

Bio-Inspired Swarm Intelligence for Decentralized UAV Fleet Coordination

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ABSTRACT

Coordinating fleets of unmanned aerial vehicles without a central controller is increasingly framed as a bio-inspired swarm-intelligence problem, drawing on decades of research into how flocks, ant colonies, and bee colonies achieve robust, scalable collective behavior from purely local interaction rules. This article synthesizes that literature as it applies specifically to decentralized UAV fleet coordination, tracing the line from Reynolds's boids model and stigmergic self-organization through population-based metaheuristics such as particle swarm optimization, ant colony optimization, grey wolf optimizer, and several more recent animal-inspired variants, to the consensus, potential-field, and distributed-auction theory that turns a bio-inspired optimizer into a genuinely decentralized fleet behavior. We then examine how these two threads combine in recent applied architectures for multi-UAV path planning, cooperative coverage search, and heterogeneous task allocation, and in the communication and routing substrate any of this coordination depends on. Read together, the evidence supports bio-inspired, layered swarm architectures as a coherent and increasingly well-evidenced design pattern for decentralized UAV fleets, while leaving field validation under contested communication, adversarial interference, and genuinely heterogeneous vehicle capability as substantially open research questions rather than solved engineering problems.

Keywords: swarm intelligence; unmanned aerial vehicles; decentralized coordination; bio-inspired optimization; multi-UAV path planning

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1. Introduction

A fleet of quadrotors surveying a wildfire perimeter, a swarm of fixed-wing drones relaying communications across a disaster zone, a cluster of agricultural UAVs mapping a field row by row — in every one of these scenarios, the individual vehicle is not the interesting engineering object. The fleet is. A single UAV with a good autopilot is a solved problem in most practical senses; a fleet of dozens or hundreds of UAVs that must divide a search area, avoid colliding with one another, keep formation under wind gusts, reroute around a jammed communication link, and do all of this without a central coordinator that any single vehicle's failure could take down, is a substantially different and much less settled problem. Centralized fleet management — a ground station that plans every vehicle's trajectory and pushes commands down a command-and-control link — works well for small numbers of cooperating aircraft with reliable connectivity, but it degrades badly exactly where UAV swarms are most useful: at scale, under contested or intermittent communications, and in environments where the ground station itself may be unreachable or a poor vantage point for real-time decisions.

Nature solved a structurally similar problem long before anyone was flying drones. Flocks of starlings, colonies of ants, and swarms of foraging bees all achieve coordinated, adaptive, large-scale collective behavior with no leader dictating individual movements and no member possessing anything like a global view of the group. Each individual follows a small set of local rules — respond to your nearest neighbors, deposit or follow a pheromone trail, communicate a waggle dance — and coherent, robust, scalable group behavior emerges from the aggregate of those local interactions. Craig Reynolds's boids model showed as early as 1987 that three simple local rules — separation, alignment, and cohesion — are sufficient to reproduce the qualitative look and robustness of real flocking behavior in simulation, without any bird in the model knowing where the flock as a whole was going [1]. That result, originally built for computer animation, turned out to be a founding document for an entire research program: if local rules can produce global coordination in nature, the same design principle ought to transfer to engineered multi-agent systems, including fleets of autonomous vehicles.

This article surveys that transfer as it applies specifically

to decentralized UAV fleet coordination. We are interested in two overlapping bodies of work that are often discussed separately but that, for UAV swarms, need to be read together. The first is bio-inspired swarm intelligence as an optimization and search paradigm — algorithms like particle swarm optimization, ant colony optimization, grey wolf optimizer, and a long tail of more recent metaheuristics that borrow a foraging, hunting, or migratory behavior from some organism and turn it into a population-based search procedure for hard combinatorial or continuous optimization problems such as path planning and task allocation [2,3,4]. The second is decentralized multi-agent coordination theory — consensus algorithms, potential-field methods, and distributed auction protocols that give formal guarantees about what a group of agents exchanging only local information can and cannot achieve [5,6,7]. Neither tradition alone is sufficient for real UAV fleets: swarm-intelligence optimizers are frequently formulated and benchmarked as centralized algorithms that happen to use a biologically inspired search heuristic, while pure consensus theory rarely engages with the combinatorial planning problems — where should each vehicle go, in what order should it visit its targets — that dominate practical UAV mission design. The recent UAV-swarm literature has been steadily fusing the two, producing architectures that use bio-inspired metaheuristics for the planning and optimization layer while relying on consensus- and auction-based protocols for the distributed coordination layer that keeps the fleet's individual plans consistent with each other under decentralized information [8,9].

We organize the discussion around six themes: the biological and algorithmic foundations of swarm intelligence; the specific bio-inspired optimization algorithms most heavily used in the UAV literature; the theory of decentralized coordination — consensus, potential fields, and distributed task allocation — that turns an optimizer into a genuinely decentralized fleet behavior; how these pieces combine into concrete architectures for multi-UAV path planning and task assignment; the communication and networking substrate that any of this depends on; and the open challenges that, in our reading, remain substantially unresolved. Throughout, we try to be precise about what the literature actually demonstrates versus what is often implied: a great deal of this research is validated in

simulation on benchmark scenarios with idealized communication, and the gap between "an ant-colony-inspired planner converges faster than a genetic algorithm on a benchmark routing instance" and "a fleet of physical UAVs coordinates itself robustly over a contested battlefield or disaster zone" is real and worth naming plainly rather than eliding.

It is also worth being explicit about scope. This is a literature synthesis, not a report of new experiments, and every quantitative claim below is drawn from a cited source and can be traced back to it. Where the literature offers only qualitative claims — "competitive with state-of-the-art metaheuristics" rather than a specific percentage — we report it as such rather than inventing a number that sounds more precise than the evidence supports.

2. Biological Foundations of Swarm Intelligence

Swarm intelligence, as a computational discipline, formalizes an observation from biology: complex, adaptive, robust collective behavior can arise from many simple agents interacting locally, without centralized control or even a shared global representation of the group's state. Bonabeau, Dorigo, and Theraulaz's foundational synthesis of this idea, drawing on decades of entomological and ecological research into social insects, lays out the core mechanisms that recur across biological swarms: local sensing and simple response rules, indirect coordination through modification of a shared environment (a mechanism entomologists call stigmergy, most famously realized in ant pheromone trails), and self-organization through positive feedback (reinforcing a good solution, such as a short foraging path, so that it attracts more followers) balanced against negative feedback (evaporation, saturation, or resource depletion that prevents the whole population from collapsing onto a single, possibly suboptimal, choice) [10]. These are not narrowly biological curiosities; they are design patterns, and virtually every bio-inspired algorithm used in UAV coordination today is a computational instantiation of one or more of them. Brambilla and colleagues' review of swarm robotics from an engineering perspective makes the same point from the robotics side of the field: a swarm-robotic system is defined less by any particular hardware than by design principles — decentralization, local sensing and communication, and robustness through redundancy rather than fault-tolerant individual components — that

were extracted directly from the biological self-organization mechanisms described above and are now treated as engineering requirements in their own right when a research team sets out to build a genuinely swarm-based system rather than merely a group of independently controlled robots [11].

Reynolds's boids model, though developed for computer graphics rather than robotics, remains the clearest illustration of why this design pattern is attractive for engineered systems specifically. The model's three rules operate on strictly local information — each simulated bird reacts only to flockmates within a limited neighborhood — and yet the emergent flock exhibits properties that are difficult to engineer directly: it holds together over long simulated flights, it splits and rejoins fluidly around obstacles, and it has no single point of failure, because removing any one boid from the simulation does not require recomputing anything for the rest of the flock [1]. Translated into UAV fleet terms, this is precisely the failure-mode robustness that centralized fleet management struggles to provide: a vehicle lost to mechanical failure, jamming, or being shot down should degrade the fleet's collective performance gracefully rather than catastrophically, and a purely local-interaction architecture achieves that property more or less for free, as a structural consequence of the design rather than as a bolted-on fault-tolerance feature.

The other biological mechanism that recurs constantly in the UAV literature is stigmergic coordination — agents communicating indirectly by modifying a shared environment rather than by messaging each other directly. Ant colonies performing pheromone-trail foraging are the canonical example, and Dorigo, Maniezzo, and Coloni's original Ant System formalized this behavior as a general-purpose combinatorial optimization procedure: simulated ants construct candidate solutions probabilistically, biased toward edges with higher accumulated "pheromone," and deposit pheromone on the edges they use, in an amount related to solution quality, with the whole trail evaporating over time to prevent premature convergence [3]. For UAV swarms specifically, stigmergic coordination has an appealing systems property beyond its algorithmic elegance: it decouples coordination from continuous direct communication. A UAV that updates a shared map, a shared occupancy

grid, or a shared "visited" record and lets other UAVs read that record opportunistically is far more tolerant of the intermittent, high-latency, bandwidth-constrained links that characterize real aerial networks than an architecture requiring continuous pairwise message exchange, a point we return to when discussing communication constraints later in this article.

3. Bio-Inspired Optimization Algorithms for Swarm Coordination

Most of the bio-inspired algorithms applied to UAV coordination in the past decade descend, directly or by imitation of its structure, from particle swarm optimization (PSO). Kennedy and Eberhart's original 1995 formulation modeled a population of candidate solutions as "particles" moving through a search space, each particle's velocity pulled probabilistically toward both its own best-known position and the best position found by the whole swarm (or a neighborhood within it), producing a search dynamic loosely inspired by the synchronized, information-sharing movement of a flock or a school [2]. PSO's appeal for UAV path planning is almost immediate: a particle's position can directly encode a candidate trajectory or waypoint sequence, and the algorithm's velocity-update rule is cheap enough computationally to run on modest onboard hardware, which matters when the optimization needs to happen in flight rather than purely as offline mission planning.

Ant colony optimization, in its many UAV-specific variants, targets a complementary structure: problems that are naturally graph-based, such as routing a UAV through a sequence of waypoints or allocating a set of targets across multiple vehicles, where the stigmergic pheromone-trail mechanism described above maps cleanly onto edge selection in a routing graph [3]. A large family of more recent metaheuristics has extended this same population-based, bio-inspired search template with a different animal behavior as the source metaphor: grey wolf optimizer models the social hierarchy and cooperative hunting behavior of grey wolf packs, using three "leader" wolves (alpha, beta, and delta) to guide the rest of the population toward promising regions of the search space, and its original benchmark evaluation against PSO, gravitational search, differential evolution, and other well-known metaheuristics reported that GWO was "very competitive" across the tested optimization functions [4]. The whale optimization

algorithm, from the same research group, models the bubble-net hunting strategy of humpback whales — a spiral, encircling attack maneuver — as a search operator, and its original paper likewise reports competitive performance against state-of-the-art metaheuristics and conventional optimization methods across 29 mathematical benchmark problems and six structural design problems [12]. Artificial bee colony optimization, developed by Karaboga and Basturk, models the division of labor among employed foragers, onlooker bees, and scouts in a honeybee colony, giving the algorithm a built-in mechanism for balancing exploitation of known good regions against exploration of unvisited ones [13]. Cuckoo search, introduced by Yang and Deb, borrows the brood-parasitism strategy of cuckoo birds combined with Lévy-flight step-length statistics — a heavy-tailed random-walk pattern also observed in the foraging trajectories of several animal species — to balance local refinement against occasional long jumps to unexplored regions of the search space [14]. Yang's firefly algorithm uses a different metaphor again, modeling attraction between fireflies as a function of relative brightness (encoding solution quality) that decays with distance, which naturally produces a multimodal search behavior well suited to problems, like many real path-planning landscapes, that have several comparably good but structurally distinct solutions rather than one obvious global optimum [15].

Table 1: Representative bio-inspired swarm-intelligence algorithms used in UAV fleet coordination, their biological source behavior, and how their originating papers characterize their performance. [2,3,4,12,13,14,16].

Algorithm	Biological Source Behavior	Origin Reference	Reported Performance Characterization
Particle Swarm Optimization (PSO)	Coordinated, information-sharing movement of bird flocks / fish schools	Kennedy & Eberhart [2]	Original formulation as a population-based social-learning search procedure
Ant Colony Optimization (Ant System)	Stigmergic pheromone-trail foraging in ant colonies	Dorigo, Maniezzo & Colnari [3]	Established as a general combinatorial-optimization metaheuristic via trail reinforcement/evaporation
Grey Wolf Optimizer (GWO)	Social hierarchy and cooperative hunting of grey wolf packs	Mirjalili et al. [4]	"Very competitive" vs. PSO, GSA, DE, EP and ES on benchmark functions
Whale Optimization Algorithm (WOA)	Bubble-net hunting strategy of humpback whales	Mirjalili & Lewis [12]	"Very competitive" vs. state-of-the-art metaheuristics on 29 math + 6 design problems

Algorithm	Biological Source Behavior	Origin Reference	Reported Performance Characterization
Artificial Bee Colony (ABC)	Employed/onlooker/scout foraging roles in honeybee colonies	Karaboga & Basturk [13]	Numerical function optimization performance validated against classic benchmark suites
Cuckoo Search	Brood parasitism plus Levy-flight foraging step statistics	Yang & Deb [14]	Levy-flight step distribution shown to improve global search over fixed-step random walks
Pigeon-Inspired Optimization (PIO)	Map-and-compass plus landmark homing navigation in pigeons	Duan & Qiao [16]	Proposed and validated directly on air-robot path-planning tasks

Pigeon-inspired optimization deserves particular mention because it was proposed with air-vehicle path planning as an explicit, stated target application rather than as a general-purpose benchmark optimizer later repurposed for aerospace problems. Duan and Qiao modeled the homing behavior pigeons use for long-distance navigation — a map-and-compass mechanism early in flight, refined by landmark-based correction as the destination nears — as a two-phase search operator, and demonstrated the resulting algorithm specifically on air robot path planning tasks [16]. This design lineage, from a navigation-specific biological behavior straight to an aerial path-planning algorithm, is echoed in a good deal of the more recent literature discussed in the next section, where bio-inspired optimizers are increasingly evaluated directly against realistic UAV constraints — three-dimensional terrain, threat zones, energy budgets — rather than against abstract mathematical benchmark functions alone.

It is worth being candid about what these original benchmark papers do and do not establish. Nearly all of them report competitive or superior performance against a handful of other well-known metaheuristics on standard mathematical test functions, which is a reasonable first validation step but is a different claim from "this algorithm is the right choice for UAV fleet coordination." The papers discussed in the following section are, in our reading, the more directly relevant evidence base for that latter claim, because they apply these bio-inspired search procedures to path-planning and coordination problems with UAV-realistic constraints and report performance relative to other planners on those specific tasks.

4. Decentralized Coordination Theory: Consensus, Potential Fields, and Distributed Task Allocation

A bio-inspired optimizer, on its own, does not make a fleet decentralized; it makes a search procedure that happens to be inspired by decentralized biological behavior, and that search procedure can just as easily be run centrally on a single ground-station computer that then dictates trajectories to every vehicle. Turning swarm-intelligence optimization into genuinely decentralized fleet coordination — where each vehicle computes its own behavior from locally available information and no single point of failure exists — requires a second layer of theory concerned specifically with what groups of agents exchanging only local information can provably achieve.

Consensus theory is the most mathematically developed part of this second layer. Olfati-Saber, Fax, and Murray's widely cited framework analyzes exactly this question: under what conditions on a time-varying communication network's topology, and in the presence of communication delays, will a group of agents each running a simple local update rule converge to agreement on some shared quantity — a heading, a formation reference point, an estimate of a target's location? Their paper explicitly connects this abstract consensus problem to flocking and formation control, and its results on network robustness to topology changes are directly applicable to a UAV fleet whose communication graph is constantly changing as vehicles move in and out of each other's radio range [5]. In practice, this consensus machinery underlies a large share of the "distributed formation control" literature for UAV swarms: rather than every vehicle knowing every other vehicle's exact position and computing a globally consistent formation directly, each vehicle exchanges a small amount of state with its current neighbors and runs a local update rule that is provably guaranteed, under the conditions the theory specifies, to converge the whole fleet toward the desired collective behavior.

Potential-field methods provide a complementary, more local and reactive layer, historically developed for robot manipulator and mobile-robot obstacle avoidance well before UAV swarms existed as an application. Khatib's original formulation treats a robot's motion as governed by a combination of an attractive potential pulling it toward its goal and repulsive potentials pushing it away

from obstacles (and, in the multi-vehicle extension used throughout the UAV swarm literature, away from other vehicles), computed and reacted to in real time from only locally sensed information [6]. The appeal of this mechanism for UAV fleets is its computational cheapness and its natural fit with the boids-style local-interaction pattern described earlier — separation, in Reynolds's terms, is essentially a repulsive potential field applied to neighboring flockmates [1] — but potential-field methods are also well known to suffer from local-minimum traps, where an agent can become stuck in a configuration where the attractive and repulsive forces balance without the goal being reached, a limitation the UAV path-planning literature routinely addresses by hybridizing potential fields with a global bio-inspired optimizer that handles the coarse route and leaves local reactive collision avoidance to the potential field.

Task allocation is the third pillar, and it is where the swarm-intelligence and consensus traditions most directly meet. When a fleet must decide which vehicle covers which search sector, or which subset of targets each UAV visits, a purely centralized solver can compute a globally optimal assignment quickly for small fleets, but that approach reintroduces exactly the single point of failure and communication bottleneck that decentralized swarm architectures are meant to avoid. Choi, Brunet, and How's consensus-based bundle algorithm (CBBA) addresses this directly: each agent builds up a "bundle" of tasks it will perform through a greedy, locally computed auction process, and then a consensus phase — structurally similar to the consensus algorithms discussed above — resolves conflicts where multiple agents have bid on the same task, using only local, pairwise communication between neighboring agents in the network rather than requiring any agent to have global knowledge of the whole fleet's bids [7]. CBBA and its descendants are now something close to a standard building block in the multi-UAV task-allocation literature specifically because they give a formally decentralized alternative to the market-based and auction mechanisms that dominate centralized multi-robot task allocation, while retaining most of the desirable near-optimality properties of a centralized auction under reasonable assumptions about the communication network.

5. Bio-Inspired Architectures for Multi-UAV Path

Planning and Task Allocation

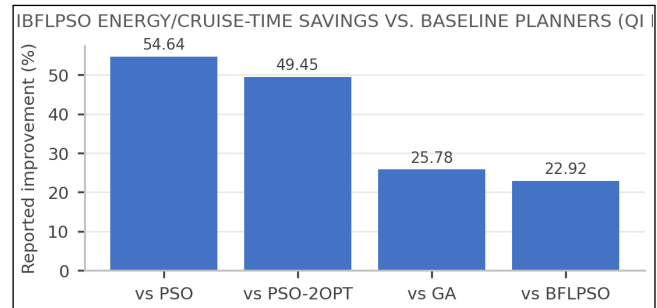


Figure 1: Reported energy/cruise-time savings of an improved bee-foraging-learning particle swarm optimizer (IBFLPSO) over four baseline planners on the same multi-UAV energy-aware path-planning task, as reported by Qi et al. -- illustrating the scale of gains bio-inspired refinements of PSO can deliver against progressively closer baselines [17].

Recent applied literature has moved from proposing general-purpose bio-inspired optimizers to embedding them directly in multi-UAV path-planning and task-allocation pipelines, evaluated against UAV-realistic constraints — energy budgets, threat zones, three-dimensional terrain, and formation-keeping requirements — rather than abstract benchmark functions alone. Qi and colleagues' improved bee-foraging-learning particle swarm optimization (IBFLPSO) is a representative and unusually well-quantified example: applied to multi-UAV path planning under multiple energy-consumption models, the algorithm's optimal solution was reported as 54.64% better than standard PSO, 49.45% better than a PSO-2OPT hybrid, 25.78% better than a genetic algorithm baseline, and 22.92% better than the earlier bee-foraging-learning PSO variant it builds on, translating concretely into hundreds of thousands to over a million fewer joules of energy expenditure and thousands of fewer seconds of cruise time across the paper's benchmark scenarios [17]. Liu and colleagues' spherical vector-based adaptive evolutionary PSO targets a related but distinct problem — UAV path planning under explicit threat conditions, where the planner must trade path length against exposure to modeled threat zones — and reports that their method outperforms both standard PSO and a spherical-vector PSO baseline in initial solution quality, final solution accuracy, convergence stability, and scalability across six benchmark scenarios with varying threat levels, producing visibly smoother and shorter paths in the paper's reported comparisons [18]. Deng and colleagues' Lévy-flight-enhanced PSO variant, evaluated specifically on UAV path planning, illustrates how directly the foundational metaheuristics discussed

in the previous section — in this case Yang and Deb's Lévy-flight search mechanism, originally proposed for cuckoo search — are being recombined and re-applied within the UAV planning literature rather than displaced by newer algorithms [19,14].

Beyond single-vehicle path planning, several papers directly target the cooperative, multi-vehicle version of the problem, which is closer to genuine fleet coordination. Zeng, Tong, and Xia's differential-evolution-based coverage-search algorithm for multiple UAVs addresses cooperative area coverage — dividing a search region among a fleet so that it is covered efficiently while respecting collision-avoidance and energy constraints — and the authors report that their algorithm achieves high coverage with a low energy-consumption index while maintaining stability and generality across different region shapes and fleet configurations [20]. Shen and colleagues' multi-objective dung beetle optimizer, adapted from a dung-beetle rolling and navigation behavior into a population-based metaheuristic, targets cooperative path planning for multiple UAVs directly, treating path length, smoothness, and safety as simultaneous objectives to be balanced rather than collapsed into a single weighted score [21]. Kyriakakis and colleagues' work on the "moving peak drone search problem" tackles a genuinely dynamic version of cooperative UAV search — locating a moving or intermittently detectable target using an online, adaptive multi-swarm intelligence approach rather than a fixed offline plan — which is a meaningfully harder and more realistic setting than the static point-to-point path-planning benchmarks that dominate much of the rest of this literature, since a real search-and-rescue or surveillance mission rarely has a fully known, static target configuration in advance [22].

Task allocation across heterogeneous UAV fleets — where vehicles differ in sensor payload, endurance, or role, not just in position — is treated in depth by Li and colleagues' survey, which organizes the collaborative task-assignment literature around the artificial-intelligence methods used to solve it, including swarm-intelligence metaheuristics, auction and market-based mechanisms in the CBBA family, and learning-based approaches, and explicitly frames heterogeneity (rather than a homogeneous fleet of identical drones) as the harder and more operationally

realistic version of the assignment problem [9]. Han's integration of the whale optimization algorithm and grey wolf optimizer for real-time aerial tracking is a further illustration of how directly foundational metaheuristics are being recombined for UAV-specific perception-and-control tasks beyond path planning proper — in this case fusing WOA's exploration behavior with GWO's hierarchical exploitation behavior to keep a tracking UAV locked onto a moving target under the same kind of real-time computational constraints that path planners face [23,4,12]. Alqudsi and Makaraci's broader 2025 review of UAV swarm research situates all of this applied path-planning and task-allocation work within the wider set of challenges facing UAV swarm deployment — including coordination algorithms, communication architectures, and the open research questions the field has yet to resolve — and its publication as a comprehensive, recent survey is itself a useful signal of how much the field has consolidated around the bio-inspired-optimization-plus-decentralize d-coordination pattern this article describes [8]. Taken as a set, the architectures surveyed in this section share a recognizable shape: a bio-inspired metaheuristic, often a PSO or ant-colony-optimization variant, or metaheuristics such as GWO, WOA, ABC, or the dung-beetle and bee-foraging variants discussed above, handles the combinatorial or continuous optimization core (which waypoints, which targets, which routes), while a consensus or auction-based coordination layer, drawn from the theory discussed in the previous section, resolves conflicts and keeps individual vehicles' locally computed plans mutually consistent without requiring a central planner [17,7,5].

6. Communication Constraints and Networking for Decentralized UAV Fleets

None of the coordination architecture described above functions without a communication substrate to carry it, and that substrate is, for UAV swarms specifically, considerably less forgiving than the wired or well-provisioned wireless networks assumed by much of the general multi-agent systems literature. Campion, Ranganathan, and Faruque's review of UAV swarm communication and control architectures surveys the range of network topologies — centralized star architectures, mesh networks, and hybrid designs — that swarm designers choose among, and the tradeoffs each involves between coordination simplicity, scalability, and resilience to individual node or link failure,

concluding that architectures relying on infrastructure-free, mesh-style peer-to-peer connectivity among the UAVs themselves are generally more resilient to the loss of any single vehicle or ground link than architectures that route all coordination traffic through a central hub [24]. This finding reinforces, from a purely networking perspective, the same design conclusion the biological and swarm-intelligence literature reaches from a coordination-algorithm perspective: distributing both the computation and the communication reduces single points of failure, at the cost of a more complex protocol design.

Kumar, Vasudeva, and Sood's survey of bio-inspired routing algorithms for UAV-based networks addresses the layer immediately below coordination — how packets actually get from one UAV to another, or back to a ground station, across a network whose topology is constantly changing as vehicles move — and finds that ant-colony-optimization-style routing protocols, which build up and reinforce good routing paths stigmergically in a manner directly analogous to Dorigo, Maniezzo, and Colomni's original Ant System, are among the most extensively studied bio-inspired approaches specifically because their incremental, locally-updated trail-reinforcement mechanism tolerates topology churn better than routing protocols that require a full, globally consistent routing table [25,3]. This is a useful reminder that "bio-inspired" in the UAV swarm literature operates at more than one layer simultaneously: the same stigmergic design pattern that inspires a high-level path-planning optimizer can also, independently, inspire the low-level network routing protocol that carries the coordination messages those planners depend on, and a fleet architecture is only as decentralized and resilient as the weakest of these layers.

The practical upshot for fleet designers is that communication should be treated as a first-class constraint on the coordination algorithm's design, not an afterthought layered on top of an algorithm developed assuming reliable, low-latency messaging. Consensus algorithms, as noted above, are explicitly formulated to tolerate a time-varying communication topology, and stigmergic, environment-mediated coordination mechanisms tolerate intermittent connectivity better than protocols requiring synchronous message exchange between specific pairs of agents [5]. Architectures that combine a bio-inspired

planning optimizer with a mesh-style, stigmergically-routed communication layer are, in our reading of this literature, the ones best positioned to actually deliver the failure-tolerant, infrastructure-independent coordination that swarm intelligence promises in principle.

7. Open Challenges

Several gaps recur across this literature and deserve to be named directly rather than glossed over. First, evaluation realism: the large majority of the bio-inspired path-planning and coordination results surveyed here, including the strongest quantitative results such as Qi and colleagues' reported energy savings, are demonstrated in simulation, on benchmark scenarios with idealized sensing and communication, rather than on physical fleets operating under real wind disturbance, GPS-denied navigation, and contested radio links [17,18]. The gap between "this metaheuristic converges faster than a genetic algorithm on a simulated path-planning benchmark" and "this metaheuristic coordinates a physical fleet reliably in the field" remains large, and relatively few of the papers reviewed here report field trials with real hardware at meaningful scale.

Second, the theoretical guarantees of consensus algorithms and the empirical performance claims of bio-inspired metaheuristics are, in practice, rarely validated together in the same system. Consensus theory gives precise conditions under which a decentralized coordination scheme is guaranteed to converge [5], but once a swarm-intelligence optimizer such as GWO or a dung-beetle-inspired planner is embedded inside that coordination loop, the combined system's convergence and stability properties are typically established empirically, through simulation, rather than proven formally — a reasonable engineering compromise, but one that leaves an open theoretical question about what guarantees, if any, survive the combination.

Third, adversarial and contested environments remain comparatively under-addressed relative to their operational importance, particularly for UAV swarms considered for search-and-rescue, disaster response, or defense applications, where communication jamming, spoofed sensor data, or the deliberate loss of individual vehicles are not edge cases but expected operating conditions. The communication-architecture literature discussed above establishes that mesh-style, infrastructure-free networking is more resilient to

individual node loss than centralized alternatives [24], but resilience to active, adversarial interference is a meaningfully harder and less thoroughly evaluated property than resilience to passive node failure.

Fourth, heterogeneity — in vehicle capability, sensor payload, and role — is increasingly recognized as the operationally realistic case rather than the exception, as Li and colleagues' survey makes explicit [9], but a large fraction of the bio-inspired optimization literature, including several of the path-planning papers discussed above, is still validated primarily on fleets of identical, homogeneous vehicles, leaving open how cleanly these algorithms' reported performance gains transfer to a fleet where, say, one vehicle carries a thermal sensor with a narrow field of view and another carries a wide-area optical camera with different endurance and speed characteristics.

Fifth, energy and endurance constraints, while explicitly modeled in some of the more recent path-planning literature [17], are still frequently abstracted away or simplified in the broader swarm-coordination and communication literature, even though battery-limited flight endurance is arguably the single hardest physical constraint separating UAV swarms from the ground-robot and simulated-agent swarms that much of the underlying consensus and swarm-intelligence theory was originally developed or tested against.

None of these gaps, in our assessment, undermine the basic architectural case for bio-inspired, decentralized UAV fleet coordination; if anything, the consistency with which independent research groups have converged on broadly similar designs — a bio-inspired metaheuristic for planning, paired with consensus- or auction-based decentralized coordination, paired with mesh-style or stigmergically-routed communication — across search, coverage, path-planning, and task-allocation problems suggests the pattern is sound. But claims of field-ready maturity for any specific architecture in this space should be read against these gaps rather than against the more polished simulation results that dominate the published literature.

8. Conclusion

The literature surveyed here supports a reasonably specific claim: decentralized coordination of UAV fleets is best understood not as a single algorithm but as a layered architecture, in which biologically inspired

local-interaction rules and population-based metaheuristics provide the search and planning core — deciding routes, coverage patterns, and task assignments — while consensus theory, potential-field reactive control, and distributed auction protocols provide the coordination layer that keeps individually-computed decisions consistent across the fleet without any central authority [1,2,5,7]. This layered pattern inherits biology's core structural advantage — no single point of failure, because coordination emerges from local interaction rather than centralized command [10] — while giving engineers formal tools, from consensus convergence conditions to auction-based near-optimality guarantees, that pure biological mimicry alone does not provide.

The applied path-planning and task-allocation literature reviewed in this article shows this pattern being actively refined against increasingly realistic UAV constraints: energy budgets that translate directly into reported joule and cruise-time savings [17], explicit threat and terrain modeling [18], cooperative multi-vehicle coverage and dynamic search [20,22], and heterogeneous fleet composition [9]. What remains substantially open is less the core architectural pattern than its validation against the conditions real UAV fleets actually operate under — contested communication, adversarial interference, physical hardware rather than simulation, and genuinely heterogeneous vehicle capability. Closing that gap, rather than proposing yet another biologically-inspired metaheuristic validated on the same simulated benchmarks, is, in our reading of this literature, the field's most valuable open task, and one that the consistent convergence of independent research groups on this same layered architectural pattern suggests is worth pursuing rather than abandoning for a fundamentally different design.

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The authors declare that they have no conflict of interest.

Data Availability Statement

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Ethical Approval

Not applicable, as this work involved no human participants, animal subjects, or primary data collection.