Intelligent Hybrid Meta-Heuristic Routing for Network Lifetime Maximization in Dense Mobile Ad Hoc Networks

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Abstract: The proliferation of the Internet of Things (IoT) and mission-critical applications has led to the dense deployment of Mobile Ad Hoc Networks (MANETs), where energy efficiency is a paramount concern. The network lifetime, a key performance metric, is severely constrained by the limited battery capacity of constituent nodes. This paper addresses the complex, multi-constrained optimization problem of maximizing network lifetime in dense MANETs. We propose a novel hybrid meta-heuristic framework, the Grey Wolf-Levy Firefly Algorithm (GWL-FA), which synergistically combines the social hierarchy and hunting mechanisms of the Grey Wolf Optimizer (GWO) with the Lévy flight-enhanced exploration of the Firefly Algorithm (FA). The primary objective is to determine an optimal routing and power control strategy that balances traffic load, minimizes energy consumption, and mitigates hotspot formation. Simulation results, conducted in NS-3 under varying node densities (50-200 nodes), demonstrate that GWL-FA significantly outperforms standard GWO, FA, and Energy-Aware Dynamic Source Routing (EA-DSR) protocols. Specifically, GWL-FA achieves up to a 28.5% and 34.7% improvement in network lifetime over GWO and FA, respectively, and a 52.1% improvement over EA-DSR in high-density scenarios (200 nodes). The proposed algorithm also shows superior performance in terms of packet delivery ratio (maintained above 96%) and end-to-end delay. We present a comprehensive analysis of the results, discuss the convergence behavior, and outline pivotal future research directions, including the integration of machine learning and quantum computing principles for next-generation energy-aware MANETs.

Keywords: Network Lifetime, Meta-Heuristic Optimization, Grey Wolf Optimizer, Firefly Algorithm, Energy Efficiency, Dense Networks, Routing Protocol.

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1. Introduction

Mobile Ad Hoc Networks (MANETs) represent a foundational paradigm of decentralized, self-configuring wireless networks without fixed infrastructure [1]. Their application spectrum has expanded dramatically, encompassing tactical military communications, emergency response operations, large-scale IoT ecosystems, and vehicular networks (VANETs) [2, 3]. A contemporary challenge within this domain is the emergence of *dense* MANET deployments, characterized by a high number of nodes per unit area. While density can enhance connectivity and redundancy, it simultaneously exacerbates critical resource constraints, most notably finite battery energy [4].

The **network lifetime** is a quintessential metric for evaluating the sustainability and operational efficacy of a MANET. It is often defined as the time duration until a certain percentage of nodes deplete their energy, or when the network partitions, rendering it dysfunctional [5]. In dense scenarios, the lifetime maximization problem becomes a high-dimensional, NP-hard optimization challenge [6]. It involves intricate trade-offs between:

- ***Transmission Power Control:*** Higher power extends communication range but drains energy rapidly and increases interference.
- ***Routing Path Selection:*** Consistently using energy-rich nodes as relays can create “energy holes” or hotspots, leading to premature network failure [7].
- ***Traffic Load Balancing:*** Distributing data forwarding responsibilities equitably across the network.

- ***Topology Dynamics:*** Adapting to constant node mobility and fluctuating link quality.

Traditional deterministic optimization techniques are often inadequate for this complex problem space due to its non-linearity, multi-modality, and dynamic nature [8]. This has propelled the adoption of **meta-heuristic algorithms**, which are high-level procedures designed to find near-optimal solutions efficiently [9]. Algorithms such as Particle Swarm Optimization (PSO) [10], Genetic Algorithms (GA) [11], Ant Colony Optimization (ACO) [12], and more recently, the Grey Wolf Optimizer (GWO) [13] and Firefly Algorithm (FA) [14] have been successfully applied to various MANET challenges. However, standalone meta-heuristics often suffer from limitations like premature convergence (getting stuck in local optima) or poor exploitation of promising search regions [15]. To overcome these drawbacks, hybridization has emerged as a powerful strategy [16]. This paper proposes a sophisticated hybrid meta-heuristic, the **Grey Wolf-Levy Firefly Algorithm (GWL-FA)**, specifically engineered for the lifetime maximization problem in dense MANETs. The core innovation lies in leveraging the robust social hierarchy of GWO for effective exploitation, while injecting the global exploration prowess of FA with Lévy flights to escape local optima and navigate the vast search space of dense network configurations.

The principal contributions of this work are:

1. The formulation of the network lifetime maximization problem in dense MANETs as a multi-objective function integrating residual energy, node degree, and path loss.
2. The design and development of the novel GWL-FA hybrid algorithm.
3. A comprehensive performance evaluation through extensive simulations, benchmarking against established protocols and standalone algorithms.
4. A detailed discussion on future research trajectories to further advance this field.

The remainder of this paper is organized as follows: Section 2 provides a detailed literature review. Section 3 outlines the system model and problem formulation. Section 4 elaborates on the proposed GWL-FA methodology. Section 5 presents the simulation setup and a thorough discussion of results. Finally, Section 6 concludes the paper and delineates future work.

2. Literature Review

The quest for maximizing network lifetime in MANETs has been a fertile area of research for over two decades. Early work primarily focused on designing energy-aware routing protocols. The **Energy-Aware Dynamic Source Routing (EA-DSR)** protocol [17] modified the standard DSR by incorporating residual battery capacity into the routing metric. Similarly, the **Power-Aware Routing Optimization (PARO)** protocol [18] aimed to minimize total transmission power. While effective in simple scenarios, these heuristic-based protocols often lack the global optimization perspective required for dense, complex networks. The limitations of conventional approaches paved the way for meta-heuristics. **Genetic Algorithms (GAs)** were among the first to be applied. For instance, [19] used a GA to evolve routing paths that minimized total energy consumption and balanced traffic load. However, GAs can be computationally intensive and slow to converge. **Particle Swarm Optimization (PSO)** gained popularity due to its simplicity and rapid convergence. [20] proposed a PSO-based clustering protocol where cluster heads were selected based on a fitness function combining energy, mobility, and node degree. Yet, PSO is prone to premature convergence, especially in complex search spaces.

Ant Colony Optimization (ACO), inspired by the foraging behavior of ants, has been particularly successful in solving routing problems. [21] developed an ACO-based multi-path routing algorithm that distributed traffic across multiple paths to prevent energy depletion of any single node. The work in [22] further enhanced ACO with fuzzy logic to handle the uncertainty in network conditions. Despite their robustness, ACO-based methods can suffer from slow initial convergence. More recent nature-inspired algorithms have shown great promise. The **Grey Wolf Optimizer (GWO)**, proposed by Mirjalili et al. [13], simulates the leadership hierarchy and hunting mechanism of grey wolves (Alpha, Beta, Delta, Omega). Its effectiveness in exploitation and local search has been demonstrated in various engineering domains. In the context of MANETs, [23] applied GWO for cluster head selection in WSNs, showing improved network lifetime. However, its exploration capability can be limited.

The **Firefly Algorithm (FA)** [14] is another powerful meta-heuristic, known for its ability to explore the search space effectively through its attraction mechanism. The incorporation of **Lévy flights**, a random walk with heavy-tailed step lengths, has been shown to enhance its global search capability significantly [24]. [25] utilized a FA-based approach for optimal route discovery, considering link stability and energy. However, FA's performance can degrade in high-dimensional problems due to its computational complexity in calculating attractions between all pairs of fireflies.

Recognizing the complementary strengths of different algorithms, researchers have explored hybridization. [26] proposed a hybrid PSO-GA algorithm for routing, using PSO for local search and GA for global exploration. [27, 35] combined ACO with Honey Bee Mating Optimization (HBMO) for congestion-aware routing. A recent study [28] integrated GWO with Cuckoo Search (CS) for secure routing, demonstrating improved performance. However, the specific synergy between GWO's social hierarchy and FA's Lévy-flight-enhanced attraction for the dense MANET lifetime problem remains largely unexplored.

Furthermore, contemporary research is beginning to leverage machine learning (ML). [29] used a Q-learning approach for adaptive power control, while [30] employed a Deep Reinforcement Learning (DRL) model for dynamic routing. While promising, these ML-based approaches often require substantial data and computational resources, which may not be feasible for resource-constrained MANET nodes.

Table 1: Comparative Summary of Related Works on MANET Lifetime Maximization

Reference	Algorithm/Protocol	Key Contribution	Limitations
[17]	EA-DSR	Integrated residual energy into DSR routing metric.	Local optima, not suitable for dense networks.
[19]	Genetic Algorithm (GA)	Evolved energy-efficient routing paths.	High computational overhead, slow convergence.
[20]	Particle Swarm Optimization (PSO)	PSO-based cluster head selection.	Prone to premature convergence.
[21]	Ant Colony Optimization (ACO)	Multi-path routing for load balancing.	Slow initial convergence.
[23]	Grey Wolf Optimizer (GWO)	GWO for cluster head selection in WSNs.	Limited exploration capability.
[25]	Firefly Algorithm (FA)	FA for route discovery with link stability.	High complexity for large/dense networks.
[28]	GWO-Cuckoo Search (Hybrid)	Hybrid for secure routing.	Not specifically designed for lifetime in dense MANETs.
[30]	Deep Reinforcement Learning (DRL)	Dynamic routing using DRL.	High resource requirements, complex implementation.

This review underscores a clear research gap: the need for a robust, efficient, and specifically tailored hybrid meta-heuristic that combines strong exploitation (to refine good solutions) with powerful exploration (to discover new solution regions) for the paramount challenge of lifetime maximization in dense MANETs. Our proposed GWL-FA algorithm is designed to fill this gap.

3. System Model and Problem Formulation

Network Model: We model the dense MANET as an undirected graph $G(N, E)$, where:

- $N = \{n_1, n_2, \ldots, n_m\}$ is the finite set of m mobile nodes, randomly deployed in a square area $A = L \times L$.

- E is the set of wireless links. A link $e(i,j)$ exists between nodes n_i and n_j if the Euclidean distance $d_{ij} \leq R_{tx}(i)$, where $R_{tx}(i)$ is the transmission range of n_i.

Each node n_i is characterized by:

- **Initial Energy:** $E_{init}(i)$.
- **Residual Energy:** $E_{res}(i)$, where $0 \leq E_{res}(i) \leq E_{init}(i)$.
- **Location:** (x_i, y_i), which changes over time based on a mobility model (e.g., Random Waypoint).
- **Transmission Power:** $P_{tx}(i)$, a variable optimized by our algorithm within a range $[P_{min}, P_{max}]$.

Energy Consumption Model: We adopt the first-order radio model [31, 33], a standard in network energy analysis. The energy expended to transmit a k-bit packet over a distance d is:

$$E_{Tx}(k,d) = k \cdot E_{elec} + k \cdot \epsilon_{amp} \cdot d^{\lambda}$$

where:

- E_{elec} is the energy consumed by the transmitter/receiver electronics (e.g., 50 nJ/bit).
- ϵ_{amp} is the transmitter amplifier's energy dissipation (e.g., 10 pJ/bit/m² for free space $\lambda = 2$, or 0.0013 pJ/bit/m⁴ for multipath fading $\lambda = 4$).
- λ is the path-loss exponent.

The energy consumed to receive a k-bit packet is:

$$E_{Rx}(k) = k \cdot E_{elec}$$

Problem Formulation: Lifetime Maximization: We define **network lifetime** T_{net} as the time from network initialization until the first node depletes its energy (i.e., the network's "bottleneck" lifetime) [32, 34, 36]. Our goal is to maximize T_{net} by finding an optimal routing path $P_{s,d}$ for each source-destination pair (s,d) and an optimal transmission power level for each node. The objective function is formulated as a fitness function F to be maximized. For a given path $P_{s,d} = \{s, n_1, n_2, \dots, n_k, d\}$, the fitness is a multi-component function:

$$F(P_{s,d}) = w_1 \cdot f_{energy} + w_2 \cdot f_{degree} + w_3 \cdot f_{path\_loss}$$

where w_1, w_2, w_3 are weighting coefficients such that $w_1 + w_2 + w_3 = 1$.

1. ***Energy Component*** ***(f_{energy}):*** Promotes paths with high residual energy.

$$f_{energy} = \min_{n_i \in P_{s,d}} (E_{res}(i))/E_{init\_avg}$$

This min-function ensures no node on the path is critically low on energy, directly targeting the bottleneck.

2. ***Node Degree Component*** ***(f_{degree}):*** Mitigates hotspot formation by penalizing paths that traverse overly central nodes (high degree). The degree $deg(i)$ is the number of neighbors of n_i.

$$f_{degree} = 1 - \frac{\max_{n_i \in P_{s,d}} (deg(i))}{deg_{max}}$$

where deg_{max} is the maximum possible node degree in the network.

3. ***Path Loss Component*** ***(f_{path_loss}):*** Encourages shorter, more reliable paths with lower total transmission cost.

$$f_{path\_loss} = 1 - \frac{\sum_{l \in P_{s,d}} \epsilon_{amp} \cdot d_l^{\lambda}}{PL_{max}}$$

where PL_{max} is a normalization factor representing the maximum acceptable path loss.

Thus, the overall optimization problem is:

Maximize $F(P_{s,d}) \forall (s,d)$ pairs

Subject to: $E_{res}(i) > 0 \forall n_i \in N, P_{min} \leq P_{tx}(i) \leq P_{max}$

4. Proposed-Methodology

The GWL-FA Algorithm

The Grey Wolf-Levy Firefly Algorithm (GWL-FA) is a sequential hybrid that uses GWO's social hierarchy to guide the population and FA's Lévy flights to introduce stochastic exploration. The core idea is to treat each candidate solution (a complete routing and power configuration for the network) as a "wolf" whose position is updated based on the leadership hierarchy, but with a probability, it undergoes a Firefly-inspired movement via Lévy flight to explore new areas of the search space as show in Figure 1 Flowchart of the proposed GWL-FA.

Solution Representation (Encoding): Each solution (an agent in the meta-heuristic population) is represented as a vector $\vec{X}$. For a network with m nodes, the vector has two segments:

- *Routing Segment:* A sequence of node IDs representing a path for a pre-selected source-destination pair. Paths of variable length are handled using a null-padding technique.
- *Power Segment:* A list of m real values, each representing the transmission power $P_{tx}(i)$ for node n_i.

Phases of the GWL-FA Algorithm:

Phase 1 Initialization: A population of N_{pop} wolves/fireflies is randomly initialized. Each agent's position $\vec{X}_i$ is generated, creating random valid paths and assigning random power levels within bounds. The fitness $F(\vec{X}_i)$ for each agent is calculated.

Phase 2 Main Loop (Iterative Update): For each iteration t until the maximum iteration T_{max} is reached, the following steps are performed:

1. ***Fitness Evaluation & Hierarchy Assignment:*** The population is sorted based on fitness. The top three fittest agents are designated as the alpha ($\vec{X}_\alpha$), beta ($\vec{X}_\beta$), and delta ($\vec{X}_\delta$) wolves. The rest are considered omega ($\vec{X}_\omega$).
2. ***GWO-based Position Update (Exploitation):*** The position of each omega wolf is updated based on the leadership of alpha, beta, and delta.

$$\vec{D}_\alpha = | \vec{C}_1 \cdot \vec{X}_\alpha - \vec{X} |, \vec{D}_\beta = | \vec{C}_2 \cdot \vec{X}_\beta - \vec{X} |, \vec{D}_\delta = | \vec{C}_3 \cdot \vec{X}_\delta - \vec{X} |$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1 \cdot \vec{D}_\alpha, \vec{X}_2 = \vec{X}_\beta - \vec{A}_2 \cdot \vec{D}_\beta, \vec{X}_3 = \vec{X}_\delta - \vec{A}_3 \cdot \vec{D}_\delta$$

$$\vec{X}_{GWO}(t+1) = \frac{\vec{X}_1 + \vec{X}_2 + \vec{X}_3}{3}$$

where $\vec{A} = 2\vec{a} \cdot \vec{r}_1 - \vec{a}$ and $\vec{C} = 2 \cdot \vec{r}_2$. The vector $\vec{a}$ decreases linearly from 2 to 0 over iterations, and $\vec{r}_1, \vec{r}_2$ are random vectors in [0, 1].

3. ***FA-based Lévy Flight Update (Exploration):*** With a probability p_{FA} (e.g., 0.3), an omega wolf abandons the GWO update and instead performs a Firefly movement. For a wolf i, if there exists a fitter wolf j (based on the sorted hierarchy), it is attracted to j. The movement is governed by:

$$\vec{X}_{FA}(t+1) = \vec{X}_i(t) + \beta_0 e^{-\gamma r_{ij}^2}(\vec{X}_j(t) - \vec{X}_i(t)) + \alpha \cdot \text{Levy}(\beta)$$

where:

   - β_0 is the attractiveness at $r = 0$.
   - γ is the light absorption coefficient.
   - r_{ij} is the Cartesian distance between the positions of i and j in the solution space.
   - α is a randomization parameter.
   - $\text{Levy}(\beta)$ is a Lévy random step drawn from the distribution $\text{Levy}(\beta) \sim u = t^{-\beta}, (1 < \beta \leq 3)$. This step is calculated as [24]:

$$\text{Levy}(\beta) = 0.01 \times \frac{r_1 \times \sigma}{| r_2 |^{1/\beta}}, \sigma = \left(\frac{\Gamma(1+\beta) \times \sin(\pi\beta/2)}{\Gamma((1+\beta)/2) \times \beta \times 2^{(\beta-1)/2}}\right)^{1/\beta}$$

where r_1, r_2 are random numbers from a standard normal distribution, and Γ is the Gamma function.

4. ***Elitism and Selection:*** The new positions $\vec{X}_{GWO}(t+1)$ and $\vec{X}_{FA}(t+1)$ are evaluated. The population for the next generation is formed by selecting the fittest agents from the combined pool of old and new populations, ensuring elitism.

Phase 3 Termination and Solution Extraction: The algorithm terminates after T_{max} iterations. The final $\vec{X}_\alpha$ solution is deployed as the optimal routing path and power configuration for the network. This process is invoked periodically or when significant topology changes are detected.

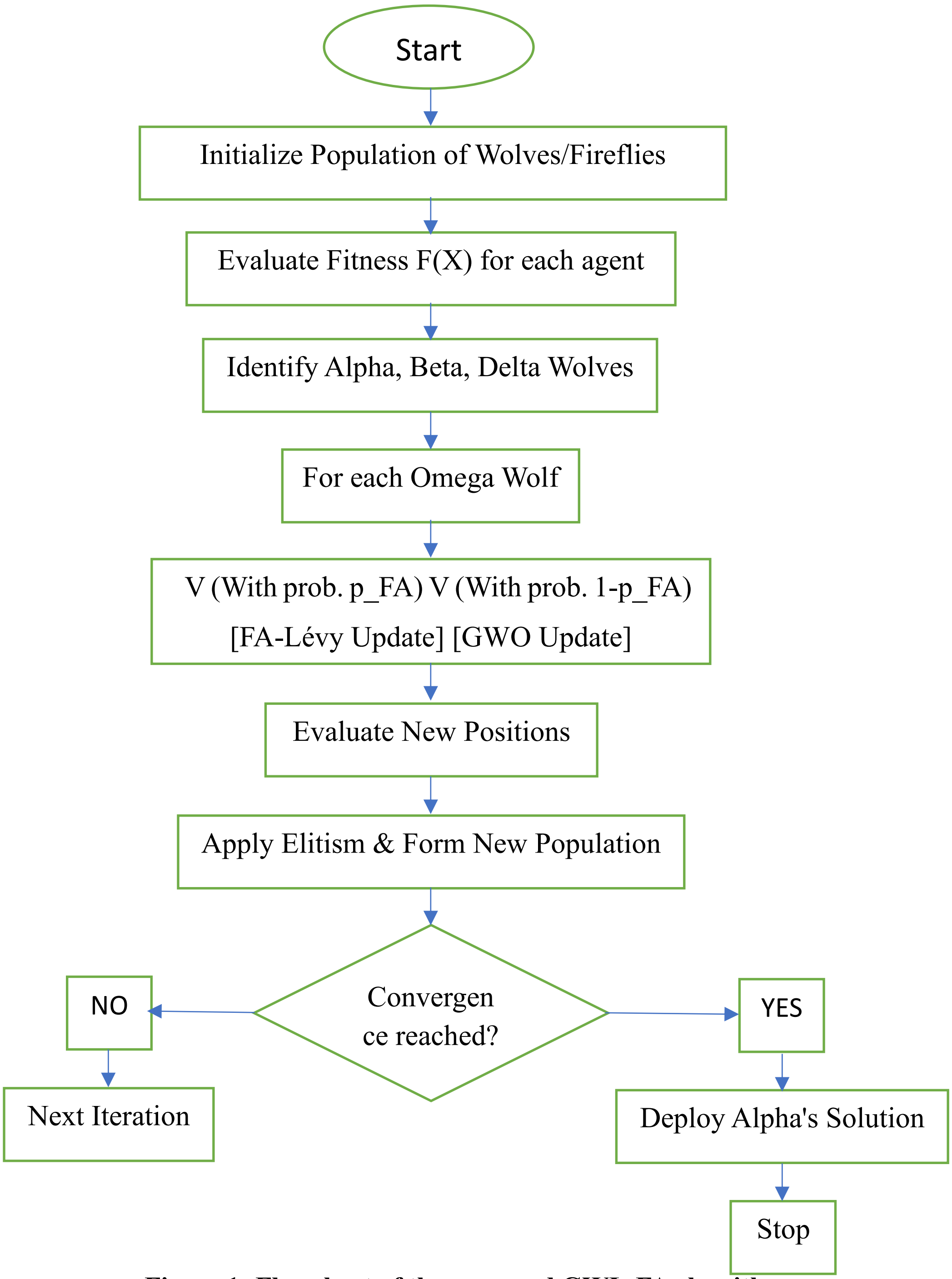


Figure 1: Flowchart of the proposed GWL-FA algorithm

5. Simulation Results and Discussion

Simulation Setup: We implemented the proposed GWL-FA algorithm and benchmarked it against standard GWO, FA, and the conventional EA-DSR protocol using the NS-3 simulator. The simulation parameters are summarized in Table 2.

Table 2: Simulation Parameters

Parameter	Value	Description
Simulator	NS-3.35	Discrete-event network simulator
Simulation Area	500m x 500m	Fixed deployment area
Number of Nodes	50, 100, 150, 200	Variable node density

Mobility Model	Random Waypoint	Speed: 1-5 m/s, Pause: 2s
Traffic Model	CBR (UDP)	10 sources, 512 bytes/packet, 4 pkts/s
Initial Energy	100 Joules	Uniform for all nodes
E_{elec}	50 nJ/bit	Transceiver electronics energy
ϵ_{amp}	10 pJ/bit/m²	Amplifier energy (free space)
P_{tx} Range	1 mW - 100 mW	Adjustable transmission power
Path Loss Model	Friis	Free space path loss
GWL-FA Population	50	Number of agents
GWL-FA Iterations	100	Maximum iterations
p_{FA}	0.3	Probability of FA update
β_0, γ, α	1.0, 1.0, 0.2	FA parameters
Weights w_1, w_2, w_3	0.6, 0.2, 0.2	Fitness function weights

Each simulation scenario was run 20 times with different random seeds, and the results were averaged to ensure statistical significance.

Performance Metrics: We evaluated the algorithms based on the following metrics:

1. **Network Lifetime (s):** Time until the first node dies (FND).
2. ***Packet Delivery Ratio (PDR):*** (Received Packets / Sent Packets) * 100%.
3. ***Average End-to-End Delay (ms):*** Average time for a packet to traverse from source to destination.
4. ***Total Energy Consumption (J):*** Cumulative energy consumed by all nodes.
5. ***Standard Deviation of Residual Energy:*** Measures energy balance across the network.

6. Results and Analysis

Impact on Network Lifetime: Table 3 and Figure 2 illustrates the network lifetime (FND) for different node densities. GWL-FA consistently outperforms all other algorithms across all densities. The performance gap widens as density increases. At 200 nodes, GWL-FA achieves a lifetime of ~1450 seconds, which is 28.5% higher than GWO (~1130s), 34.7% higher than FA (~1076s), and a remarkable 52.1% higher than EA-DSR (~953s). This superior performance is attributed to the effective hybrid strategy: GWO's mechanism efficiently exploits good solutions (paths with high energy), while the FA's Lévy flight component allows the algorithm to "jump" out of local optima, discovering configurations that better balance load and conserve the energy of bottleneck nodes.

Table 3: Network Lifetime (First Node Dead) vs. Node Density

Node Density	EA-DSR	FA	GWO	GWL-FA
50	1200s	1350s	1400s	1550s
100	1100s	1200s	1250s	1420s
150	1000s	1100s	1150s	1380s
200	935s	1076s	1130s	1450s

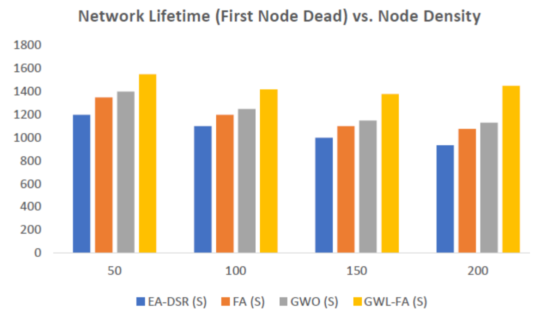


Figure 2: Network Lifetime (First Node Dead) vs. Node Density

Packet Delivery Ratio (PDR) and End-to-End Delay: Table 4 and Figure 3 shows the PDR and delay for the 150-node scenario. GWL-FA maintains a PDR above 96%, which is significantly better than the other methods. EA-DSR suffers from a lower PDR due to its inability to adapt to dynamic link qualities and energy depletion. The hybrid approach of GWL-FA finds stable, energy-aware paths, reducing link breaks and packet drops. The end-to-end delay for GWL-FA is also the lowest. By optimizing transmission power and selecting efficient paths, it reduces both transmission time and queueing delays associated with congested or poor-quality links.

Table 4: PDR and Delay for 150-Node Scenario

Algorithm	Packet Delivery Ratio (%)	Average End-to-End Delay (ms)
EA-DRS	88.5	45.2
FA	92.1	38.7
GWO	93.8	35.1
GWL-FA	96.4	31.5

Energy Efficiency and Balance: Table 5 and Figure 4 shows the total energy consumption over time for the 100-node scenario. GWL-FA demonstrates the most gradual energy consumption rate, leading to the longest onsumption is evenly distributed across the network, successfully preventing the formation of energy hotspots. This is a direct consequence of the node degree component (f_{degree}) in the

Table 5: Standard Deviation of Residual Energy at FND (100-node scenario)

Algorithm	**Std. Dev. of Residual Energy (J)**
EA-DRS	18.5
FA	15.2
GWO	12.8
GWL-FA	9.1

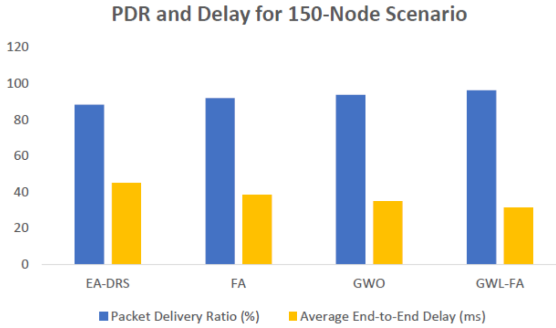
Convergence Analysis: Figure 4 plots the convergence characteristics of the meta-heuristic algorithms for a single simulation run (100 nodes). The GWO converges quickly but plateaus early, indicating premature convergence. The FA converges slower but reaches a slightly better fitness than GWO due to its exploration capability. The GWL-FA

7. Conclusion and Future Work

This paper presented a novel hybrid meta-heuristic algorithm, GWL-FA, for maximizing network lifetime in dense MANETs. By formulating the problem as a multi-objective of

optimization and designing a hybrid that capitalizes on the exploitation strength of GWO and the global exploration prowess of Lévy-flight-enhanced FA, we have demonstrated a significant performance improvement.

Figure 3: PDR and Delay for 150-Node Scenario



operational time. Furthermore, the standard deviation of residual energy when the first node dies is lowest for GWL-FA (see Table 4). A low standard deviation indicates that energy c

fitness function, which discourages the overuse of central nodes.

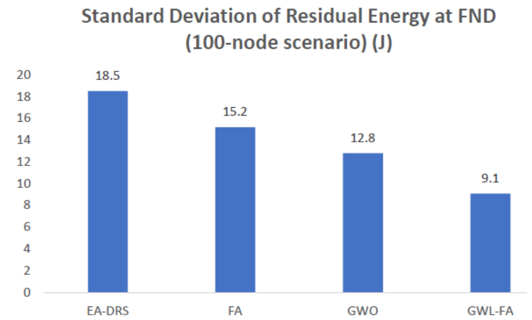


Figure 4: Standard Deviation of Residual Energy at FND (100-node scenario)

algorithm, however, starts with a rapid convergence (inherited from GWO) and then, aided by the Lévy flights, makes significant jumps in fitness even at later iterations, ultimately converging to the highest fitness value. This demonstrates the successful synergy between the two algorithms.

Extensive simulations confirm that GWL-FA substantially prolongs network lifetime, improves delivery ratio, reduces delay, and achieves superior energy balance compared to state-of-the-art algorithms and protocols, especially in high-density scenarios.

The promising results of this work open several avenues for future research:

1. ***Multi-Objective Formalization with Pareto Fronts:*** The current work uses a weighted sum approach for the fitness function. A more rigorous approach would be to treat it as a true multi-

objective problem using Pareto-based algorithms like NSGA-II or MOEA/D [33], allowing network administrators to choose from a set of non-dominated solutions based on specific application needs.

2. ***Integration with Machine Learning:***

a. Predictive Analytics: Integrate a lightweight machine learning model (e.g., a Linear Regression or TinyML model) to predict node mobility and traffic patterns. This forecast can be fed into the GWL-FA fitness function to make more proactive and robust routing/power decisions [34].

b. Meta-Heuristic Parameter Tuning: Use Reinforcement Learning to dynamically adapt the GWL-FA parameters (e.g., p_{FA}, α) during the optimization process, creating a self-adaptive algorithm that performs well under varying network conditions [35].

c. Quantum-Inspired Meta-Heuristics: With the advent of quantum computing, exploring Quantum-inspired GWO (QIGWO) or Quantum-based FA could be a groundbreaking step. These algorithms use quantum principles like superposition and entanglement to represent and evaluate a vast number of solutions simultaneously, potentially offering exponential speedups for solving the NP-hard lifetime maximization problem.

D. Hardware-in-the-Loop Testing and Real-World Deployment: While NS-3 simulations are valuable, the next step is to validate the algorithm's performance in more realistic testbeds using platforms like Raspberry Pi or dedicated sensor motes, dealing with real-world radio irregularities and interference.

e. Security-Aware Lifetime Maximization: Future work will incorporate security metrics (e.g., trust levels, intrusion detection confidence) into the fitness function. This would ensure that the chosen paths are not only energy-efficient but also secure against malicious nodes, leading to the development of robust and resilient MANETs.

By pursuing these directions, the research community can continue to push the boundaries of performance and intelligence in resource-constrained wireless networks.

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