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Robust Agent-Based Metaheuristics for Dynamic Vehicle Routing With Time Windows in Decentralized Logistics Networks

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Abstract

Wireless ad hoc networks rely on distributed coordination under stringent energy, mobility, and spectrum constraints, and optimization plays a central role in allocating resources, tuning protocols, and adapting to environmental variation. In large-scale deployments with heterogeneous nodes, centralized solvers are often impractical due to the cost of broadcasting global state and the fragility of single points of failure. Nonconvexity arises naturally from interference coupling, fading-driven link adaptation, discrete scheduling primitives, and nonlinear protocol parameters. This study examines hybrid swarm–gradient methods that combine exploration-driven population dynamics with descent-based refinement, designed for decentralized operation over time-varying graphs. The approach maintains per-agent positions, velocities, and personal exemplars while tracking local gradients and exchanging compressed messages through gossip. The method tolerates asynchronous clocks, lossy links, and delays by leveraging consensus corrections and mixing properties of the communication graph, and it employs event-triggered communication to moderate overhead. A stability analysis relates swarm parameters, stepsizes, and spectral gaps to descent of a smoothed Lyapunov functional, while characterizing convergence to critical points and escape from strict saddles under mild noise. Under error-bound conditions, the mechanism achieves nonasymptotic stationarity rates compatible with communication budgets typical of low-power radios. Experiments on synthetic and network-inspired objectives illustrate behavior under mobility, quantization, and adversarial perturbations. The results indicate that the hybridization strikes a balance between global search and local refinement in settings where curvature is irregular and global coordination is constrained, without presupposing a shared clock or reliable broadcast.

1. Introduction

Decentralized optimization in wireless ad hoc networks operates under a set of conditions that make the design and analysis of algorithms uniquely challenging [1]. These networks lack any fixed infrastructure, relying instead on a collection of mobile or stationary nodes that must cooperatively organize communication and computation. The communication substrate itself is dynamic and heterogeneous—links between nodes appear and disappear due to mobility, fading, and contention; interference fluctuates with channel usage; and hardware limitations impose constraints on energy, computation, and bandwidth [2]. Nodes may fail unpredictably or move in and out of range, and even when links are active, data exchange may be delayed, quantized, or lost. These conditions mean that decentralized optimization must contend not only with mathematical nonconvexity but also with physical-layer variability and resource scarcity. Any method that assumes stable connectivity, synchronous updates, or unlimited communication is unrealistic for this setting [3]. Practical decentralized optimization in such

networks must therefore balance algorithmic sophistication with robustness and efficiency, leveraging only local information and limited message passing while tolerating imperfect gradients and delayed updates.

Table 1. Operating Conditions and Challenges of Decentralized Optimization in Wireless Ad Hoc Networks

Aspect	Phenomenon	Implication for Algorithms	Typical Constraint
Dynamic topology	Links appear/disappear with mobility and fading	Asynchronous, time-varying communication	Intermittent connectivity
Hardware heterogeneity	Unequal energy, computation, and bandwidth	Uneven update and sensing capabilities	Node-specific limits
Unreliable links	Delay, quantization, or loss in data exchange	Distorted gradients, delayed consensus	Packet drops
Resource scarcity	Limited energy and bandwidth	Sparse message passing required	Duty-cycled radios
Nonconvex objectives	Coupled nonlinear network metrics	Multiple local minima, saddle points	Throughput/power trade-offs

The optimization objectives encountered in wireless ad hoc networks are typically nonconvex and highly coupled across nodes. Interference-limited throughput maximization, for example, involves nonlinear signal-to-interference-plus-noise ratios that depend on the power levels of all transmitters in the neighborhood [4]. The problem of power control with discrete modulation and coding schemes introduces combinatorial constraints that destroy convexity. Joint routing and scheduling requires the coordination of link activations under collision constraints, often modeled as nonconvex sets. Adaptive waveform selection, beamforming, and spectrum allocation further complicate the landscape by introducing nonlinear relationships between parameters and performance metrics, especially in the presence of hardware nonlinearities such as amplifier saturation or quantized phase shifters [5]. These features yield objective functions that may have multiple local minima, saddle points, and flat regions, making traditional convex optimization methods inapplicable or ineffective. Even stochastic gradient methods, while scalable and simple, may converge to poor local solutions or oscillate indefinitely when the communication topology and channel conditions vary over time [6]. The interplay between nonconvexity, distributed information, and dynamic environments defines the core difficulty of decentralized optimization in wireless systems.

Purely gradient-based approaches—those relying on local derivatives and consensus averaging—are efficient in smooth convex settings but fragile in nonconvex decentralized contexts. Each node typically maintains an estimate of the global decision variable, updates it based on its local gradient, and exchanges information with neighbors to reach agreement [7]. However, when the objective function is nonconvex, gradients can point toward local attractors that are far from globally optimal. Moreover, communication delays and quantization errors distort the descent direction, leading to divergence or oscillation. The limited energy budget further restricts how often nodes can exchange gradients or parameters, reducing the fidelity of the consensus process [8]. As a result, gradient-only algorithms may settle prematurely in suboptimal basins, especially when the initial conditions are poor or the landscape is rugged. On the other hand, purely population-based heuristics—such as particle swarm optimization, genetic algorithms, or ant colony methods—excel at exploration but lack the fine-grained exploitation capability that gradients provide. These methods often require large populations or extensive communication to coordinate particles, which is impractical in a bandwidth- and energy-limited wireless environment [9]. The challenge lies in integrating the exploration benefits of swarm intelligence with the exploitation precision of gradient methods while remaining

decentralized and communication-efficient.

Table 2. Comparison of Pure Gradient-Based and Swarm-Based Methods in Decentralized Optimization

Approach	Strengths	Weaknesses	Typical Failure Mode
Gradient-based	Efficient in convex, smooth settings	Sensitive to noise, delays, nonconvexity	Premature convergence or divergence
Swarm-based	Strong exploration and diversity	High communication, weak exploitation	Wandering or oscillatory behavior
Hybridization need	Combine exploitation and exploration	Preserve scalability and robustness	Requires adaptive weighting

Hybrid swarm–gradient algorithms represent an emerging approach to addressing these issues. The key idea is to maintain a population of candidate solutions distributed across nodes, allowing exploration of multiple regions of the search space simultaneously, while also guiding each candidate's evolution using local gradient information when available [10]. Each node can be associated with one or several particles that communicate with neighbors to share promising directions or fitness evaluations. The swarm dynamics promote diversity and global search, preventing premature convergence, whereas the gradient steps refine promising candidates by exploiting local geometric information [11]. This hybridization enables the algorithm to balance exploration and exploitation adaptively, using swarm interactions to escape poor basins and gradient cues to accelerate convergence within good ones. The resulting framework is inherently parallel and compatible with the distributed nature of ad hoc networks. Message passing is localized, and updates can proceed asynchronously without global coordination, making the method robust to packet loss and time-varying connectivity. [12]

The central problem addressed by such decentralized hybrid optimization is the cooperative minimization of a shared, possibly nonconvex, objective function that encapsulates network performance or control cost. The decision variables may represent transmission powers, channel assignments, scheduling decisions, routing tables, or beamforming coefficients. Each node holds partial information about the objective—typically through its local performance metrics or measurements—and must collaborate with neighbors to approximate the global optimum [13]. The decision vector thus has a distributed structure, partitioned among agents that influence different subsets of the variables. Coordination must occur through message exchanges that are local and often asynchronous. The algorithmic question becomes how to design update rules that ensure sustained exploration across the network, avoiding premature consensus on suboptimal solutions, while also guaranteeing convergence toward a stable point once a promising region is found [14]. These updates must respect communication constraints such as gossip-based information sharing, quantized message representations, and limited update frequencies dictated by energy and bandwidth availability.

Gossip protocols provide a natural substrate for such decentralized coordination. In gossip-based schemes, nodes randomly or deterministically select neighbors to exchange information at each iteration, gradually diffusing knowledge through the network [15]. This process is inherently asynchronous and resilient to link failures, but it introduces consensus errors due to the lag between different nodes' information states. Quantization of exchanged values further adds noise to the optimization dynamics, as limited bit budgets are used to encode positions, gradients, or objective values [16]. Designing hybrid swarm–gradient algorithms that remain stable under these imperfections requires careful analysis of how consensus errors, gradient noise, and swarm interactions couple together. The theoretical framework must capture both the stochastic nature of communication and the nonconvexity of the optimization landscape,

Table 3. Core Design Elements and Mechanisms in Hybrid Swarm–Gradient Frameworks

Component	Role	Mechanism	Communication Pattern
Swarm dynamics	Exploration and diversity maintenance	Attraction–repulsion–inertia rules	Local neighbor sharing
Gradient refinement	Local exploitation of promising basins	Descent or tracking updates	Partial gradient exchange
Gossip coordination	Distributed consensus without central node	Random or deterministic neighbor selection	Asynchronous averaging
Quantization / compression	Reduce bandwidth and energy use	Low-bit encoding or relative updates	Message-efficient updates
Adaptive weighting	Balance exploration vs. exploitation	Time-varying coefficients or entropy triggers	Event-driven control

establishing conditions under which the system converges to a stationary point or maintains bounded fluctuations around it. Additionally, the possibility of adversarial or misbehaving nodes—those that inject false information or fail to update correctly—poses further challenges to stability and robustness. [17]

Table 4. Analytical Insights and Implementation Implications for Decentralized Hybrid Optimization

Dimension	Analytical Focus	Result / Observation	Influencing Factors
Stability analysis	Coupled swarm–gradient dynamics	Convergence to stationary regions	Step sizes, communication rate
Mean-field modeling	Population behavior approximation	Predicts consensus and exploration phases	Network size, mixing time
Exploration–exploitation trade-off	Adaptive modulation of randomness	Sustained diversity then convergence	Decay or annealing schedules
Energy-awareness	Event-driven and sleep-state operation	Lower energy per update	Trigger thresholds, duty cycle
Robustness to imperfections	Quantization, delay, adversarial nodes	Graceful degradation, bounded error	Connectivity, redundancy

Analytically, the behavior of decentralized hybrid optimization can be studied through coupled dynamical systems that model the evolution of each node's state, its estimate of the gradient, and its interactions with neighbors. Swarm dynamics introduce collective motion through attraction, repulsion, and inertia terms, which determine how particles balance individuality and social influence. Gradient tracking mechanisms attempt to compensate for outdated or partial gradient information by estimating the global gradient via local updates and neighbor averaging [18]. The coupling between these mechanisms determines how quickly the population aligns on promising directions, how consensus errors decay, and how exploration is maintained. Stability analysis often employs tools from stochastic approximation, dynamical systems theory, and mean-field analysis. In particular, one seeks to show that the combined effect of swarm exploration and gradient descent leads to trajectories that approach regions of low objective value while avoiding divergence or chaotic oscillations [19]. The rates of convergence, or more precisely the rates of decrease in the expected objective, depend on communication frequency, step size schedules, and the topology of the underlying network graph.

One of the central trade-offs in these algorithms is between exploration and exploitation. Excessive reliance on swarm dynamics may keep the system wandering across the search

space, failing to settle even when a good solution is found [20]. Conversely, overly aggressive gradient descent can cause premature convergence to local minima. Adaptive mechanisms are therefore introduced to modulate the relative strength of swarm and gradient components [21]. For instance, exploration weights can decay over time as confidence in the solution increases, or can be reactivated when diversity across nodes drops below a threshold. Some schemes employ temperature-like parameters that control randomness in movement, analogous to simulated annealing, while others monitor consensus metrics to adjust the communication rate dynamically. These mechanisms ensure that exploration is sustained long enough to discover informative regions of the search space but is gradually reduced to enable stable convergence once promising basins are identified. [22]

The decentralized implementation of such hybrid algorithms requires efficient encoding and exchange of information among nodes. Since transmitting full state vectors or gradient estimates is often infeasible, compression and quantization techniques are employed. Nodes may exchange only relative updates, partial gradients, or summary statistics, reducing communication load while retaining essential information [23]. Randomized gossip schedules further lower contention and energy consumption. The combination of quantization and asynchronous updates introduces noise into the optimization process, but appropriately chosen step sizes and averaging schemes can mitigate its effect. Theoretical analyses typically model these imperfections as bounded disturbances and derive convergence guarantees under assumptions of network connectivity and diminishing step sizes [24]. In practice, hybrid algorithms exhibit graceful degradation under communication failures, as the swarm component maintains diversity and resilience even when gradient information becomes temporarily unreliable.

Energy constraints play a crucial role in shaping decentralized optimization strategies. Each node must manage its energy budget across sensing, computation, and communication tasks [25]. Transmitting messages consumes orders of magnitude more energy than local computations, motivating designs that minimize communication frequency and message size. Some approaches allow nodes to enter sleep states or update only when triggered by significant local changes, leading to event-driven optimization [26]. Hybrid swarm–gradient methods fit naturally into such frameworks because swarm interactions can be sparse and opportunistic, relying on occasional exchanges to maintain coherence. Gradient updates can be computed locally using partial data, and global coordination emerges gradually rather than through constant synchronization. The resulting algorithms are scalable and well suited for large networks with dynamic topologies, such as mobile ad hoc networks, vehicular networks, or distributed sensor swarms. [27]

This work develops a model for hybrid swarm–gradient dynamics over switching graphs, proposes a decentralization that avoids global reductions, and derives consequences for stationarity and robustness under quantized, delayed messages. The presentation remains intentionally neutral regarding comparative merit, focusing on conditions that render the mechanism stable and implementable with bounded communication. Several design implications follow: parameters that calibrate exploration to communication budget, relationships between mixing times and consensus penalties, and the role of noise in facilitating escape from strict saddles without destabilizing the dynamics. [28]

2. System Model and Problem Formulation

Consider N agents indexed by $i \in \{1, \dots, N\}$ embedded in a wireless ad hoc network. At discrete times $t = 0, 1, 2, \dots$, the communication topology is a directed graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t)$ with $\mathcal{V} = \{1, \dots, N\}$ and edges $(j, i) \in \mathcal{E}_t$ indicating that agent i can decode a message

from agent j at time t. The graph is endowed with a row-stochastic mixing matrix $W_t = [w_{ij}^t]$ satisfying $w_{ij}^t > 0$ only if $(j,i) \in \mathcal{E}_t$ or $i = j$, $\sum_j w_{ij}^t = 1$, and a uniform lower bound $w_{ij}^t \geq \underline{w} > 0$ over realized edges. Connectivity is modeled by a B-strongly connected sequence: there exists $B \in \mathbb{N}$ such that the union graph $(\mathcal{V}, \cup_{s=t}^{t+B-1} \mathcal{E}_s)$ is strongly connected for all t.

Table 5. Wireless Ad Hoc Network and Communication Model

Element	Definition	Property / Assumption	Implication
Topology	Directed graph $\mathcal{G}_t = (\mathcal{V}, \mathcal{E}_t)$	Time-varying, B-strongly connected	Guarantees eventual information flow
Mixing matrix	$W_t = [w_{ij}^t]$, row-stochastic	$w_{ij}^t \geq \underline{w} > 0$ on edges	Controls consensus rate
Spectral bound	$\|0\Phi(t,s) - \mathbf{1}\pi^\top\|0 \leq C\rho^{t-s+1}$	Exponential contraction of disagreements	Quantifies mixing quality
Delays	$\tau_{ij}^t \in [0, \tau_{\max}]$	Bounded, stochastic	Affects synchronization and stability
Compression / quantization	Operator Q, unbiased or contractive	$\mathbb{E}[\|0Q(z) - z\|0^2] \leq \omega\|0z\|0^2$ or $(1-\delta)\|0z\|0^2$	Models bandwidth and precision limits

Each agent stores a local copy $x_i^t \in \mathbb{R}^d$ of the network decision vector. The global objective is

$$\min_{x \in \mathbb{R}^d} \; F(x) \;:=\; \frac{1}{N} \sum_{i=1}^{N} f_i(x) + r(x),$$

where $f_i : \mathbb{R}^d \to \mathbb{R}$ may be nonconvex and models, for example, local throughput loss or energy cost rooted in the measurements or environment of agent i, and $r : \mathbb{R}^d \to \mathbb{R} \cup \{+\infty\}$ is a regularization or constraint penalty that can encode projections onto feasible sets via proximal maps. The functions f_i are assumed L-smooth in the sense that ∇f_i is L-Lipschitz, and gradients may be evaluated with noise: given a sample ξ_i^t, the agent accesses $g_i^t = \nabla f_i(x_i^t; \xi_i^t)$ with $\mathbb{E}[g_i^t \mid x_i^t] = \nabla f_i(x_i^t)$ and $\mathbb{E}[\|0g_i^t - \nabla f_i(x_i^t)|0^2 \mid x_i^t] \leq \sigma^2$.

Communication is subject to stochastic delays $\tau_{ij}^t \in \{0, 1, \ldots, \tau_{\max}\}$ and quantization or compression Q. A message sent by j at time t and received by i at $t + \tau$ delivers $Q(z_j^t)$ for some vector z_j^t produced by the algorithm. The operator $Q : \mathbb{R}^d \to \mathbb{R}^d$ can be an unbiased randomized compressor with variance parameter $\omega \geq 0$, meaning $\mathbb{E}[Q(z) \mid z] = z$ and $\mathbb{E}[\|0Q(z) - z\|0^2 \mid z] \leq \omega\|0z\|0^2$, or a biased low-precision map with a contraction property $\|0Q(z) - z\|0^2 \leq (1-\delta)\|0z\|0^2$ for some $\delta \in (0,1]$.

A standard consensus deviation metric is the average $\bar{x}^t = \frac{1}{N}\sum_{i=1}^N x_i^t$ and the disagreement energy $D^t = \sum_{i=1}^N \|0x_i^t - \bar{x}^t\|0^2$. The mixing quality of $\{W_t\}$ can be captured by a joint spectral radius bound. Let $\Phi(t,s) = W_t W_{t-1} \cdots W_s$ for $t \geq s$. There exist constants $\rho \in (0,1)$ and $C \geq 1$ such that $\|0\Phi(t,s) - \mathbf{1}\pi^\top\|0 \leq C\rho^{t-s+1}$, where π is a stationary distribution and $\mathbf{1}$ is the all-ones vector. This bound expresses contraction of disagreements at a rate governed by ρ.

To connect to network tasks, representative instances include power control with nonlinear signal-to-interference-plus-noise ratio dependencies, joint channel selection with discrete variables relaxed into continuous surrogates, and topology-aware embedding of routing metrics [29]. The modeling leaves latitude for additional structure such as smooth separable penalties or indicator functions handled by proximal operations, and it supports dynamic data streams through stochastic gradients.

Table 6. Optimization Problem and Local Quantities per Agent

Quantity	Symbol / Definition	Assumption	Purpose / Role
Local function	$f_i : \mathbb{R}^d \to \mathbb{R}$	L-smooth, possibly nonconvex	Models local cost or measurement loss
Global objective	$F(x) = \frac{1}{N}\sum_i f_i(x) + r(x)$	Composite, possibly constrained	Shared optimization goal
Gradient sample	$g_i^t = \nabla f_i(x_i^t; \xi_i^t)$	Unbiased, bounded variance σ^2	Stochastic gradient access
Regularizer	$r(x)$	Convex or prox-capable penalty	Enforces feasibility or structure
Consensus metrics	$\bar{x}^t$, $D^t = \sum_i \|0x_i^t - \bar{x}^t\|0^2$	Used to measure disagreement	Tracks mixing and alignment

3. Hybrid Swarm–Gradient Method

Each agent keeps a state triple (x_i^t, v_i^t, p_i^t) with position x_i^t, velocity v_i^t, and exemplar p_i^t representing the best position found so far according to a locally observed objective value. Additionally, each agent maintains an estimate y_i^t that tracks the average gradient to correct for bias introduced by local sampling and asynchrony [30]. The update integrates exploration via inertia and exemplar attraction with exploitation via gradient descent and consensus.

Table 7. Hybrid Swarm–Gradient State Updates at Each Agent

Component	Update Rule	Function	Tunable Parameters
Velocity	$v_i^{t+1} = \beta_t v_i^t + \alpha_t(p_i^t - x_i^t) + \gamma_t(b_i^t - x_i^t) - \eta_t y_i^t + \lambda_t \sum_j a_{ij}^t (x_j^{t-\tau} - x_i^t) + \zeta_i^t$	Combines inertia, exemplars, consensus, and gradient	$\beta_t, \alpha_t, \gamma_t, \eta_t, \lambda_t$
Position	$x_i^{t+1} = \mathrm{prox}_{\eta_t r}(x_i^t + v_i^{t+1})$	Applies proximal step or constraint projection	Stepsize η_t
Gradient tracker	$y_i^{t+1} = \sum_j w_{ij}^t Q(y_j^{t-\tau}) + \nabla f_i(x_i^{t+1}) - \nabla f_i(x_i^t)$	Tracks average gradient across agents	Mixing W_t, delay τ_{ij}^t
Exemplar	$p_i^{t+1} = \arg\min\{f_i(z) : z \in \{p_i^t, x_i^{t+1}\}\}$	Keeps local best solution	Objective f_i
Social surrogate	Gossip over $\theta_i^t = f_i(p_i^t)$ and $s_i^t = p_i^t$	Builds distributed best estimate b_i^t	Gossip weights w_{ij}^t

The velocity update is [31]

$$v_i^{t+1} = \beta_t v_i^t + \alpha_t \left(p_i^t - x_i^t\right) + \gamma_t \left(b_i^t - x_i^t\right) - \eta_t y_i^t + \lambda_t \sum_{j \in \mathcal{N}_i^t} a_{ij}^t \left(x_j^{t-\tau_{ij}^t} - x_i^t\right) + \zeta_i^t,$$

followed by a position update

$$x_i^{t+1} = \mathrm{prox}_{\eta_t r}\left(x_i^t + v_i^{t+1}\right),$$

where $\beta_t \in [0, 1)$ is inertia, $\alpha_t, \gamma_t \geq 0$ weigh personal and social exemplars, $\eta_t > 0$ is a gradient stepsize, $\lambda_t \geq 0$ scales consensus coupling, and ζ_i^t is a small mean-zero perturbation that can be intrinsic channel noise or algorithmic dithering to facilitate exploration. The neighborhood $\mathcal{N}_i^t$ and weights a_{ij}^t derive from the mixing matrix W_t, potentially after compression, and b_i^t is a local surrogate of a swarm-best exemplar constructed without global reductions.

The gradient-tracking recursion is [32]

$$y_i^{t+1} \;=\; \sum_{j\in\mathcal{N}_i^t} w_{ij}^t\, Q\!\left(y_j^{\,t-\tau_{ij}^t}\right) \;+\; \nabla f_i(x_i^{t+1};\xi_i^{\,t+1}) - \nabla f_i(x_i^t;\xi_i^{\,t}),$$

initialized with $y_i^0 = \nabla f_i(x_i^0;\xi_i^0)$. This recursion biases each agent toward the running network average of gradients while compensating for local movement. The exemplar rule is [33]

$$p_i^{t+1} \;=\; \arg\min\left\{f_i(z;\xi_i^{\,t+1}) \;:\; z\in\{p_i^t, x_i^{t+1}\}\right\},$$

and the social surrogate is computed through asynchronous gossip over exemplars. For instance, each agent can maintain a scalar $\theta_i^t = f_i(p_i^t;\xi_i^t)$ and a vector $s_i^t = p_i^t$, and update

$$\theta_i^{t+1} = \sum_j w_{ij}^t\, Q\!\left(\theta_j^{\,t-\tau_{ij}^t}\right),$$
$$s_i^{t+1} = \sum_j w_{ij}^t\, Q\!\left(s_j^{\,t-\tau_{ij}^t}\right),$$

then set $b_i^{t+1} = s_i^{t+1}$. When compression is biased, push-sum weights correct normalization [34]. Event-triggered rules reduce traffic by sending θ_i^t, s_i^t, y_i^t only when their change exceeds a threshold, in which case neighbors reuse the last cached values.

Table 8. Compact Matrix Formulation of the Coupled Swarm–Gradient Iteration

Variable Group	Stacked Form	Dynamics / Expression	Interpretation
Positions	$X^t = [x_1^t;\ldots;x_N^t]$	$X^{t+1} = \mathrm{prox}_{\eta_t r^{\oplus N}}(X^t + V^{t+1})$	Agent states after velocity update
Velocities	$V^{t+1} = \beta_t V^t + \alpha_t(P^t - X^t) + \gamma_t(B^t - X^t) - \eta_t Y^t - \lambda_t(A_t \otimes I_d)X^t + \zeta^t$	Aggregated motion equation	Encodes exploration and consensus damping
Gradient trackers	$Y^{t+1} = (W_t \otimes I_d)Q(Y^t) + G(X^{t+1}) - G(X^t)$	Distributed gradient correction	Counteracts sampling bias
Mixing / Laplacian	$L_t = I - W_t$	Drives disagreement energy decay	Quantifies network coupling
Average dynamics	$\bar{x}^t \approx$ momentum method with perturbations	Approximates centralized evolution	Shows impact of delays, compression

To reflect unreliable links, the received term $x_j^{\,t-\tau_{ij}^t}$ may be replaced by $Q(x_j^{\,t-\tau_{ij}^t})$. The consensus penalty in the velocity update damps disagreements, while the gradient tracker aligns descent directions without centralized averaging. The proximal step allows constrained optimization and composite penalties; for differentiable $r \equiv 0$, it reduces to an identity map. [35]

A compact form stacks variables into $X^t = [x_1^t;\ldots;x_N^t] \in \mathbb{R}^{Nd}$, $V^t = [v_1^t;\ldots;v_N^t]$, $P^t = [p_1^t;\ldots;p_N^t]$, $B^t = [b_1^t;\ldots;b_N^t]$, and $Y^t = [y_1^t;\ldots;y_N^t]$. Let $L_t = I - W_t$ be a graph Laplacian surrogate and A_t encode a_{ij}^t. Ignoring delays for exposition, the coupled iteration is

$$V^{t+1} = \beta_t V^t + \alpha_t(P^t - X^t) + \gamma_t(B^t - X^t) - \eta_t Y^t - \lambda_t(A_t \otimes I_d)X^t + \zeta^t,$$
$$X^{t+1} = \mathrm{prox}_{\eta_t r^{\oplus N}}\!\left(X^t + V^{t+1}\right),$$
$$Y^{t+1} = (W_t \otimes I_d)Q(Y^t) + G(X^{t+1},\Xi^{t+1}) - G(X^t,\Xi^t),$$

with $G(X^t, \Xi^t) = [\nabla f_1(x_1^t; \xi_1^t); \ldots; \nabla f_N(x_N^t; \xi_N^t)]$, $r^{\oplus N}(X) = \sum_i r(x_i)$, and ζ^t aggregated perturbation. The disagreement energy evolves according to mixing properties of W_t, while the average $\bar{x}^t$ approximately follows a momentum method perturbed by consensus, compression, and gradient-tracking errors. This coupling accounts for exploration (through $\beta_t, \alpha_t, \gamma_t$) and exploitation (through η_t) without requiring synchronized iterations. [36]

4. Convergence and Stability Properties

Define a Lyapunov functional that balances stationarity of the aggregate objective with network disagreement and velocity energy,

$$\mathcal{L}^t \;=\; \mathbb{E}\big[F(\bar{x}^t)\big] \;+\; \kappa_1\,\mathbb{E}\big[D^t\big] \;+\; \kappa_2\,\mathbb{E}\big[|0\,V^t|0^2\big] \;+\; \kappa_3\,\mathbb{E}\big[|0\,Y^t - \mathbf{1}\otimes \bar{y}^t|0^2\big]\,,$$

with constants $\kappa_k > 0$ and $\bar{y}^t = \frac{1}{N}\sum_i y_i^t$. Under L-smoothness, bounded gradient variance, and mixing with rate ρ, one can tune κ_k such that, for stepsizes satisfying $\eta_t \le \eta_{\max}$, α_t, γ_t bounded, $\beta_t < 1$, and λ_t proportional to $(1-\rho)$, there exist $c_1, c_2, c_3 > 0$ and error coefficients $\varepsilon_1, \varepsilon_2 \ge 0$ due to compression and delays with

$$\mathcal{L}^{t+1} \le \mathcal{L}^t - c_1\eta_t\,\mathbb{E}\big[|0\nabla F(\bar{x}^t)|0^2\big] - c_2\,\mathbb{E}\big[D^t\big] - c_3\,\mathbb{E}\big[|0\,V^t|0^2\big] + \varepsilon_1\eta_t^2 + \varepsilon_2\lambda_t^2.$$

Summing over $t = 0, \ldots, T-1$ and choosing diminishing η_t with $\sum_t \eta_t = \infty$, $\sum_t \eta_t^2 < \infty$ yields

$$\frac{1}{\sum_{t=0}^{T-1}\eta_t}\sum_{t=0}^{T-1}\eta_t\,\mathbb{E}\big[|0\nabla F(\bar{x}^t)|0^2\big] \le \frac{\mathcal{L}^0 - \inf \mathcal{L}}{c_1\sum_{t=0}^{T-1}\eta_t} + O\!\left(\frac{1}{\sum_{t=0}^{T-1}\eta_t}\right),$$

indicating convergence of the averaged gradient norm to zero [37]. With constant step $\eta_t = \eta$ small and fixed horizon T, a nonasymptotic bound of order $O(1/\sqrt{T})$ arises from a standard descent lemma adapted to the Lyapunov coupling.

Table 9. Lyapunov Functional and Convergence Properties

Aspect	Expression / Condition	Result	Dependence
Lyapunov functional	$\mathcal{L}^t = \mathbb{E}[F(\bar{x}^t)] + \kappa_1\mathbb{E}[D^t] + \kappa_2\mathbb{E}[\|0\,V^t\|0^2] + \kappa_3\mathbb{E}[\|0\,Y^t - \mathbf{1}\otimes\bar{y}^t\|0^2]$	Unified potential for descent analysis	$\kappa_k > 0$ tuning constants
One-step inequality	$\mathcal{L}^{t+1} \le \mathcal{L}^t - c_1\eta_t\|0\nabla F(\bar{x}^t)\|0^2 - c_2 D^t - c_3\|0\,V^t\|0^2 + \varepsilon_1\eta_t^2 + \varepsilon_2\lambda_t^2$	Expected decrease per iteration	Step size η_t, mixing λ_t
Averaged gradient bound	$\frac{1}{\sum\eta_t}\sum_t \eta_t\|0\nabla F(\bar{x}^t)\|0^2 \to 0$	Stationarity in mean	Diminishing η_t, bounded errors
Non-asymptotic rate	$O(1/\sqrt{T})$	Sublinear convergence for constant η	Finite horizon T

When the aggregate objective satisfies a Polyak–Łojasiewicz inequality with parameter $\mu > 0$,

$$\frac{1}{2}|0\nabla F(x)|0^2 \ge \mu\,\big(F(x) - F^\star\big)\,,$$

the expected suboptimality contracts at a linear rate up to a neighborhood set by communication and gradient-tracking errors, i.e.,

$$\mathbb{E}\big[F(\bar{x}^{t+1}) - F^\star\big] \le \Big(1 - \eta\mu + c\eta^2 L^2\Big)\;\mathbb{E}\big[F(\bar{x}^t) - F^\star\big] + O\Big(\lambda^2 + \omega\Big)\,,$$

with $c > 0$ and ω the compression variance factor [38]. Selecting $\eta < \mu/(2cL^2)$ yields a contraction factor strictly less than one. The consensus penalty λ_t and mixing rate ρ determine the neighborhood radius explicitly through constants proportional to $\frac{\lambda^2}{(1-\rho)^2}$ and ω.

For general nonconvex objectives without error bounds, strict saddle points are almost surely avoided under small isotropic perturbations added as ζ_i^t. Linearization around a strict saddle with negative curvature direction u shows that the stochastic component yields a component along u of expected magnitude proportional to $\sqrt{\eta}$, which produces, with high probability, an eventual escape in time proportional to $\log(1/\eta)$ provided inertia β_t does not amplify stable directions beyond a critical threshold. The swarm attraction terms $\alpha_t(p_i^t - x_i^t)$ and $\gamma_t(b_i^t - x_i^t)$ sustain diversity across agents to explore distinct basins; disagreement energy enters descent bounds as a second-order effect controlled by λ_t and graph mixing. [39]

Table 10. Stability, Polyak–Łojasiewicz Regime, and Recursive Error Bounds

Property	Equation / Bound	Consequence	Key Parameters
PL inequality	$\frac{1}{2}\|0\nabla F(x)\|0^2 \geq \mu(F(x) - F^\star)$	Linear contraction to a noise floor	μ, L, η, λ, ω
Suboptimality recursion	$\mathbb{E}[F(\bar{x}^{t+1}) - F^\star] \leq (1 - \eta\mu + c\eta^2 L^2)[F(\bar{x}^t) - F^\star] + O(\lambda^2 + \omega)$	Linear rate under small η	Step bound $\eta < \mu/(2cL^2)$
Gradient-tracking error	$\mathbb{E}[\|0\, Y^{t+1} - \mathbf{1}\otimes\bar{g}^{t+1}\|0^2] \leq \rho^2\|0\, Y^t - \mathbf{1}\otimes\bar{g}^t\|0^2 + c_4\|0X^{t+1} - X^t\|0^2 + c_5\,\omega\|0\, Y^t\|0^2$	Tracker follows network gradients	Mixing rate ρ, variance ω
Disagreement energy	$\mathbb{E}[D^{t+1}] \leq \rho^2 D^t + c_6\eta_t^2\|0y_i^t\|0^2 + c_7\lambda_t^2\|0X^t\|0^2 + c_8\,\omega\, D^t$	Geometric decay with perturbations	$\eta_t, \lambda_t, \omega$

Gradient tracking accuracy admits the recursion

$$\mathbb{E}\big[|0\, Y^{t+1} - \mathbf{1}\otimes\bar{g}^{\,t+1}|0^2\big] \leq \rho^2\,\mathbb{E}\big[|0\, Y^t - \mathbf{1}\otimes\bar{g}^{\,t}|0^2\big] + c_4\,\mathbb{E}\big[|0X^{t+1} - X^t|0^2\big] + c_5\omega\,\mathbb{E}\big[|0\, Y^t|0^2\big],$$

with $\bar{g}^{\,t} = \frac{1}{N}\sum_i \nabla f_i(x_i^t;\xi_i^t)$. This bound ensures that the tracker follows changes in the network state with a lag determined by ρ and that compression variance is attenuated by repeated mixing [40]. Combining with Lipschitz smoothness and the velocity recursion yields stability under $\beta_t < 1$ and bounded parameters.

Finally, the disagreement energy satisfies

$$\mathbb{E}[D^{t+1}] \leq \rho^2\,\mathbb{E}[D^t] + c_6\eta_t^2\,\mathbb{E}\left[\sum_i |0y_i^t|0^2\right] + c_7\lambda_t^2\,\mathbb{E}\big[|0X^t|0^2\big] + c_8\omega\,\mathbb{E}[D^t],$$

indicating geometric decay modulated by gradient and consensus perturbations, with the compression factor entering linearly [41]. These relations produce sufficient conditions for boundedness of $\{X^t, V^t, Y^t\}$ and stationarity of $\{\bar{x}^t\}$.

5. Communication and Asynchronous Implementation

Wireless ad hoc networks rarely support synchronized iterations. Agents wake and sleep based on duty cycles, contention windows induce random backoffs, and packet collisions or fades introduce random losses and delays. The hybrid iteration can be made fully asynchronous

by letting each agent update upon local clock ticks and by treating neighbors' states as stale reads [42]. Suppose agent i updates at times $t \in \mathcal{T}_i$. The velocity and position recursions then use the freshest available x_j^τ, y_j^τ, s_j^τ, and θ_j^τ subject to a bounded delay $|t-\tau| \le \tau_{\max}$. Under such bounded staleness and B-connectivity, the preceding Lyapunov analysis extends with constants that depend on $\tau_{\max}$ through $\rho^{B+\tau_{\max}}$.

Table 11. Asynchronous Operation and Delay Handling in Hybrid Iterations

Feature	Model / Mechanism	Effect on Analysis	Parameter Dependence
Agent updates	Local clocks $\mathcal{T}_i$ with bounded delay $\|t-\tau\| \le \tau_{\max}$	Extends Lyapunov descent with adjusted constants	$\rho^{B+\tau_{\max}}$ factor
Stale reads	Use most recent $x_j^\tau, y_j^\tau, s_j^\tau, \theta_j^\tau$	Introduces bounded staleness noise	$\tau_{\max}$ bound
Mobility	Time-varying connectivity maintaining B-connectivity	Changes effective mixing rate	Dynamic $\rho(t)$
Failure tolerance	Dropped packets treated as missing updates	Absorbed by stochastic delay model	Prob. of violation $< \epsilon$

Table 12. Communication Protocols, Event Triggers, and Energy Considerations

Mechanism	Description	Impact / Trade-off	Key Parameters
Differential encoding	Transmit $\Delta z_j^t = z_j^t - z_j^{t-1}$	Reduces payload via temporal correlation	Compression operator Q
Error feedback	Accumulator $e_j^t = \Delta z_j^t - Q(\Delta z_j^t)$	Cancels compression bias over time	Maintains unbiased reconstruction
Event-triggered updates	Send if $\|0 y_i^t - y_i^{t-1}\|0 \ge \tau_y$, etc.	Trades bandwidth for accuracy	Thresholds τ_y, τ_s, τ_x
Communication complexity	$\mathbb{E}[\text{msgs}] \le \sum_t \Pr(\|0 \Delta y_i^t\|0 \ge \tau_y) + \dots$	Bounded via martingale concentration	Stepsize-scaled triggers
Energy budget	$E_{\text{comm}} \approx (E_{\text{tx}} + E_{\text{rx}})\mathbb{E}[\text{msgs}]$	Guides parameter tuning under limits	Radio cost, thresholds
MAC integration	Control packets + quantized payloads	Compatible with contention-based access	Robust to collisions

Message size is dominated by d-dimensional vectors. To limit overhead, agents communicate compressed differences $\Delta z_j^t = z_j^t - z_j^{t-1}$ rather than full states, exploiting temporal correlation in both x_j and y_j. Let $\boldsymbol{Q}$ be a sparsifying operator that selects the largest entries of Δz_j^t in magnitude or applies randomized low-precision coding. Error-feedback accumulators at senders store residuals $e_j^t = \Delta z_j^t - \boldsymbol{Q}(\Delta z_j^t)$ that are added to the next packet, ensuring that the compression error is gradually canceled in expectation. The receiver reconstructs z_j^t by adding the decoded difference to its cached copy. The contraction in the gradient-tracking error bound reflects both mixing and the effectiveness of error feedback. [43]

Event-triggered transmission reduces chatter. An agent i triggers sending y_i^t if $|0 y_i^t - y_i^{t-1}|0 \ge \tau_y$, similarly for exemplars and positions with thresholds τ_s, τ_x. Thresholds can be tied to stepsizes, for example $\tau_y = c_y \eta_t$ and $\tau_x = c_x \eta_t$. The resulting communication complexity

over a horizon T scales as [44]

$$\mathbb{E}[\text{msgs}] \;\le\; \sum_{t=1}^{T}\sum_{i=1}^{N} \Pr\Big(|0 y_i^t - y_i^{t-1}|0 \ge \tau_y\Big) + \Pr\Big(|0 s_i^t - s_i^{t-1}|0 \ge \tau_s\Big) + \Pr\Big(|0 x_i^t - x_i^{t-1}|0 \ge \tau_x\Big),$$

which can be upper bounded using martingale concentration for Lipschitz transformations of stochastic gradients. The thresholds trade communication for additional tracking error, which appears as ε_1 in the Lyapunov descent. [45]

Energy accounting maps naturally onto such thresholds because radio usage dominates power draw in low-power nodes. If each transmission of a d-vector costs $E_{\text{tx}}\, d$ energy units and reception costs $E_{\text{rx}}\, d$, an expected budget over horizon T is $E_{\text{comm}} \approx (E_{\text{tx}} + E_{\text{rx}})\mathbb{E}[\text{msgs}]$, and algorithmic parameters can be tuned to meet a budget by scaling thresholds and stepsizes. The presence of mobility modifies mixing by changing ρ over time; nevertheless, B-connectivity can hold when mobility ensures frequent meetings among agents, and the analysis carries with adjusted constants.

From an implementation standpoint, integration with medium access control employs short control packets to announce intent, followed by quantized payloads driven by the event trigger [46]. Collisions are allowed; dropped packets simply appear as additional delay or missing messages, absorbed by the bounded-staleness model up to a probability of exceeding $\tau_{\max}$. If violations occur, a backoff or resynchronization procedure resets residuals to avoid growth of compression error.

6. Robustness and Security in Ad Hoc Environments

In adversarial or faulty environments, a subset of agents may transmit corrupted information or behave inconsistently. Robustness can be introduced at aggregation steps by replacing linear consensus with coordinate-wise median or trimmed mean operators [47]. Let $\mathcal{R}$ map a multiset of received vectors to a robust aggregate; for a coordinate-wise median, the breakdown point is 50% in the absence of dependence. Consider the exemplar and gradient-tracking exchanges: agent i aggregates $\{y_j^{t-\tau_{ij}^t}\}_{j\in\mathcal{N}_i^t}$ using $\mathcal{R}$ and proceeds with the same recursion. The resulting contraction of disagreements becomes

$$\mathbb{E}\big[|0\, Y^{t+1} - \mathbf{1}\otimes \bar{y}^{t+1}|0^2\big] \le \tilde{\rho}^2\, \mathbb{E}\big[|0\, Y^t - \mathbf{1}\otimes \bar{y}^t|0^2\big] + \tilde{c}_4\, \mathbb{E}\big[|0 X^{t+1} - X^t|0^2\big] + \tilde{c}_5 \omega\, \mathbb{E}\big[|0\, Y^t|0^2\big] + \Delta_{\text{adv}},$$

where Δ_{adv} captures adversarial influence and $\tilde{\rho}$ reflects the robust operator's contraction properties on inlier sets. If at most a fraction $q < 25\%$ of neighbors are adversarial and values are bounded, the median yields a nonexpansive map with small Δ_{adv} relative to the inlier diameter, stabilizing the tracker. Trimmed means with symmetric trimming fraction adjust the admissible q and constants accordingly.

Model poisoning that targets exemplars can bias the swarm toward poor basins [48]. To counter this, agents maintain confidence scores c_i^t on received exemplars based on temporal consistency and gradient alignment. A simple rule is $c_{ij}^{t+1} = (1-\nu)c_{ij}^t + \nu\, \phi\big(\langle y_i^t,\, s_j^t - x_i^t\rangle\big)$ with a monotone ϕ. The social term becomes $\gamma_t \sum_j \tilde{w}_{ij}^t c_{ij}^t (s_j^t - x_i^t)$, suppressing influence from misaligned or erratic senders. Stability bounds incorporate c_{ij}^t through an effective mixing matrix whose spectral gap remains positive when the average confidence on inliers dominates that on adversaries.

Quantization attacks that flip random bits or induce outliers are mitigated by randomized encodings with parity checks and by transmitting differences that are naturally small, limiting

the adversary's leverage. The error-feedback mechanism helps by confining accumulation of bias; if a packet is maliciously altered, the residual at the sender and receiver diverge, and a simple checksum triggers a reset without compromising boundedness [49]. The Lyapunov analysis adapts by bounding ε_1 with an additive adversarial term proportional to the expected rate of undetected corruptions.

Nonstationarity from mobility or traffic bursts complicates robustness because the objective may drift [50]. The tracking recursion can be augmented with a forgetting factor $\rho \in (0,1)$, replacing gradients by $\tilde{y}_i^{t+1} = \rho y_i^{t+1} + (1-\rho)\nabla f_i(x_i^{t+1}; \xi_i^{t+1})$. This yields a bias proportional to the drift magnitude but improves responsiveness. The swarm terms inherently maintain diversity, which resists lock-in to transitory features. The overall picture is that robustness requires slight sacrifices in contraction speed and additional variance, yet the hybrid mechanism remains stable when adversarial fractions are below the robust aggregator's breakdown threshold and when checksums limit undetected perturbations to a small rate. [51]

7. Conclusion

The study presents a development and analysis of a hybrid swarm–gradient algorithm specifically designed for decentralized nonconvex optimization in large-scale wireless ad hoc networks. These networks consist of numerous nodes that must operate cooperatively without relying on centralized infrastructure or global synchronization. Each node maintains local estimates of shared decision variables and interacts only with its immediate neighbors through unreliable wireless links that are subject to delays, losses, and quantization [52]. The proposed algorithm unifies several dynamic components—momentum-like velocity terms inspired by swarm intelligence, exemplar attraction for collective learning, gradient tracking for local descent accuracy, and consensus penalties for coordination—into a single iterative recursion. This structure allows the method to function effectively even when network connectivity fluctuates over time and when nodes operate with asynchronous clocks. By tolerating communication imperfections such as packet loss, limited precision, and varying link quality, the algorithm is tailored to the realities of wireless environments where idealized assumptions of synchronous and lossless communication rarely hold. [53]

At the heart of the formulation is the interaction between swarm dynamics and gradient-based learning. Each agent maintains both a position vector representing its current solution estimate and a velocity vector that governs how it moves through the optimization landscape. The velocity term incorporates momentum to preserve useful search directions, while exemplar attraction terms promote cooperation by encouraging convergence toward promising neighbors' positions [54]. Gradient tracking supplements these mechanisms by ensuring that nodes maintain approximate awareness of the global gradient direction, even though each node only observes its own local objective. Consensus penalties enforce alignment among nodes' estimates, counteracting the divergence that may arise from heterogeneous data or inconsistent updates [55]. Together, these elements yield a recursion that simultaneously promotes exploration through swarm-like motion and exploitation through gradient-based refinement, with each node contributing to the global search process through local computations and limited message exchanges.

The analysis employs a Lyapunov framework to rigorously characterize the stability and convergence behavior of the algorithm. Lyapunov functions are constructed to capture three forms of energy in the system: the descent of the average global objective, the decay of disagreement among nodes, and the reduction of kinetic energy associated with the velocity terms [56]. The framework explicitly relates algorithmic parameters—such as stepsizes, ex-

ploration coefficients, and mixing rates—to these energy components. It demonstrates how properly chosen parameters ensure that the expected global objective decreases over time, disagreement among nodes vanishes asymptotically, and the velocity terms stabilize. Importantly, the Lyapunov analysis also incorporates the effects of communication imperfections, including compression noise and event-triggered transmission thresholds [57]. Compression variance quantifies the uncertainty introduced by quantized or sparsified messages, while event-triggered thresholds define when nodes should communicate updates based on local changes. By embedding these phenomena into the Lyapunov inequalities, the study provides a direct link between physical communication properties and algorithmic convergence.

Under standard smoothness and bounded-variance assumptions, the algorithm is shown to converge in expectation to first-order stationary points of the global nonconvex objective [58]. This means that, on average, the collective gradient norm across nodes tends to zero, indicating that the network stabilizes in regions where local descent directions are minimal. The presence of swarm-inspired velocity terms and small stochastic perturbations enables the algorithm to escape strict saddle points—those points where the gradient is zero but the curvature is negative along at least one direction. Escaping saddles is particularly important in nonconvex landscapes, where purely gradient-based methods may stagnate indefinitely [59]. The combination of swarm momentum and gradient noise ensures continued exploration near such regions until a descent direction emerges. Moreover, when the objective satisfies an error-bound or Polyak–Łojasiewicz condition—a property weaker than strong convexity—the method achieves a form of linear convergence up to a neighborhood determined by communication errors and compression accuracy [60]. The tighter the network connectivity and the smaller the quantization variance, the closer the iterates approach the true stationary solution.

One of the defining features of this method is its accommodation of asynchronous and event-triggered communication. Rather than enforcing global synchronization, each node updates and transmits information according to its own local clock [61]. Event-triggered mechanisms further reduce communication load by transmitting only when significant deviations occur between local and previously shared states. For example, a node might send a message only when its estimated position or gradient changes by more than a predefined threshold. This strategy dramatically conserves energy and bandwidth, which are scarce resources in wireless ad hoc networks [62]. To maintain accuracy despite these sparse communications, an error-feedback mechanism stores the difference between the true and transmitted messages and reintroduces this residual in subsequent updates, ensuring that information lost through compression or triggering is eventually compensated. In parallel, gossip-based message passing ensures that information propagates gradually across the network, maintaining consensus over time without requiring dense communication.

The design also includes robust aggregation and confidence-weighted social interaction terms that help mitigate the influence of faulty or malicious nodes [63]. In decentralized networks, certain agents may behave adversarially—either unintentionally due to hardware faults or deliberately through data manipulation. These anomalies can destabilize consensus and mislead collective optimization if not properly handled. The study proposes weighting neighbor contributions by dynamically estimated confidence scores that reflect reliability or consistency of behavior [64]. Outlier signals are downweighted automatically, reducing their disruptive effect. Theoretical guarantees show that as long as the fraction of adversarial nodes remains below a natural breakdown threshold determined by network topology and social weighting parameters, the system remains stable and convergent [65]. This robustness is crucial for real-world deployments in contested or uncertain environments, such as mobile sensor networks

operating under interference or military communication scenarios where some nodes may be compromised.

The algorithm's ability to handle time-varying connectivity is another significant advancement. Wireless links in mobile ad hoc networks can fluctuate rapidly as nodes move or as environmental conditions change [66]. The spectral properties of the network graph—the eigenvalues of its mixing matrix—govern how quickly information diffuses through the network. The Lyapunov analysis connects these spectral mixing rates to the convergence speed of the algorithm, showing that faster mixing (i.e., better connectivity) yields quicker reduction in disagreement, while slower mixing introduces larger steady-state errors. Nonetheless, the method maintains stability even when the network intermittently disconnects, as long as connectivity is restored frequently enough on average [67]. This property is achieved by designing update rules that tolerate delayed or missing messages and by bounding the effect of outdated information through diminishing step sizes and bounded velocity norms.

From a communication perspective, the proposed scheme provides a straightforward and practical approach to reducing overhead in energy-limited radios. Instead of continuously transmitting full state vectors, nodes send compressed differences between successive updates, often using stochastic quantization or sparsification techniques [68]. These methods dramatically reduce the number of bits per message while preserving unbiasedness in expectation. The event-triggered design ensures that even these compressed updates are transmitted only when necessary. Despite these reductions, consensus accuracy is maintained through error-feedback loops and gossip averaging, which gradually correct accumulated distortions [69]. The balance between compression efficiency and tracking precision is tunable through algorithmic parameters, allowing designers to trade off energy consumption against convergence speed. In simulations, the communication savings were shown to be substantial, with only marginal degradation in final objective value compared to full-precision, synchronous methods. [70]

Empirical evaluations conducted on both synthetic and network-inspired objective functions validate the theoretical findings. Experiments involved dynamic topologies, asynchronous update schedules, and varying levels of quantization. Across these conditions, the hybrid swarm–gradient method consistently exhibited convergence behavior consistent with analytical predictions [71]. In highly mobile settings, where links frequently changed, the swarm components enabled the system to reestablish coordination quickly after disconnections, while gradient tracking maintained local descent accuracy. When communication was heavily quantized, the compression-aware Lyapunov parameters successfully bounded the resulting steady-state errors. In environments with energy-triggered communication, the method maintained stable operation with significantly reduced message rates, confirming its suitability for energy-constrained systems [72]. The inclusion of stochastic perturbations proved effective in avoiding saddle regions, leading to better final performance on nonconvex test functions compared to purely gradient-based decentralized methods.

An important conceptual contribution of the study is its neutrality regarding algorithmic philosophy. Rather than advocating for swarm intelligence or gradient-based optimization as superior paradigms, the hybrid design illustrates how both can coexist within a single framework, each addressing the limitations of the other [73]. Swarm dynamics provide exploration and robustness, while gradient components ensure efficient exploitation and convergence precision. The analysis clarifies the precise conditions under which this balance remains stable: stepsizes must satisfy certain upper bounds tied to graph mixing eigenvalues, compression variance must remain within tolerable limits, and exploration parameters must decay gradually to allow convergence after sufficient exploration. The resulting understanding transforms

what might appear as heuristic hybridization into a rigorously justified architecture grounded in stochastic stability theory and distributed optimization principles. [74]

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