Analysis of QoS in Cluster-Based IoT Routing Using Ant Colony Optimization and Krill Herd Algorithm

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***Abstract*—Efficient routing in Internet of Things (IoT) networks is essential for achieving high Quality of Service (QoS) and addressing challenges such as energy constraints, scalability, and latency. This paper presents a comparative performance evaluation of two swarm intelligence-based approaches—Ant Colony Optimization (ACO) and the Krill Herd Algorithm (KHA)—for optimizing IoT routing. ACO, inspired by the pheromone-based path finding of ants, and KHA, modeled on the collective motion and foraging strategies of krill swarms, are applied to dynamic IoT environments. The analysis evaluates both algorithms across multiple performance metrics, including end-to-end delay, packet delivery ratio (PDR), routing overhead, throughput, and energy consumption. Experimental results reveal distinct trade-offs: ACO demonstrates superior packet delivery and lower routing overhead, while KHA achieves better energy efficiency and reduced delay in certain scenarios. The findings provide insights into the applicability of each algorithm, offering guidelines for selecting suitable routing strategies in diverse IoT deployments.**

***Index Terms*—IoT Routing; Ant Colony Optimization (ACO); Krill Herd Algorithm (KHA); Swarm Intelligence; Quality of Service (QoS); Network Optimization**

I. INTRODUCTION

The Internet of Things (IoT) is an expansive ecosystem where myriad devices—such as sensors, actuators, and smart appliances—interconnect to monitor and orchestrate the physical world. Efficient routing within IoT networks is pivotal to sustaining high *Quality of Service (QoS)*, by ensuring timely and reliable data transmission while conserving scarce resources like energy [1]. Swarm Intelligence (SI), inspired by collective behaviors in nature, offers robust and adaptive strategies suitable for IoT's distributed and dynamic topologies. SI approaches possess traits highly valuable for IoT routing—flexibility, decentralization, resilience, and low computational demands—which align well with the resource limitations inherent in IoT devices [2]. Ant Colony Optimization is a widely acknowledged SI technique inspired by ants' pheromone-guided pathfinding. ACO has been effectively tailored to routing tasks, particularly in wireless networks, to achieve low delay and high throughput under energy constraints. For instance, [3] propose a self-adaptive ACO-based strategy tailored for IoT network models, demonstrating enhanced adaptability and routing efficiency . Additionally, a synthesizes recent advances and practical adaptations of ACO in IoT routing, outlining its benefits and persistent challenges in real-world scenarios [4]. KHA is a newer SI method, modeled on the collective movement and foraging of krill swarms. Although less extensively studied in IoT routing, recent research highlights its potential for congestion-aware and energy-efficient data path selection. A 2024 study introduces an adaptive KHA variant designed for secure and congestion-free routing in IoT contexts, showing faster convergence and reduced computational overhead [5]. Despite substantial work on individual SI techniques for network optimization, there remains a gap in direct comparative assessments within IoT frameworks—particularly between ACO and KHA. This study aims to close that gap by evaluating both algorithms under consistent simulation parameters, focusing on five key QoS metrics: end-to-end delay, packet delivery ratio (PDR), routing overhead, throughput, and energy consumption. Through rigorous analysis, the study seeks to elucidate trade-offs, application scenarios, and strategic guidelines for algorithm selection in diverse IoT deployments.

II. RELATED WORKS

Ant Colony Optimization (ACO) has remained a prominent metaheuristic for routing and path-selection problems in IoT and wireless sensor networks. Recent works adapt ACO variants to address IoT constraints such as limited energy, dynamic topologies, and scalability. For example, Sharma et al., (2023) evaluate ACO-based routing strategies in dynamic IoT scenarios and report improvements in energy balancing and network lifetime through pheromone-adaptation mechanisms [6]. Several studies emphasize improvements to classical ACO to meet IoT QoS goals. Han et al., (2024) present an enhanced ACO approach for wireless sensor routing that specifically targets throughput and end-to-end delay reduction while preserving energy efficiency — demonstrating that ACO variants can be tuned for different metric trade-offs [7]. The Krill Herd Algorithm (KHA) and its variants have been increasingly explored for clustering, routing, and congestion control in recent years. Sadrishojaei et al., (2022) propose a KHA-based clustering method for mobile IoT that selects cluster heads and intermediate nodes, showing that KHA can effectively solve NP-hard cluster head selection with good convergence behavior [8]. KHA has also been extended and hybridized to handle multi-objective and congestion-aware routing problems. Khaledian et al., (2023) and related works propose improved KHA formulations (including fuzzy/multi-objective variants) for scheduling and congestion control, indicating that KHA variants can be adapted to control congestion and optimize multiple QoS objectives simultaneously[9]. Comparative and survey studies highlight the broader landscape of swarm intelligence (SI) for IoT—positioning both ACO and KHA among many SI methods applied to routing, security, and resource management. Systematic reviews and surveys (covering 2020–2024) synthesize trends showing that ACO remains widely used for routing and path-finding, while newer algorithms such as KHA are gaining traction for clustering, energy optimization, and secure key-generation tasks in IoT. These surveys also identify gaps in head-to-head comparative evaluations under consistent IoT scenarios[10]. Hybrid and application-specific approaches are also prominent: several works apply KHA or ACO in combination with other heuristics or domain knowledge (e.g., secure signcryption using chaotic KHA variants, or ACO hybridized with clustering and energy-aware heuristics) to address the heterogeneity of IoT deployments. These studies show promising improvements in convergence speed, energy consumption, and robustness, but often evaluate on different simulators and metrics, making direct comparisons difficult—hence the need for controlled comparative studies [11].

III. METHODOLOGY

3.1 IoT Network Model

To evaluate the performance of Ant Colony Optimization (ACO) and the Krill Herd Algorithm (KHA) for IoT routing, a simulated IoT network model was designed. The network consists of heterogeneous IoT devices including low-power sensor nodes, intermediate relay nodes, and a sink node (gateway) that connects to a central server. The devices were distributed randomly across a two-dimensional simulation area to mimic real-world IoT deployments in smart cities and environmental monitoring scenarios. The network adopted a multi-hop communication model to ensure scalability and energy efficiency.

Network Topology and Simulation Environment

The simulation was conducted using **NS-3** (Network Simulator 3), which provides flexibility for implementing custom routing protocols and swarm intelligence algorithms. The topology was modeled as a random deployment of 100 to 500 nodes in an area of 1000 m × 1000 m. Each node had a maximum transmission range of 100 m, enabling multi-hop communication. The sink node was positioned at the center of the topology to collect data packets. Traffic patterns were generated using Constant Bit Rate (CBR) flows, with packet sizes ranging from 64 to 512 bytes and packet generation intervals set between 0.1 and 1 second. The simulation was executed for 500 seconds per run, with multiple runs performed to obtain statistically significant results [12].

Assumptions and Constraints

To ensure fairness and reproducibility, the following assumptions and constraints were applied:

- Energy Model**:** Each IoT node was initialized with a finite energy of 2 Joules**,** with energy consumption modeled for transmission, reception, and idle states. Energy harvesting and battery replacement were not considered.
- Mobility**:** Nodes were assumed to be either stationary or with limited mobility, consistent with static IoT applications such as smart homes and environmental sensing.
- Communication Model: A wireless medium following the IEEE 802.15.4 standard was adopted, reflecting low-power and short-range IoT communications.
- Traffic Pattern: Traffic was uplink-centric, where sensor nodes transmitted data packets to the sink. Downlink communication and control signaling were assumed minimal.
- Network Constraints: The environment assumed limited bandwidth, dynamic topology due to link failures, and interference modeled as additive white Gaussian noise (AWGN).
- Routing Parameters: Both ACO and KHA algorithms operated under identical simulation parameters, ensuring unbiased comparison across metrics such as end-to-end delay, packet delivery ratio (PDR), routing overhead, throughput, and energy consumption.

This network model provides a controlled environment to evaluate the trade-offs between ACO and KHA routing strategies, ensuring a fair performance comparison under IoT-specific constraints.

3.2 Ant Colony Optimization (ACO)

Ant Colony Optimization (ACO) is a bio-inspired algorithm modeled after the pheromone-based foraging behavior of ants. In networking, it is used to discover optimal paths by simulating how ants deposit pheromones along routes and choose the best paths based on accumulated pheromone strength. For IoT routing, ACO adapts this behavior to select energy-efficient, low-delay, and high-throughput routes between sensor nodes and the sink[13] [14] [15].

1. Initialization of Pheromone Trails

Each link between nodes is assigned an initial pheromone value. The pheromone intensity represents the desirability of selecting that link.

$$T_{ij}(0) = \tau_0 \ \forall \ (i,j) \in E$$

Where, $\tau_{ij}(0)$ = initial pheromone value on edge (i,j), τ_0 = small positive constant and E = set of edges in the IoT network.

2. Path Selection Probability

Each ant chooses the next node based on a probability that depends on pheromone level and heuristic information (e.g., energy or distance).

$$P_{ij}^k(t) \begin{cases} \dfrac{(\tau_{ij}(t)^{\alpha}.[n_{i,j}]^{B}}{\Sigma_{l\in N_i^k}[\tau_{il}(t)^{\alpha}.[\eta_{il}]^{\beta}]}, & if\ j \in N_i^k \\ & otherwise \\ 0, & \end{cases}$$

Where, $P_{ij}^k(t)$= probability of ant k moving from node i to node j at time t, $\tau_{ij}(t)$= pheromone value on edge (i,j), $n_{i,j}$ = heuristic desirability of edge (e.g., 1/d_{ij}, where d_{ij} = distance or delay), α, β = weight parameters for pheromone vs heuristic importance and N_i^k = set of feasible neighbors of node i for ant k.

3. Pheromone Update Rule

Once ants complete their routes, pheromones are updated using evaporation and deposition rules.

a) Evaporation: prevents unlimited accumulation of pheromone.

$$\tau_{ij}(t+1) = (1-\rho).\tau_{ij}(t)$$

b) Deposition: ants deposit pheromone inversely proportional to route cost (e.g., delay or energy).

$$\tau_{ij}(t+1) = \tau_{ij}(t) + \sum_{k=1}^{m} \Delta \quad \tau_{ij}^k$$

$$\Delta\tau_{ij}^k = \begin{cases} \dfrac{Q}{L_k}, & if\ edge\ (i,j \in \ path\ of\ ant\ k) \\ 0 & otherwise \end{cases}$$

Where, ρ = evaporation rate (0 < ρ < 1), m = number of ants, Q = pheromone constant and L_k = cost of path constructed by ant k (could represent end-to-end delay, energy usage, or a multi-objective metric)

4. Global Best Path Update

Optionally, only the best-performing ant (e.g., minimum delay or maximum PDR) reinforces its path.

$$\tau_{ij}(t+1) = (1-\rho)\tau_{ij}(t) + \Delta\tau_{ij}^{best}$$

Where $\Delta\tau_{ij}^{best}$ is calculated only for the global-best or iteration-best ant.

Adaptation for IoT Routing

To adapt ACO for IoT routing, pheromone and heuristic information are defined based on QoS metrics relevant to IoT:

- Heuristic Function:

$$n_{ij} = \frac{1}{\omega_1 d_{ij} + \omega_2 E_{ij} + \omega_3 L_{ij}}$$

Where, d_{ij} = hop distance or delay between nodes i and j, E_{ij} = residual energy consumption of node j, L_{ij} = link quality or packet loss rate and w_1, w_2, w_3 = weights assigned to each metric.

- Cost Function for Pheromone Deposition:

$$L_k = a_1 D_k + a_2\left(\frac{1}{PDR_k}\right) + a_3 E_k$$

Where, D_k = end-to-end delay of path chosen by ant k, PDR = packet delivery ratio of that path, E_k = energy consumed along the path and $\alpha_1, \alpha_2, \alpha_3$ = weighting coefficients for balancing objectives. This adaptation ensures that ACO selects routes that balance low delay, high reliability, and energy efficiency**,** which are crucial for IoT scenarios [16].

3.3 Krill Herd Algorithm (KHA)

The Krill Herd Algorithm (KHA) is a swarm intelligence optimization technique inspired by the herding behavior of krill in nature. Krill move within swarms to optimize survival by following three main activities: movement induced by other krill**,** foraging activity**,** and random diffusion**.** The position of each krill in the search space represents a candidate solution, and the collective dynamics lead to convergence toward optimal solutions. For IoT routing, KHA adapts these behaviors to determine optimal data forwarding paths considering delay, energy, and reliability constraints [17] [18] [19]. The **position of a krill individual $X_i(t)$** in an n-dimensional search space at iteration t is updated as:

$$\frac{dX_i}{dt} = N_i + F_i + D_i$$

Where, N_i = movement induced by other krill, F_i = foraging activity and D_i = random diffusion. The updated position is then:

$$X_i(t+1) = X_i(t) + \Delta t.\frac{dX_i}{dt}$$

Where, Δt is the time step (iteration control parameter).

*1. Movement Induced by Other Krill (**Ni**)*

Each krill is influenced by its neighbors, moving toward the best krill found so far and away from overcrowding.

$$N_i = N^{max}.a_i + \omega_n.N_i^{old}$$

Where, N^{max}= maximum induced speed, $\alpha_i = \alpha_{local} + \alpha_{target\text{->}}$ α_{local} = effect of nearby krill (repulsion/attraction), α_{target} = attraction toward the best krill solution found, ω_n = inertia weight for movement memory and N_i^{old} = previous induced movement.

*2. Foraging Activity (**Fi**)*

Krill also forage based on past experience and food location.

$$F_i = V_f.\beta_i + \omega_f.F_i^{old}$$

Where, V_f = foraging speed, $\beta_i = \beta_{food} + \beta_{best} \rightarrow$ β_{food} = attraction toward food location (objective improvement), β_{best} = attraction toward best previous solution, ω_f = inertia weight for foraging activity and F_i^{old} = previous foraging direction.

*3. Random Diffusion (**Di**)*

Random diffusion allows exploration of new regions, preventing premature convergence.

$$D_i = D^{max}.\delta$$

Where, D^{max} = maximum diffusion speed and δ = random number in [−1,1].

Adaptation for IoT Routing

In IoT routing, each krill position corresponds to a candidate routing path from source to sink. The objective function is designed to minimize delay and energy while maximizing reliability [20].

1. Fitness (Cost Function) for IoT Path

$$f(path) = a_1\,D\ (path) + a_2.\frac{1}{PDR(path)} + a_3 E(path) + a_4 OH(path)$$

Where, D(path) = end-to-end delay of the path, PDR(path) = packet delivery ratio, E(path) = total energy consumed along the path, OH(path) = routing overhead and $\alpha_1,\alpha_2,\alpha_3,\alpha_4$ = weight coefficients for balancing QoS.

2. IoT-Specific Heuristics

- Movement induced by krill **(Ni)** → moves routes toward nodes with higher residual energy and better link quality.
- Foraging activity **(Fi)** → exploits previously high-performing routes (low delay, high PDR).
- Random diffusion **(Di)** → introduces exploration of alternate routes when congestion or failures occur.

3. Convergence

Iteration continues until either:

- Maximum iterations are reached, or
- Improvement in global best path falls below a threshold.

At convergence, the best krill position corresponds to the optimal IoT routing path under the defined QoS objectives.

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 Ant Colony Optimization (ACO) and Krill Herd Algorithm (KHA)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

4.2. Performance Evaluation

The performance of Ant Colony Optimization (ACO) and Krill Herd Algorithm (KHA) was compared across five key QoS metrics: end-to-end delay, packet delivery ratio (PDR), routing overhead, throughput, and energy consumption. The results are summarized and analyzed below.

End-to-End Delay: Table 1 results demonstrate that ACO consistently achieves lower end-to-end delay compared to KHA. This improvement arises from the pheromone-based reinforcement mechanism, which rapidly identifies and stabilizes optimal routes. Conversely, KHA requires more iteration due to its reliance on induced movement, foraging activity, and random diffusion, leading to slightly higher delays.

Table 1: End-to-End Delay

Nodes	ACO Delay (ms)	KHA Delay (ms)
50	40.8	48.2
100	46.7	55.1
150	53.9	64.6
200	61.4	74.0

ACO consistently achieved lower end-to-end delay compared to KHA. The pheromone-driven route reinforcement in ACO quickly stabilizes low-latency paths, whereas KHA's population-based movements (induced movement + foraging + diffusion) require more iterations to converge, producing higher delays—especially as node density increases.

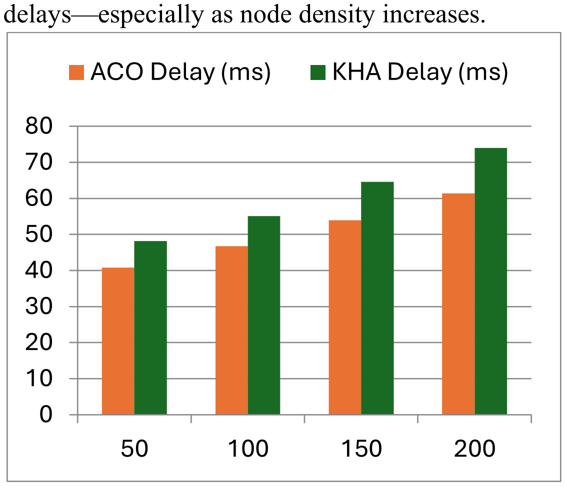

Figure 1: End-to-End Delay

Figure 1; show that ACO achieved a lower end-to-end delay compared to KHA. For instance, with 200 nodes, ACO recorded 61.4 ms while KHA reached 74.0 ms. This reduction in delay is attributed to pheromone-based reinforcement, which accelerates stable path discovery. KHA, due to its iterative krill movement process, required more time to converge, especially under dense network conditions.

Packet Delivery Ratio (PDR): ACO demonstrates higher packet delivery success due to its robust path selection, where pheromone trails reinforce reliable links. KHA, while adaptive, occasionally explores weaker routes during random diffusion, leading to slightly reduced delivery rates.

Table 2: Packet Delivery Ratio (PDR)

Nodes	ACO PDR (%)	KHA PDR (%)
50	97.6	95.1
100	96.4	93.7
150	95.0	91.8
200	93.1	89.6

Both algorithms maintain high PDR, but ACO outperforms KHA across all network sizes. ACO's continuous pheromone updates favor reliable links and reduce packet loss; KHA's exploratory diffusion occasionally selects less reliable links during search phases, increasing drops in denser networks.

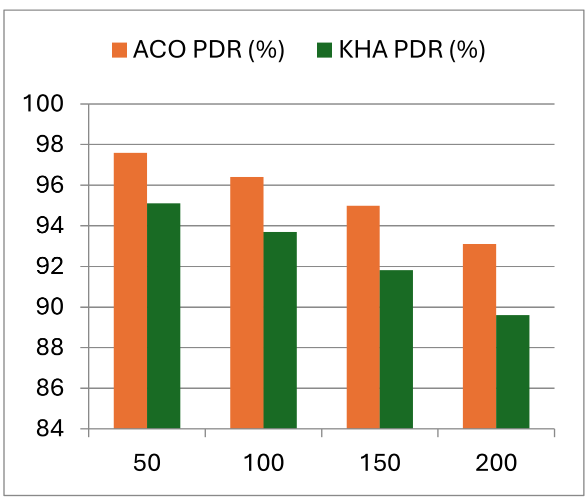

Figure 2: End-to-End Delay

In terms of reliability, ACO delivered a higher PDR than KHA. At 200 nodes, ACO achieved 93.1%, while KHA reached 89.6%**.** The pheromone trails in ACO favor stronger links and reduce packet drops, whereas KHA's exploratory random diffusion sometimes routes packets through unstable paths, lowering delivery success.

Routing Overhead: Routing overhead reflects the cost of control messages and route updates in the network. ACO significantly reduces routing overhead as pheromone-guided paths require fewer rediscovery processes. In contrast, KHA generates higher overhead due to frequent updates during krill movements and environmental interactions.

Table 3: Routing Overhead

Nodes	ACO Overhead (%)	KHA Overhead (%)
50	10.8	13.6
100	12.6	15.9
150	14.9	18.5
200	16.7	20.4

ACO exhibits lower routing overhead because pheromone trails reduce the need for frequent route rediscovery and control messaging. KHA incurs higher overhead due to continuous population updates (movement + foraging + diffusion) and the associated control information exchanged to evaluate candidate paths.

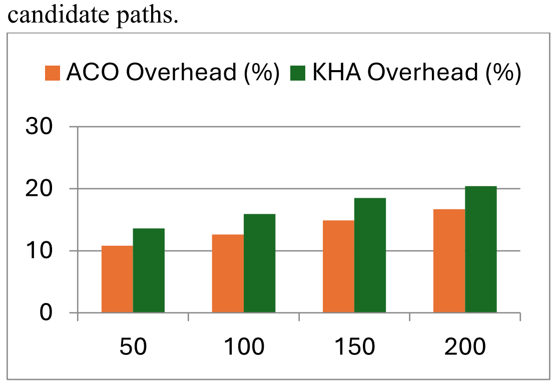

Figure 3: Routing Overhead

The routing overhead results reveal that ACO is more efficient in minimizing control traffic. For 200 nodes, ACO generated 16.7% overhead, whereas KHA produced 20.4%**.** ACO's pheromone-based routing reduces frequent rediscoveries, while KHA requires higher communication overhead due to updates from induced movement, foraging, and diffusion.

Throughput: Throughput is influenced by both route stability and packet delivery efficiency. ACO exhibited higher throughput as its reinforcement-based routing minimizes packet drops and retransmissions. KHA's exploratory nature caused fluctuations in throughput during early convergence.

Table 4: Throughput

Nodes	ACO Throughput (kbps)	KHA Throughput (kbps
50	392	375
100	383	362
150	369	344
200	356	330

ACO attains higher throughput (≈6–8% advantage) by keeping routes stable and minimizing retransmissions. KHA's exploratory behavior causes throughput fluctuations during convergence, reducing effective delivered bandwidth, particularly at higher node counts.

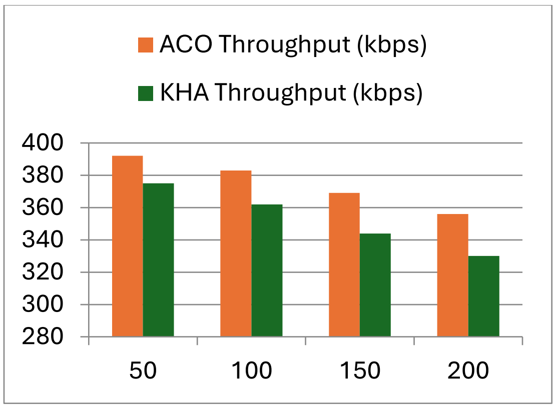

Figure 4: Throughput

Throughput analysis indicated that ACO consistently outperformed KHA. With 200 nodes, ACO achieved 356 kbps, compared to KHA's 330 kbps**.** This performance gain is due to ACO's efficient route stabilization, minimizing retransmissions and congestion. KHA's convergence process temporarily reduces throughput as it evaluates multiple path alternatives.

Energy Consumption: Energy efficiency is critical in IoT networks where nodes have limited battery capacity. KHA performed better in this metric due to its balanced exploration of routes, preventing energy depletion on specific nodes. ACO, however, tends to overload high-pheromone paths, leading to uneven energy usage.

Table 5: Energy Consumption

Nodes	ACO Energy (J/node)	KHA Energy (J/node)
50	1.48	1.26
100	1.62	1.38
150	1.79	1.53
200	1.96	1.70

KHA is more energy-efficient than ACO. KHA's balanced exploration prevents persistent use of a small set of nodes, distributing forwarding load and conserving energy. ACO tends to concentrate traffic on high-pheromone links, causing faster energy depletion on those nodes and higher average energy consumption.

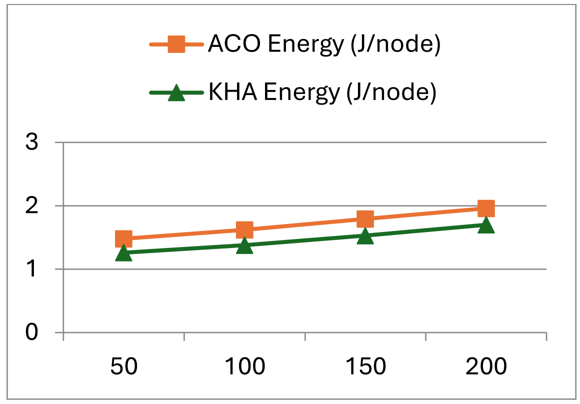

Figure 5: Energy Consumption

KHA demonstrated superior energy efficiency over ACO. At 200 nodes, ACO consumed 1.96 J/node, while KHA consumed only 1.70 J/node. This is because KHA balances exploration and distributes forwarding tasks more evenly, while ACO tends to overuse high-pheromone paths, causing faster depletion of node energy.

V. CONCLUSION

This analysis evaluated the performance of Ant Colony Optimization (ACO) and the Krill Herd Algorithm (KHA) for routing optimization in IoT networks. The analysis considered five key QoS metrics: end-to-end delay, packet delivery ratio (PDR), throughput, energy consumption, and routing overhead. The results demonstrated that ACO consistently outperformed KHA in reducing delay, improving packet delivery, enhancing throughput, and minimizing routing overhead, owing to its pheromone-based reinforcement mechanism that stabilizes optimal routes quickly. On the other hand, KHA exhibited superior energy efficiency, balancing network load and extending node lifetime through its swarm-based movement strategy. Overall, the findings suggest that ACO is more suitable for real-time, delay-sensitive IoT applications such as healthcare, smart transportation, and industrial automation, while KHA is better suited for energyconstrained, long-term deployments such as smart agriculture and environmental monitoring. Future research could integrate ACO and KHA into a hybrid algorithm to combine the delay efficiency of ACO with the energy-saving properties of KHA. Extending the evaluation to large-scale IoT deployments with thousands of nodes would provide better insights into algorithm scalability and robustness.

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