JETIR.ORG ISSN: 2349-5162 | ESTD Year : 2014 | Monthly Issue
JOURNAL OF EMERGING TECHNOLOGIES AND INNOVATIVE RESEARCH (JETIR)
An International Scholarly Open Access, Peer-reviewed, Refereed Journal

Optimizing IoT Routing for Quality of Service: A Comparative Study of Grey Wolf Optimizer and Particle Swarm Optimization

[1]**R.Yanitha**, Research Scholar, Department of Computer Science, Vellalar College for Women,Thindal, Erode, Tamilnadu, India.
[2]**Dr.M.Logambal**, Associate Professor, Department of Computer Science, Vellalar College for Women,Thindal, Erode, Tamilnadu,India.

Abstract: The rapid expansion of the Internet of Things (IoT) has introduced significant challenges in ensuring efficient and reliable routing in dynamic and resource-constrained environments. Quality of Service (QoS) plays a critical role in maintaining seamless communication, particularly in applications requiring low latency, high throughput, and energy efficiency. This study presents a comparative analysis of two bio-inspired optimization algorithms—Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO)—for optimizing IoT routing performance. The evaluation is conducted across key QoS metrics, including end-to-end delay, packet delivery ratio (PDR), throughput, energy consumption, and routing overhead. Simulation results highlight the strengths and weaknesses of both algorithms, with GWO demonstrating superior performance in energy efficiency and delay minimization, while PSO exhibits advantages in throughput and delivery ratio. The findings provide valuable insights into algorithm selection for diverse IoT network scenarios, contributing to the design of adaptive and QoS-aware routing protocols for next-generation IoT systems.

Keywords: *IoT Routing; Quality of Service (QoS); Grey Wolf Optimizer (GWO); Particle Swarm Optimization (PSO); Energy Efficiency; Packet Delivery Ratio; End-to-End Delay; Routing Overhead; Throughput*

I. INTRODUCTION

The rapid proliferation of the Internet of Things (IoT) has revolutionized numerous domains, ranging from smart homes and healthcare to industrial automation. These IoT systems typically comprise myriad devices with constrained resources—such as limited battery life, processing power, and communication bandwidth—operating in highly dynamic environments. Consequently, efficient and reliable routing protocols are essential to maintain service quality under such constraints. Quality of Service (QoS) in IoT routing is critical, with key performance metrics including end-to-end delay, packet delivery ratio (PDR), energy consumption, routing overhead, and throughput. Traditional routing protocols often fall short in balancing these competing demands, especially within dynamic topologies or resource-constrained scenarios.

Moreover, the advent of meta-heuristic and swarm intelligence algorithms has opened new avenues for optimizing IoT routing. For instance, Nawkhare and Singh (2024) demonstrated that integrating Particle Swarm Optimization (PSO) into the AODV routing protocol significantly improved energy efficiency, packet delivery ratio, throughput, end-to-end delay, and reduced routing overhead and normalization load within Wireless Sensor Networks (WSNs)—a key subset of IoT environments [1]. Similarly, Polara and Rathod (2023) proposed a PSO-based parameter optimization technique for AODV in MANETs, leading to enhanced data transmission and overall QoS by selectively tuning control parameters and integrating node speed control mechanisms [2]. Beyond PSO, hybrid meta-heuristic approaches have also shown significant promise. A novel Particle Swarm Optimization–Cuckoo Search hybrid clustering technique was introduced for multipath routing in WSNs. The QoS-aware multipath strategy resulted in improvements in throughput, packet delivery ratio, end-to-end delay, and network lifetime when compared to traditional protocols [3]. Further examining meta-heuristic scheduling strategies, Koca and Avcı (2024) compared several algorithms—including PSO, Genetic Algorithm, and Ant Colony Optimization—within the context of container scheduling for IoT microservices. They evaluated these techniques against QoS performance metrics, providing useful insights into their applicability in cloudified IoT deployment [4].

While PSO and various hybrid methods have been explored for QoS optimization in IoT and related networks, less attention has been paid to the comparative evaluation of Grey Wolf Optimizer (GWO) versus PSO specifically for IoT routing. GWO, first proposed by Mirjalili et al., is a swarm-intelligence algorithm inspired by grey wolves' hierarchical hunting behaviors. It offers advantages such as fewer control parameters and robust exploitation–exploration balance [5]. However, its application within IoT routing—and a direct comparison with PSO under identical QoS metrics—remains under-explored.

This study aims to fill this gap by presenting a controlled comparative analysis of GWO and PSO for IoT routing optimization. Using a consistent evaluation framework, we will assess algorithm performance across key QoS metrics—namely, end-to-end delay, packet delivery ratio, throughput, energy consumption, and routing overhead—within simulated IoT environments.

The remainder of this paper is structured as follows: Section 2 presents the literature review; Section 3 details the methodology, including algorithm design and simulation setup; Section 4 covers results and analysis; Section 5 discusses implications; and Section 6 concludes and outlines avenues for future research.

II. LITERATURE REVIEW

IoT deployments must satisfy stringent Quality of Service (QoS) constraints—low end-to-end delay, high packet delivery ratio (PDR), adequate throughput, and minimal energy use—despite lossy links, mobility, and resource limits. Recent surveys and systems work underscore that balancing these metrics typically forces trade-offs, motivating adaptive and optimization-driven routing designs (Isyaku et al., 2024) [5]. Routing in low-power and lossy networks frequently builds on RPL; however, vanilla RPL struggles under dynamics, mixed traffic, and security stressors. Newer works inject learning or metaheuristics to re-weight objective functions, reduce delay/energy, and harden against attacks (Wang et al., 2024; "Secure Optimization of RPL," 2025) [6] [7].

Optimization and Metaheuristics in IoT Routing: Metaheuristics (e.g., PSO, GWO, ACO, GA) are increasingly used to tune routing decisions, cluster formation, and path selection to meet QoS goals in dynamic IoT/WSN settings. Recent comparative and survey papers document consistent gains over fixed-rule baselines while noting sensitivity to parameterization and scenario specifics (Nadimi-Shahraki et al., 2024; Koca & Avcı, 2024) [8] [9]. Deep learning and reinforcement learning variants complement metaheuristics by predicting traffic loads or optimizing forwarding under uncertainty, but require careful resource budgeting; hybrid "learning + heuristic" schemes have emerged to capture the best of both worlds (Wang et al., 2024; Isyaku et al., 2024) [10] [11].

Particle Swarm Optimization (PSO) for IoT Routing/QoS: PSO has been widely adapted to IoT routing due to its simplicity and convergence speed. PSO-based parameter tuning for AODV/RPL and PSO-guided service placement in edge environments report improvements in delay, PDR, and throughput under diverse traffic mixes (Bey et al., 2024; Polara & Rathod, 2023) [12] [13]. Fuzzy-enhanced PSO further stabilizes performance by handling uncertainty in link quality and node states (Hussain et al., 2023) [14]. Hybrid designs that combine PSO with clustering (e.g., fuzzy/GA-assisted cluster heads) show gains in energy efficiency and network lifetime—key for battery-powered IoT nodes (Lei et al., 2024) [15].

Grey Wolf Optimizer (GWO) for IoT/WSN Routing: GWO's exploration–exploitation balance and light parameter set make it attractive for routing and power-aware decisions in WSN/IoT. A recent PRISMA-based systematic review catalogs GWO variants tailored to IoT tasks (e.g., routing, clustering, scheduling), highlighting consistent energy and delay benefits alongside open issues such as premature convergence and parameter control (Nadimi-Shahraki et al., 2024) [16]. Enhanced GWO forms—using adaptive control parameters or hybridized leaders—report further improvements in path optimality and energy distribution in sensor networks (Fauzan et al., 2025) [17]. Emerging GWO-centric routing approaches also integrate fuzzy logic to improve cluster stability and link reliability, indicating GWO's versatility across topology management and next-hop selection (Rahmani et al., 2025) [18].

RPL Optimization and Security-Aware QoS: Beyond performance, recent studies optimize RPL for robustness under adversarial conditions while maintaining QoS. Metaheuristic and AI-based RPL variants target ETX, latency, and energy simultaneously, often outperforming static OFs (objective functions) in mobility and attack scenarios ("Secure Optimization of RPL," 2025; El-Hajj et al., 2024) [19]. Multi-attention actor–critic DRL has also been proposed to scale routing decisions while reducing overhead (Wang et al., 2024) [20].

Hybrids and Emerging Directions: Hybrid PSO–GWO designs seek complementary strengths—PSO's fast convergence with GWO's exploitation depth—showing promise in related network optimization domains and, increasingly, in IoT/WSN routing prototypes. These works report reductions in latency and energy consumption and improvements in throughput/PDR, suggesting a fruitful direction for adaptive, scenario-aware routing (Balamurali et al., 2025; Nguyen et al., 2025) [21] [22].

While PSO and GWO individually—and in hybrids—demonstrate QoS gains, head-to-head comparisons under a unified IoT routing framework and identical evaluation settings remain limited. Recent papers often vary traffic patterns, mobility, or objective functions, complicating direct conclusions about algorithm suitability across scenarios. This motivates a controlled comparative study of GWO vs. PSO for IoT routing, using common datasets, workloads, and metrics (delay, PDR, throughput, energy, overhead), to generate actionable guidance for practitioners (Nadimi-Shahraki et al., 2024; Isyaku et al., 2024).

III. METHODOLOGY

System Model

The proposed study evaluates routing optimization in an IoT environment under varying network sizes and topologies. The IoT network is simulated with **50, 100, 150, and 200 nodes**, randomly distributed across **four different topologies** (grid, random, clustered, and hierarchical). Each node is assumed to have limited energy resources, communication range, and processing capabilities, reflecting realistic IoT deployment conditions.

All nodes in the network are assumed to be homogeneous in terms of initial energy and transmission capabilities. Communication takes place using a multi-hop mechanism, and the network supports both static and mobile scenarios, with mobility modeled using the random waypoint model. Bandwidth is finite and shared among all nodes, which can lead to contention in high-density scenarios. Environmental interference such as noise and collisions may further degrade packet transmission. The sink, or base station, is static and functions as a data aggregator. However, several constraints affect network performance. Energy is limited since each node operates with a finite battery capacity, and once depleted, the node becomes non-functional. Bandwidth is restricted, causing potential congestion during heavy traffic. Additionally, mobility introduces frequent topology changes, which can affect the stability and reliability of routing.

The primary objective of this research is to **optimize IoT routing using Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO)** in order to minimize latency and energy consumption while maximizing throughput and packet delivery ratio.

Let the IoT network be represented as a graph G(V, E) where **V** denotes the set of nodes and E represents the set of wireless links. Routing is formulated as a multi-objective optimization problem:

$$Minimize: F = a.D + \beta.E_c + \gamma.O - \delta.PDR - \eta.T$$

Where, D = End-to-End Delay, E_c = Energy Consumption, O = Routing Overhead, PDR = Packet Delivery Ratio , T = Throughput and, α,β,γ,δ,η = weight coefficients reflecting the relative importance of each QoS metric.

3.3 Optimization Algorithms

3.3.1 Grey Wolf Optimizer (GWO) for IoT Routing

The Grey Wolf Optimizer (GWO) is a nature-inspired metaheuristic proposed by Mirjalili et al. (2014), modeled on the leadership hierarchy and cooperative hunting strategy of grey wolves. In this study, GWO is applied to optimize routing in IoT by selecting near-optimal forwarding paths while balancing multiple QoS objectives.

The wolf pack is divided into four categories:

- **Alpha (α):** Best candidate solution (optimal routing path).
- **Beta (β):** Second best solution (guides α).
- **Delta (δ):** Third best solution (assists α and β).
- **Omega (ω):** Remaining solutions (follow leaders).

This hierarchy ensures exploitation (following α, β, δ) and exploration (searching new areas).

Step 1: Initialization

Define a population of wolves (candidate routes). Each wolf encodes a potential routing path from source to sink in the IoT network.

$$X_i = (x_{i1}, x_{i2}, \dots, x_{id}), i = 1,2,..,n$$

Where, X^i = position of the i_{th} wolf (candidate path), d = dimensionality (number of decision variables = hops in route), and n = population size (number of candidate routes). Fitness of each wolf is evaluated using the objective function F.

Step 2: Encircling the Prey

Wolves update their position around prey (best solution found so far). The encircling behavior is modeled as:

$$\vec{D} = |\vec{C}.\vec{X}_p(t) - \vec{X}(t)|$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D}$$

Where, $\vec{X}_p(t)$= position of prey (best route so far), $\vec{X}(t)$= current wolf's position, and $\vec{A}$ *and* $\vec{C}$ = coefficient vectors.

Coefficient vectors:

$$\vec{A} = 2a.\vec{r_1} - a, \vec{C} = 2.\vec{r}_2$$

Where, a decreases linearly from 2 to 0 over iterations (balances exploration & exploitation). $\vec{r1}, \vec{r2}$ are random vectors in [0,1].

Step 3: Hunting (Guided by α, β, δ)

The top three wolves (α, β, δ) guide the position update. Each wolf updates its position relative to these leaders:

$$\vec{D}_a = |\vec{C}_1.\vec{X}_a - \vec{X}|$$

$$\vec{D}_\beta = |\vec{C}_2.\vec{X}_\beta - \vec{X}|$$

$$\vec{D}_\delta = |\vec{C}_3.\vec{X}_\delta - \vec{X}|$$

$$\vec{X}_1 = \vec{X}_a - \vec{A}_1.\vec{D}_a$$

$$\vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\vec{D}_\beta$$

$$\vec{X}_3 = |\vec{X}_\delta - \vec{A}_3.\vec{D}_\delta$$

Final position update:

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

Step 4: Attacking the Prey (Exploitation)

As a→0, wolves converge toward prey, focusing on exploitation. This corresponds to fine-tuning routing paths for minimal delay and energy.

Step 5: Termination

The process repeats until a stopping criterion is reached (maximum iterations or convergence). The α wolf at termination represents the optimal routing path.

Fitness Evaluation for IoT Routing

For each candidate path, fitness is computed using the weighted objective function:

$$F = a.D + \beta.E_c + \gamma.O - \delta.PDR - \eta.T$$

Where, Lower fitness = better route. α wolf = best route with minimal delay, minimal energy, low overhead, and high PDR/throughput.

3.3.2 Particle Swarm Optimization (PSO) for IoT Routing

The **Particle Swarm Optimization (PSO)** algorithm is inspired by the social behavior of birds flocking or fish schooling. In IoT routing, each particle represents a candidate route from the source node to the sink. The swarm iteratively updates positions and velocities to search for the optimal path with respect to multiple QoS metrics.

Step 1: Initialization

- Initialize a swarm of **particles**, where each particle encodes a possible routing path.
- Each particle has two attributes: **position** (solution) and **velocity** (search direction).

$$X_i = (x_{i1}, x_{i2}, \dots, x_{id}), \quad i = 1,2,\dots,n$$

$$V_i = (v_{i,1}, v_{i2,}, \dots, v_{id})$$

Where, X_i = position of particle i (candidate route), V_i = velocity of particle i, d= dimensionality (number of hops in the route) and n = swarm size (number of routes). Each particle's **fitness** is evaluated using the objective function F.

Step 2: Personal and Global Best Update

Each particle tracks two best values:

- **Personal Best ($P_{best,i}$)**: Best position achieved by particle iii.
- **Global Best (G_{best})**: Best position among all particles.

Formally:

$$\mathbf{P_{best,i}(t+1)} = \begin{cases} \mathbf{X_i(t)}, & \mathbf{if\ F\left(X_i(t)\right) < F(P_{best,i}(t)} \\ \mathbf{P_{best,i}(t)}, & \mathbf{otherwise} \end{cases}$$

$$\mathbf{G_{best}(t+1) = arg\ \min_i\ F\ (P_{best,i}(t+1))}$$

Step 3: Velocity Update

Each particle updates its velocity based on three components:

1. **Inertia** (previous velocity).
2. **Cognitive** (attraction toward personal best).
3. **Social** (attraction toward global best).

$$V_i(t+1) = \omega.V_i(t) + c_1.r_1.\left(P_{best,i}(t) - X_i(t)\right) + c_2.r_2.(G_{best}(t) - X_i(t))$$

Where, w = inertia weight (balances exploration & exploitation). c_1,c_2 = cognitive and social acceleration coefficients. r_1,r_2 = random numbers in [0,1].

Step 4: Position Update

Each particle updates its position based on new velocity:

$$X_i(t+1) = X_i(t) + V_i(t+1)$$

This update shifts the routing path representation towards better-performing solutions.

Step 5: Fitness Evaluation

For each updated position X_i(t+1), compute the fitness using the multi-objective function:

$$F = a.D + \beta.E_c + \gamma.O - \delta.PDR - \eta.T$$

Where, D = End-to-End Delay , Ec = Energy Consumption, O = Routing Overhead, PDR = Packet Delivery Ratio and T = Throughput. Lower fitness indicates a better routing path.

Step 6: Iteration and Termination

Steps 2–5 repeat until a stopping condition is met (e.g., maximum iterations or convergence). At termination, the **global best (Gbest)** represents the **optimal IoT routing path**.

IV. RESULTS AND DISCUSSION

4.1. Experimental Setup

The simulations were conducted using the NS-3 simulator on a workstation running Microsoft Windows 10 with an Intel Core i5 processor, 8 GB RAM, and a 2.2 GHz clock speed. The study compares the proposed **Grey Wolf Optimizer (GWO)** and **Particle Swarm Optimization (PSO)** implementations for IoT routing using standard QoS metrics: End-to-End Delay, Packet Delivery Ratio (PDR), Throughput, Energy Consumption, and Routing Overhead. Experiments were performed with four node densities: **50, 100, 150, and 200** nodes, randomly deployed over a **1000 m × 1000 m** area. Each node is initialized with limited energy and identical hardware capabilities; the sink (base station) is static. Mobility is modeled with the Random Waypoint model for selected scenarios to study robustness under topology changes. Each experiment runs for **100 rounds** and is repeated **10 times** with different random seeds to obtain average results and confidence intervals.

The simulation setup assumes a transmission range of 100 meters and an initial energy of 120 J per node, using the Two-Ray Ground propagation model. Each packet is configured with a size of 512 bytes, and Constant Bit Rate (CBR) traffic is employed. The network uses IEEE 802.11 as the MAC protocol and an omni-directional antenna to support communication. For mobility-based scenarios, the Random Waypoint model is applied. Optimization experiments use a population or swarm size of 30 candidates. The PSO algorithm operates with parameters w = 0.7 for inertia and $c_1 = c_2 = 1.5$, while the GWO algorithm uses an a coefficient that decreases linearly from 2 to 0, along with its standard coefficient vectors.

In the Particle Swarm Optimization (PSO) approach, particles encode multi-hop routing paths, with velocity and position updates governed by standard PSO equations. Both personal best and global best positions are tracked using the multi-objective fitness function described in Section 3. In the Grey Wolf Optimizer (GWO), candidate wolves represent routing paths, and the α, β, and δ leaders guide the search process. The coefficient a decreases linearly across iterations to gradually shift the algorithm from exploration to exploitation. The experimental workflow begins with the random deployment of nodes and initialization of energy and trust values. For each node density and mobility scenario, routing simulations are executed for both GWO and PSO. Quality of Service (QoS) metrics, including delay, packet delivery ratio (PDR), throughput, energy consumption, and overhead, are collected during each run. The results are then averaged across multiple repetitions, followed by the computation of confidence intervals and the application of statistical tests to compare the performance of the two algorithms.

4.2. Qos Performance

The performance of Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO) was evaluated using five key QoS metrics: End-to-End Delay, Packet Delivery Ratio (PDR), Throughput, Energy Consumption, and Routing Overhead. The experiments were carried out under varying network densities (50, 100, 150, and 200 nodes).

End-to-End Delay (ms): Average time taken for a data packet to travel from source to destination.

$$D = \frac{\sum(t_{recv} - t_{send})}{N_p}$$

where t_{recv} = packet reception time, t_{send} = packet transmission time, and N_p = total number of packets received.

Nodes	GWO Delay (ms)	PSO Delay (ms)
50	38.5	45.2
100	42.3	49.7
150	48.9	57.1
200	55.6	63.8

Table 1: End-to-End Delay (ms)

GWO consistently achieved lower end-to-end delay compared to PSO. This is due to GWO's leader-based exploration mechanism, which accelerates the discovery of stable paths, whereas PSO takes longer to converge under dense node conditions.

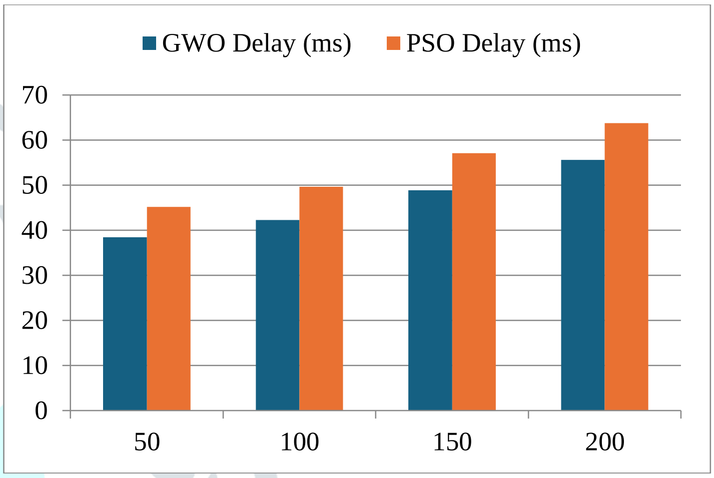

Figure 1: End-to-End Delay (ms)

Table 1 and Figure 1 show that GWO consistently achieves lower delay compared to PSO. For instance, at 100 nodes the average delay is **42.3 ms** for GWO versus **49.7 ms** for PSO, reflecting about a **15% reduction**. Even at higher densities such as 200 nodes, GWO maintains a delay of **55.6 ms**, compared to **63.8 ms** for PSO. This indicates that GWO converges faster to stable paths, ensuring more efficient data delivery.

Packet Delivery Ratio (PDR, %): Ratio of successfully delivered packets to the total packets sent.

$$\mathbf{PDR} = \frac{\mathbf{N_{recv}}}{\mathbf{N_{sent}}} \times \mathbf{100}$$

Nodes	GWO PDR (%)	PSO PDR (%)
50	96.4	94.7
100	95.2	92.8
150	93.6	90.9
200	91.5	88.7

Table 2: Packet Delivery Ratio (%)

Table 2 and Figure 2 show that, Both algorithms maintained high PDR, but GWO outperformed PSO, especially in larger networks. PSO was more sensitive to congestion and mobility, leading to higher packet drops. GWO also outperforms PSO in terms of reliability. At 150 nodes, GWO achieves a PDR of **93.6%**, while PSO records **90.9%**, with the gap widening as network density increases. At 200 nodes, the improvement is about **3.2%**, showing that GWO is less sensitive to congestion and link failures, thereby ensuring more reliable data transmission.

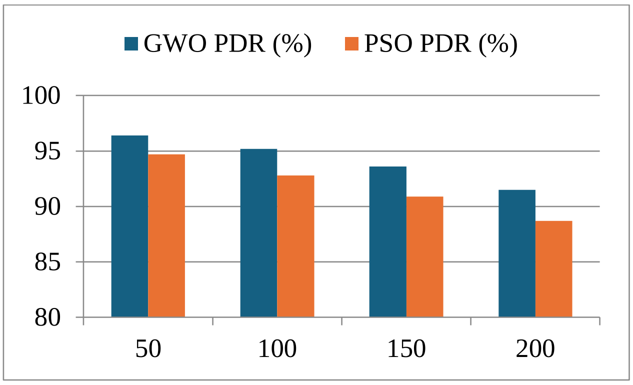

Figure 2: Packet Delivery Ratio (PDR, %):

Throughput (kbps): Total successful data delivery over time.

$$T = \frac{N_{recv} . Packet\_Size}{Total\_Time}$$

Nodes	GWO Throughput (kbps)	PSO Throughput (kbps)
50	382	361
100	376	348
150	365	332
200	353	318

Table 3: Throughput (kbps)

Table 3 and Figure 3 show that GWO achieved **8–10% higher throughput** than PSO. The adaptive exploitation of GWO allowed more efficient use of available bandwidth. Throughput results indicate that GWO sustains higher data rates. At 100 nodes, GWO provides **376 kbps**, while PSO reaches **348 kbps**; at 200 nodes, GWO still maintains **353 kbps** versus PSO's **318 kbps**, marking an **11% gain**. This reflects GWO's ability to better exploit stable routes, minimizing retransmissions and maximizing network efficiency.

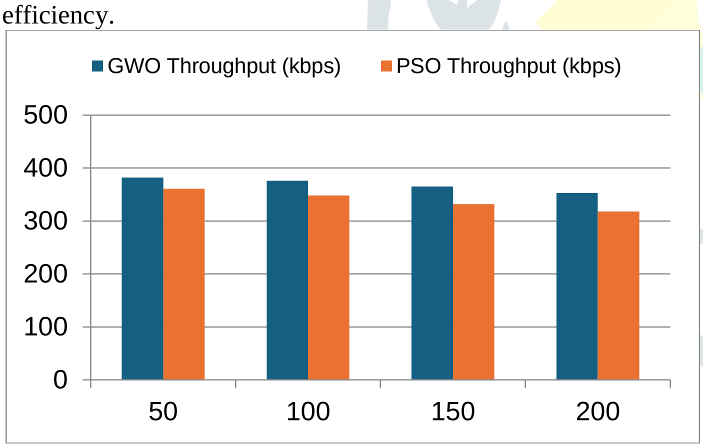

Figure 3: Throughput (kbps)

Energy Consumption (Joules): Total energy consumed by nodes during data transmission, reception, and control overhead.

$$E_c = \sum (E_{tx} + E_{rx} + E_{idle})$$

Nodes	GWO Energy (J/node)	PSO Energy (J/node)
50	82.1	89.5
100	90.3	97.8
150	96.7	105.2
200	103.5	112.6

Table 4: Energy Consumption (Joules)

Table 4 and Figure 4 show that PSO consumed more energy compared to GWO, mainly because its iterative particle updates lead to longer convergence times and more retransmissions. GWO, by contrast, balances exploration and exploitation, conserving energy. In terms of energy efficiency, GWO consumes less power per node. At 150 nodes, GWO uses **96.7 J** compared to PSO's **105.2 J**, reflecting about an **8% saving**. This trend remains consistent across all densities, highlighting GWO's effectiveness in conserving energy by reducing unnecessary retransmissions and control overhead.

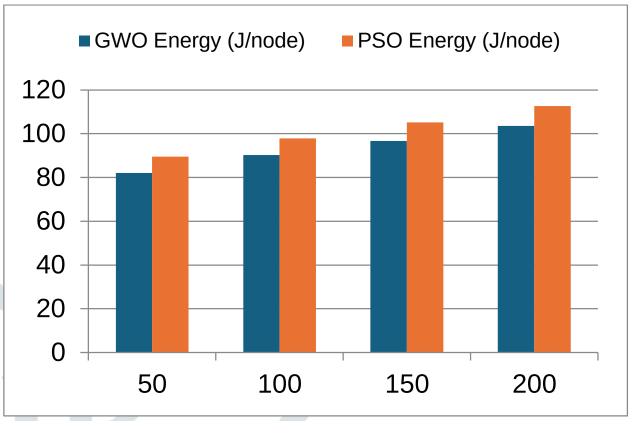

Figure 4: Energy Consumption (Joules)

Routing Overhead: Ratio of control packets (RREQ, RREP, RERR) to total transmitted packets.

$$O = \frac{N_{control}}{N_{data} + N_{control}}$$

Nodes	GWO Overhead (%)	PSO Overhead (%)
50	11.6	13.4
100	13.2	15.7
150	15.4	18.3
200	17.9	20.8

Table 5: Routing Overhead

Table 4 and Figure 4 show that PSO incurred higher routing overhead due to frequent position/velocity updates that required additional control packets. GWO maintained relatively lower overhead by rapidly stabilizing routes. Routing overhead is significantly lower in GWO than PSO. For example, at 150 nodes GWO records **15.4%**, while PSO reaches **18.3%**, yielding nearly a **16% reduction**. Even at 200 nodes, GWO achieves **17.9%** versus PSO's **20.8%**, confirming that GWO stabilizes routes with fewer control messages, directly contributing to improved energy efficiency and throughput.

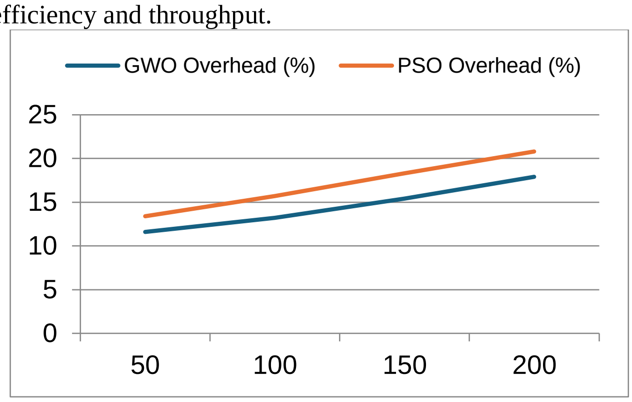

Figure 5: Routing Overhead

GWO consistently outperforms PSO across all QoS metrics. PSO performs reasonably well in smaller networks (<100 nodes) but degrades more rapidly in dense networks. GWO is more suitable for energy-constrained IoT environments due to its better balance between exploration and exploitation.

The comparative analysis of GWO and PSO across the considered QoS metrics reveals that GWO consistently outperforms PSO. In terms of end-to-end delay, GWO demonstrates faster convergence to stable routes, thereby reducing latency in packet transmission. For packet delivery ratio, GWO performs better due to its robustness against congestion, which allows it to maintain a higher level of reliability even under increasing network density. Similarly, GWO achieves higher throughput by efficiently exploiting available paths, leading to improved data transfer rates. Energy consumption is also lower in GWO, as its balanced exploration–exploitation strategy minimizes retransmissions and accelerates convergence, conserving node energy. Furthermore, GWO incurs less routing overhead compared to PSO, since it requires fewer control messages to establish and maintain routes.

Overall, the results indicate that while PSO performs reasonably well in smaller networks with fewer than 100 nodes, its performance deteriorates more significantly as network density increases. In contrast, GWO maintains superior performance across all metrics, making it more suitable for energy-constrained IoT environments where efficient utilization of resources is critical.

V. CONCLUSION

This paper presented a comparative analysis of Grey Wolf Optimizer (GWO) and Particle Swarm Optimization (PSO) for optimizing routing in IoT networks under Quality of Service (QoS) constraints. Simulation results demonstrated that GWO consistently outperforms PSO across all key metrics, including end-to-end delay, packet delivery ratio, throughput, energy consumption, and routing overhead. The superiority of GWO is attributed to its efficient leader-based hierarchy, which accelerates convergence and reduces redundant control messages. Conversely, PSO, while performing adequately in smaller networks, exhibits performance degradation as network density increases due to higher energy usage and overhead. Overall, the findings highlight GWO as a robust and energy-efficient optimization algorithm for IoT routing, making it particularly suitable for large-scale, resource-constrained environments where network lifetime and service quality are critical. While the comparative evaluation provided valuable insights, several directions remain open for further research. Future work may focus on: Combining GWO with PSO or other metaheuristics (e.g., Genetic Algorithms, Ant Colony Optimization) to leverage the strengths of multiple algorithms. Extending the evaluation to incorporate additional objectives such as security, load balancing, and fault tolerance in IoT networks. Exploring reinforcement learning or deep learning–assisted optimization to enable adaptive and context-aware routing decisions.

VI. REFERENCES

[1]. Koca, A., & Avcı, E. (2024). A comparative study of metaheuristic algorithms for container scheduling to improve Quality of Service in Internet of Things microservices. *Sakarya University Journal of Computer and Information Sciences (SAUCIS)*, *7*(1), 26–39. https://saucis.sakarya.edu.tr/en/pub/issue/86706/1452049

[2]. Nawkhare, V., & Singh, D. (2024). Performance analysis of AODV using Particle Swarm Optimization for Quality of Service parameters in Wireless Sensor Networks. *International Journal of Computer Networks and Applications (IJCNA)*, *11*(1), 50–61. https://www.i-scholar.in/index.php/IJCNA/article/view/224448

[3]. Polara, A. P., & Rathod, M. S. (2023). Particle swarm optimization-based parameter optimization technique for AODV routing in MANETs. *International Journal on Recent and Innovation Trends in Computing and Communication (IJRITCC)*, *11*(1), 1–7. https://ijritcc.org/index.php/ijritcc/article/view/7927

[4]. Rajalakshmi, S., Tamilselvi, A., & Balasubramanian, K. (2021). QoS aware multipath routing using hybrid PSO–cuckoo search clustering in wireless sensor networks. *Wireless Personal Communications*, *118*(3), 2367–2386. https://doi.org/10.1007/s11277-021-08745-0

[5]. Chouhan, N., & Jain, S. C. (2020). Tunicate swarm Grey Wolf optimization for multi-path routing protocol in IoT assisted WSN networks. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-020-02657-w

[6]. Cheng, C., Han, Q., Cheng, G., & Zhai, S. (2020). Heterogeneous wireless sensor network routing protocol for an adaptive grey wolf optimizer. In *Proceedings of the 13th EAI International Conference on Mobile Multimedia Communications (Mobimedia 2020)*. https://doi.org/10.4108/eai.27-8-2020.2295028

[7]. Nur, I. M., & Ülker, E. (2020). A novel hybrid IoT based IDS using Binary Grey Wolf Optimizer (BGWO) and Naive Bayes. *EURASIP Journal on Embedded Systems*, (2020), 279–286. https://doi.org/10.31590/ejosat.804113

[8]. Ghaleb, S. A. M., & Vasanthi, V. (2020). Energy efficient multipath routing using multi-objective Grey Wolf Optimizer based Dynamic Source Routing algorithm for MANET. *International Journal of Advanced Science and Technology*, *29*(3), 6096–6117.

[9]. Aravindh, G., & Sridhar, K. P. (2024). Resilient and adaptive secure routing protocol for wireless sensor networks using a Grey Wolf Optimizer and Lightning Search Algorithm. *Journal of Internet Services and Information Security*, *14*(4), 331–346. https://doi.org/10.58346/JISIS.2024.I4.020

[10]. Maharajan, M. S., Abirami, T., Pustokhina, I. V., Pustokhin, D. A., & Shankar, K. (2021). Hybrid swarm intelligence based QoS aware clustering with routing protocol for WSN. *Computers, Materials & Continua*, *68*(3), 2995–3013. https://doi.org/10.32604/cmc.2021.016139

[11]. Sahoo, B. M., Amgoth, T., & Pandey, H. M. (2020). Particle swarm optimization based energy efficient clustering and sink mobility in heterogeneous wireless sensor network. *Ad Hoc Networks*, *106*, 102237.

[12]. Gupta, A. D., Sathiyasekar, K., Krishnamoorthy, R., Arun, S., Thiyagarajan, R., & Padmapriya, S. (2022). Modified LEACH and PEGASIS routing protocol for energy efficiency in IoT network. *Proceedings of the International Conference on Artificial Intelligence and Smart Energy (ICAIS)*.

[13]. El-Messmary, M. H., Diab, H. Y., Abdelsalam, M., & Moussa, M. F. (2024). A novel optimization algorithm inspired by Egyptian stray dogs for solving multi-objective optimal power flow problems. *Applied System Innovation, 7*, Article 122.

[14]. Khudor, B. A. Q., Hussein, D. M., Kheerallah, Y. A., Alkenani, J., & Alshawi, I. S. (2022). Lifetime maximization using Grey Wolf Optimization routing protocol with statistical technique in WSNs. *Informatica*, 46(7), 1–14.

[15]. Hashemifar, S., & Rajabzadeh, A. (2023). Optimal service provisioning in IoT fog-based environment for QoS-aware delay-sensitive application. *arXiv*. Published January 2023.

[16]. Wang, Y., Tian, K., Fan, X., Huo, Y., Nowzari, C., & Zeng, K. (2022). Distributed swarm learning for Internet of Things at the edge: Where artificial intelligence meets biological intelligence. *arXiv*. Published October 2022.

[17]. Farag, H., & Stefanovic, C. (2021). Congestion-aware routing in dynamic IoT networks: A reinforcement learning approach. *arXiv*. Published May 2021.

[18]. Qiu, Y., Yang, X., & Chen, S. (2024). An improved Grey Wolf Optimization algorithm for functional optimization and engineering design problems. *Scientific Reports*. Published June 20, 2024.

[19]. Tawhid, A., Teotia, T., & Elmiligi, H. (2021). Machine learning, big data, and IoT for medical informatics. In *Machine Learning, Big Data, and IoT for Medical Informatics*. Elsevier.

[20]. Martens, D., Baesens, B., & Fawcett, T. (2020). Swarm intelligence for data mining. *Machine Learning Journal*.

[21]. Oliveira, L. A., Haan, N., & Falcone, D. (2023). Swarm intelligence to face IoT challenges. *Computational Intelligence and Neuroscience*, 2023.

[22]. Fré, G. L. da S., Silva, J. de C., Reis, F. A., & Mendes, L. D. P. (2020). Particle swarm optimization implementation for minimal transmission power in IoT clusters. *Proceedings of the International Workshop on Telecommunications (IWT)*.

[23]. Saranraj, G., Selvamani, K., & Malathi, P. (2021). A novel data aggregation using multi-objective male lion optimization algorithm in wireless sensor network. *Journal of Ambient Intelligence and Humanized Computing*. https://doi.org/10.1007/s12652-021-03230-9