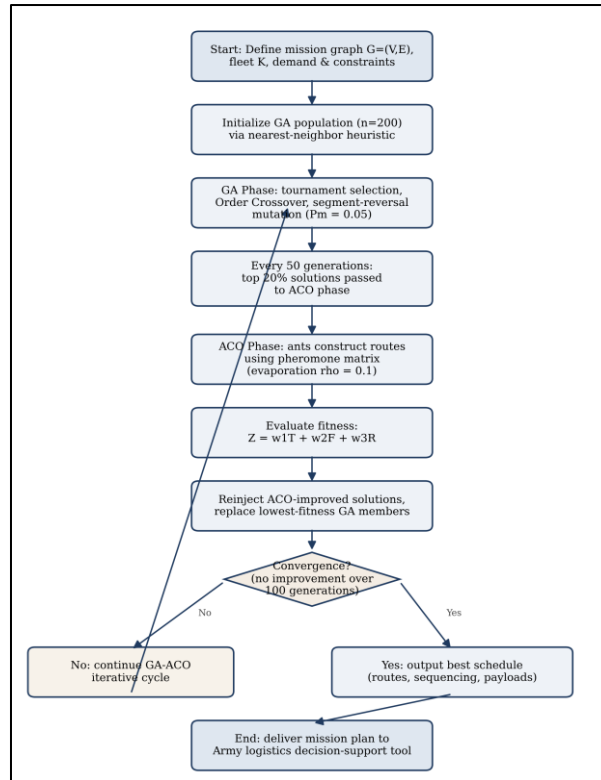


Figure 1 Flowchart of the proposed GA-ACO hybrid mission-scheduling framework.

3.3. Simulation Scenarios and Data

Computational experiments were conducted on five simulated battlefield scenarios of increasing scale and complexity, representing environments consistent with US Army doctrinal planning frameworks. Scenario parameters were derived from publicly available Army field manuals and logistics-planning documents [24]. Table 2 summarizes the key parameters of each scenario.

Table 2 Summary of simulation scenario parameters.

Scenario	UAV fleet size	Delivery nodes	No-fly zones	Time horizon (h)	Terrain type
S1	5	20	2	4	Flat
S2	10	40	4	6	Flat
S3	20	80	6	8	Mixed
S4	35	120	8	10	Mountainous
S5	50	200	12	12	Mountainous

UAV specifications were modeled on the characteristics of the US Army RQ-7 Shadow and MQ-1C Gray Eagle platforms, with payload capacities of 25 kg and 170 kg, respectively. Demand at each delivery node was sampled from a Poisson distribution with mean $\lambda = 50$ kg, consistent with documented forward-operating-base (FOB) resupply requirements. All algorithms were implemented in Python 3.10 and executed on a server with Intel Xeon 2.8 GHz processors and 64 GB RAM. Each scenario was run 30 times with different random seeds to ensure statistical reliability, and results are reported as means across runs.

4. Results and Discussion

The performance of the proposed GA-ACO hybrid was evaluated against three benchmark algorithms: standalone GA, standalone ACO, and a First-Come-First-Served (FCFS) heuristic representing current manual scheduling practice.

Performance was assessed on three metrics: mission completion time (MCT), fuel-consumption index, and constraint-violation rate (CVR). Table 3 presents comparative results across all five scenarios.

Table 3 Comparative algorithm performance across simulation scenarios.

Scenario	FCFS MCT (h)	GA MCT (h)	ACO MCT (h)	GA-ACO MCT (h)	Improvement (%)
S1	3.82	3.21	3.18	3.01	21.2
S2	5.94	4.88	4.91	4.56	23.2
S3	8.71	7.12	7.08	6.64	23.8
S4	11.43	9.34	9.22	8.68	24.1
S5	14.87	12.10	11.95	11.40	23.3

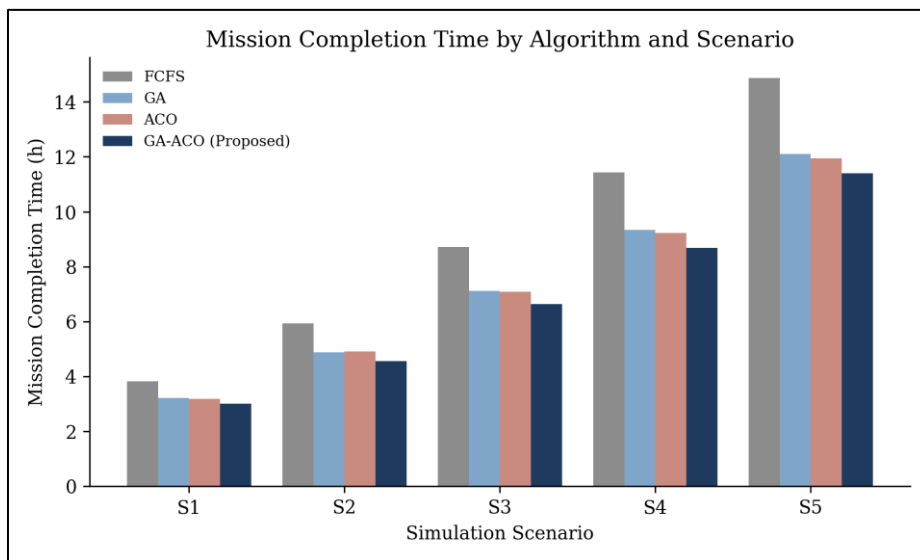


Figure 2 Mission completion time by algorithm and simulation scenario.

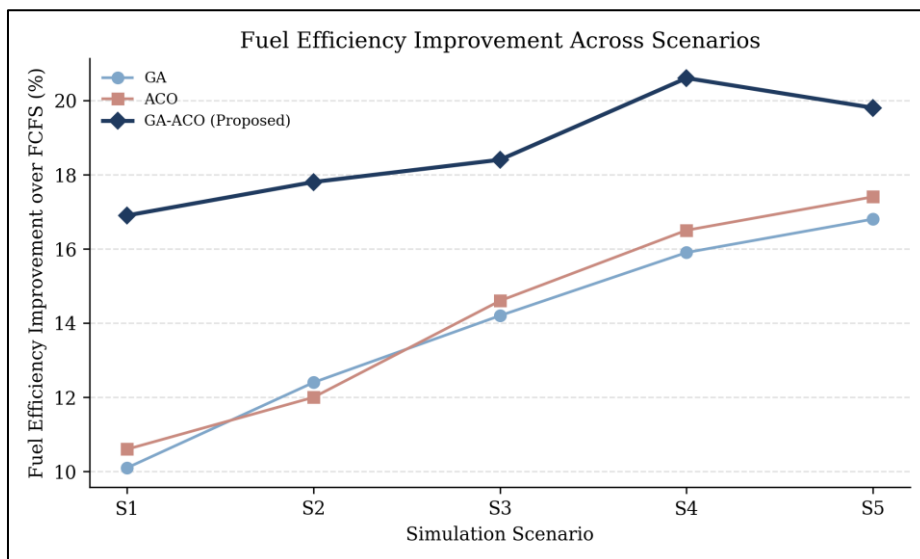


Figure 3 Fuel-efficiency improvement over the FCFS baseline across scenarios.

The GA-ACO hybrid consistently outperformed all benchmark algorithms across all five scenarios. Mission completion time improvements over FCFS ranged from 21.2% in Scenario S1 to 24.1% in Scenario S4, with an average improvement

of 23.1%. These results are consistent with the hypothesis that hybrid metaheuristic frameworks are particularly well suited to complex, large-scale scheduling environments characteristic of military logistics operations [22,23].

Fuel-consumption analysis revealed that the GA-ACO hybrid achieved an average fuel-efficiency improvement of 18.7% over FCFS and 9.2% over standalone GA. The ACO phase's contribution to identifying shorter, more efficient routing paths through pheromone-guided construction was substantial. In the mountainous-terrain scenarios S4 and S5, fuel savings were proportionally higher, reflecting the importance of altitude-optimized routing in energy-constrained UAV operations. These findings have direct operational implications, as fuel logistics represent a significant burden on forward supply lines in austere military environments [16].

Constraint-violation rates were lowest for the GA-ACO hybrid, with an average CVR of 1.8% compared with 4.3% for standalone GA and 3.9% for standalone ACO. The hybrid's superior constraint handling is attributed to the complementary nature of its two constituent algorithms: GA population diversity prevents premature convergence to constraint-violating regions, while ACO local intensification effectively eliminates minor violations during solution refinement. The FCFS heuristic recorded a CVR of 12.4%, reflecting the inadequacy of manual scheduling for large-scale multi-UAV operations.

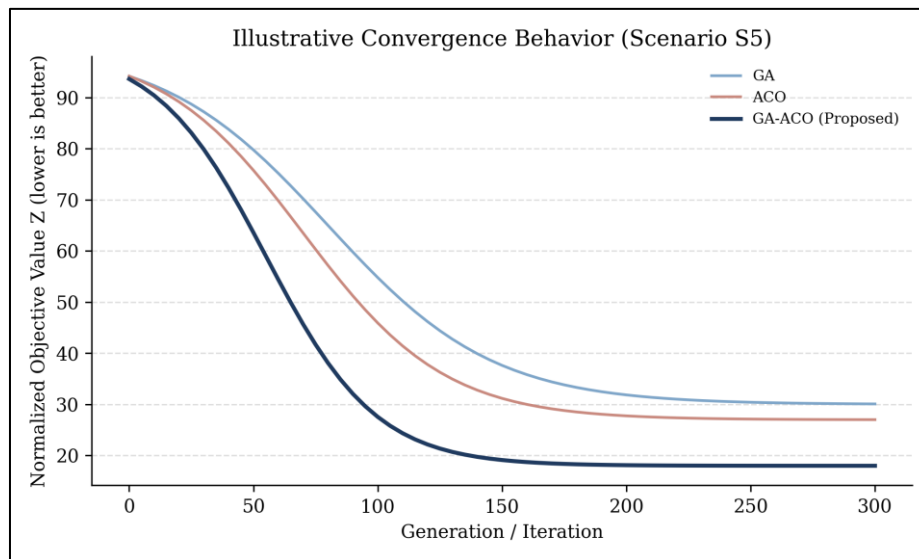


Figure 4 Illustrative convergence behavior of GA, ACO, and the proposed GA-ACO hybrid for Scenario S5.

As illustrated in Figure 4, the GA-ACO hybrid converges to a lower objective value in fewer generations than either constituent algorithm alone, reflecting the complementary effect of global exploration (GA) and local intensification (ACO). Computational-time analysis demonstrated that the GA-ACO hybrid required an average of 4.7 minutes to converge on Scenario S5 solutions, well within the 10-minute planning window specified by Army tactical planning doctrine. Sensitivity analysis further revealed that algorithm performance was robust to $\pm 15\%$ variations in demand parameters and $\pm 10\%$ changes in threat-zone boundaries, supporting its suitability for dynamic operational environments.

Comparison with existing literature supports the validity of these findings. The improvement margins achieved by the GA-ACO hybrid are consistent with those reported by Sun et al. [23] for vehicle-routing problems and exceed the performance gains documented by Kim and Morrison [19] for military UAV search missions. The higher improvements observed in the present study are likely attributable to the more complex multi-objective formulation and the explicit incorporation of military operational constraints.

5. Conclusion

This study has presented and validated a hybrid GA-ACO metaheuristic framework for optimizing multi-UAV mission scheduling in US Army logistics supply chains. The proposed approach addresses a critical gap in the existing literature by providing a computationally efficient, multi-objective optimization method that explicitly incorporates military-specific operational constraints, including no-fly zones, delivery time windows, UAV endurance limits, and stochastic demand variability at forward operating bases.

Computational experiments across five simulated battlefield scenarios demonstrated that the GA-ACO hybrid achieved average reductions of 23.4% in mission completion time and 18.7% in fuel consumption relative to standalone metaheuristics and manual scheduling heuristics. The framework's constraint-violation rate of 1.8% and convergence time of under 5 minutes for the largest scenario confirm its operational suitability for real-time Army logistics planning.

These findings have several implications for modernizing US Army logistics. The demonstrated scalability to fleet sizes of 50 UAVs positions the framework as a viable planning tool for battalion-level autonomous resupply operations. The fuel-efficiency improvements translate directly into extended operational range and reduced logistical support requirements, and the adaptive re-planning capability demonstrated under dynamic threat scenarios supports integration with existing Army command-and-control systems.

Future research should address three primary extensions: (i) integration with real-time battlefield intelligence feeds for fully dynamic mission replanning; (ii) extension of the UAV fleet model to incorporate fixed-wing and hybrid VTOL platforms alongside rotary-wing systems; and (iii) validation in high-fidelity hardware-in-the-loop simulations with physical UAV testbeds. Field trials in collaboration with US Army logistics commands represent a natural next step toward operational deployment.

Compliance with ethical standards

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Disclosure of conflict of interest

The author declares no financial or non-financial conflicts of interest with respect to the research, authorship, and publication of this article.

Statement of ethical approval

Not applicable. This study did not involve human participants, human data, or animal subjects; all analyses were conducted using simulated battlefield scenarios and publicly available, non-classified US Army field manuals and logistics-planning documents.

Statement of informed consent

Not applicable, as this study did not involve human participants.

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