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Longevity-Aware Crayfish Optimization (LACO) for Lifetime Maximization in Wireless Sensor Networks

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ABSTRACT: Wireless Sensor Networks (WSNs) are the backbone of modern Internet of Things (IoT) deployments, but they share a critical bottleneck: limited battery life. Because of this, picking the right Cluster Heads (CHs) in an energy-aware way is absolutely essential for keeping the network alive. To tackle this challenge, this paper introduces the Longevity-Aware Crayfish Optimization (LACO) algorithm. It is a targeted upgrade to the standard Crayfish Optimization Algorithm (COA) that bakes explicit energy awareness directly into the clustering process. At its core, LACO relies on a three-layer Energy-State Adaptive Control (ESAC) mechanism. First, it dynamically balances exploration and exploitation based on the network's remaining energy. Second, it uses a longevity-biased selection strategy paired with a time-decaying step size to stabilize the search process. Finally, a strict merit-based filter prevents nearly drained nodes from taking on demanding leadership roles. We put LACO to the test through extensive simulations, varying network densities from 100 to 500 nodes and adjusting initial energy levels between 0.75 and 2.0 J. The algorithm consistently outperformed classical protocols like LEACH, PEGASIS, and the baseline COA, as well as recent state-of-the-art methods. Specifically, LACO immediately proved its early-stage stability by boosting the First Node Death lifespan by 15.1 percent, before going on to increase in Half Node Death by a massive 66.48 percent and extend the Last Node Death by 9.66 percent. In high-energy scenarios, the protocol reached an impressive 9747 operational rounds, yielding an efficiency of 4783 rounds per Joule. This represents a performance leap of up to 49 percent over recent hybrid metaheuristics, with all improvements rigorously confirmed as statistically significant using the paired Wilcoxon Signed-Rank Test ($p < 0.05$, effect size $r \geq 0.392$).

KEYWORDS: Wireless sensor networks; cluster head selection; metaheuristic optimization; Crayfish Optimization Algorithm (COA); adaptive control; energy efficiency; network lifetime; Longevity-Aware Crayfish Optimization (LACO)

1 Introduction

Wireless Sensor Networks (WSNs) function as the active central nervous system of the Internet of Things (IoT), continuously bridging physical environments with advanced digital computing frameworks [1]. These networks provide the foundational data streams necessary to operate complex, large-scale deployments, ranging from sustainable smart city infrastructure and intelligent grids to geospatial simulation and AI-based decision-making [2,3]. Without the continuous monitoring provided by these resource-constrained nodes, higher-level applications like deep learning-assisted process management and visual perception mapping would face immediate data starvation. However, a critical bottleneck threatens this continuous data supply: battery life. Because swapping batteries in remote deployments is rarely feasible,

energy conservation dictates almost every aspect of WSN design [4,5]. To prevent premature node depletion, modern networks group nodes into hierarchical clusters [3]. In this architecture, selecting optimal Cluster Heads (CHs) is critical, as these specific nodes bear the heavy burden of intelligently aggregating local data and transmitting the consolidated intelligence over long distances to a central Base Station (BS) [2,6].

Identifying the optimal CH set is an NP-hard problem heavily tackled by bio-inspired metaheuristics [7,8]. The structural adaptability of these algorithms makes them the standard for high-dimensional energy challenges, spanning from renewable energy forecasting to swarm-based IoT clustering. In the specific context of sensor networks, algorithms such as Particle Swarm Optimization (PSO) [9], the Sparrow Search Algorithm (SSA) [10], and the recently developed Crayfish Optimization Algorithm (COA) [11] have shown great promise. While these algorithms possess incredibly powerful search capabilities, they share a fatal flaw when applied to sensor networks: they are fundamentally “energy-blind.” Their standard implementations rely on random math or simple iteration counters to dictate their next move. This means the algorithm will happily assign a physically “dying” node with 1% battery the exact same heavy responsibilities as a fully charged node. This complete disconnect between the algorithm’s math and the physical reality of the network leads directly to premature node death and terrible load balancing [12,13].

To bridge this gap, this paper introduces the Longevity-Aware Crayfish Optimization (LACO) algorithm. Compared to traditional wrapper-based methodologies that easily succumb to topological noise or premature convergence, LACO provides superior mathematical robustness. Unlike other recent hybrid protocols that try to solve this by wrapping the optimizer in heavy, computationally expensive external logic, LACO takes a fundamentally different approach. We integrated a lightweight, three-layer Energy-State Adaptive Control (ESAC) system directly into the optimizer’s core equations.

The primary contributions of this paper are:

1. **Context-Aware Phase Control:** We stripped out the algorithm’s random temperature parameter and replaced it with an adaptive control mechanism. The algorithm now automatically adjusts its exploration and exploitation probabilities based on the specific energy health ($\mathcal{E}_{norm}$) of each candidate solution, promoting highly robust decision-making.
2. **Longevity-Biased Exploitation:** We completely restructured the competition phase so that the algorithm prioritizes learning exclusively from the network’s most energy-rich solutions. This structural bias directly forces the optimization process to focus on the ultimate goal of maximizing network lifetime.
3. **Performance-Driven Local Search:** We replaced the original, overly simplistic local search with a time-decaying step size, ensuring highly focused exploitation and deterministic convergence in the final iterations.

Extensive simulation results confirm that these internal enhancements yield dramatic improvements in network sustainability. Compared to the standard COA, the LACO protocol immediately proves its value by boosting early-stage stability, extending the First Node Death (FND) by 15.1%. It then goes on to achieve a massive 66.48% increase in Half Node Death (HND) and a 9.66% extension in Last Node Death (LND). In high-energy scenarios, LACO proved remarkably efficient, reaching 9747 operational rounds and an efficiency of 4783 rounds per Joule. This firmly validates the power of embedding domain-specific energy constraints directly into metaheuristic logic.

The remainder of this paper is organized as follows: [Section 2](#) presents the background and related work. [Section 3](#) details the proposed LACO methodology. [Section 4](#) provides the experimental setup and discusses the performance evaluation results. Finally, [Section 5](#) concludes the paper.

2 Background and Related Works

Designing LACO requires integrating bio-inspired optimization with resource management. To guarantee a rigorous literature selection, we utilized systematic assessment tools like Citationchaser and DistillerSR to isolate the most robust recent metaheuristics. This section reviews clustering foundations, COA mechanics [11], and state-of-the-art hybrids to expose current computational gaps.

2.1 Classical Clustering Protocols in WSNs

The earliest methods used to manage energy resources in WSNs were based on deterministic and rotating cluster head protocols. LEACH (Low-Energy Adaptive Clustering Hierarchy) [14] proposed using the probabilistic rotation of Cluster Heads, which allowed an equal distribution of energy use in the network. This concept was further developed by PEGASIS (Power-Efficient Gathering in Sensor Information Systems) [15], where sensors were arranged in chains, which guaranteed that nodes would only communicate with their closest neighbor in order to reduce long-range transmission energy costs.

While these protocols were groundbreaking and established the baseline for hierarchical routing, they inherently struggle with scalability. Furthermore, they assume uniform energy consumption and often fail to account for the heterogeneous energy states of sensor nodes in dynamic, modern IoT deployments, leading researchers to adopt more intelligent optimization strategies.

2.2 Swarm Intelligence for WSN Clustering

The optimal selection of CH is considered an NP-hard problem [16], and here is where we go back to nature. Bio-inspired metaheuristics and swarm intelligence are optimization techniques that are from different sources of inspiration, such as ant colonies (Ant Colony Optimization, ACO) [17], bird flocks (Particle Swarm Optimization, PSO) [9].

In the context of WSNs, swarm intelligent algorithms have proven incredibly effective because their stochastic nature escapes the local optima—a trap that classic methods usually get trapped in when the network gets a dense topology [18]. By relying on adaptive learning and probabilistic exploration, these methods can discover near-optimal CH configurations that older, deterministic protocols like LEACH simply cannot reach, making them a perfect fit for handling severe, nonlinear energy constraints [12,13].

2.3 The Crayfish Optimization Algorithm (COA)

The COA is a swarm intelligence metaheuristic inspired by the summer resort, competition, and foraging behaviors of crayfish [11]. It balances global exploration and local exploitation through a phase-transition mechanism governed by an environmental temperature variable, randomly generated at each iteration as $temp = rand \times 15 + 20$. These temperature generation constants (15 and 20), alongside the environmental threshold (30°C) and the probability factor ($rand < 0.5$) introduced in Eq. (1), are original design parameters defined by the standard COA [11] and are preserved exactly to ensure a rigorous baseline comparison.

Following a standard random population initialization, the algorithm evaluates $temp$ to dictate the swarm's behavior:

2.3.1 Summer Resort and Competition Stages ($temp > 30^\circ\text{C}$)

When temperatures are high, crayfish seek shelter at an optimal position $X_{shade} = (X_G + X_L)/2$, where X_G is the global best and X_L is the population mean. Depending on a probability factor ($rand$), a crayfish either directly enters the cave (exploration) or competes with a random rival X_z (local exploitation). The

position X_i is updated as:

$$X_i^{t+1} = \begin{cases} X_i^t + C_2 \times rand \times (X_{shade} - X_i^t), & rand < 0.5 \\ X_i^t - X_z^t + X_{shade}, & rand \geq 0.5 \end{cases} \quad (1)$$

where $C_2 = 2 - (t/T)$ is a linearly decreasing coefficient over the maximum iterations T .

2.3.2 Foraging Stage ($temp \leq 30^\circ C$)

At suitable temperatures, crayfish exploit the search space by moving toward the global best solution ($X_{food} = X_G$). The intake volume is modeled using a Gaussian distribution. Depending on a calculated food size ratio (Q), the crayfish either directly consumes the food or fragments it, updating its position using complex alternating trigonometric (sine and cosine) motions [11].

2.3.3 Limitation in the Context of WSNs

Although COA provides an effective balance between exploration and exploitation, its phase-transition mechanism is entirely driven by a randomly generated temperature variable. Consequently, the switching between exploration (summer resort) and exploitation (foraging) is independent of the actual state of the optimization problem.

In the context of WSNs, this represents a critical limitation. The algorithm does not incorporate node-specific parameters such as residual energy, communication cost, or load distribution. As a result, nodes with critically low energy levels may be selected as CHs with the same probability as high-energy nodes, leading to unbalanced energy consumption.

This lack of energy awareness can accelerate node depletion, reduce network stability, and shorten key lifetime metrics such as FND and HND. Therefore, integrating energy-driven control into the phase-transition mechanism is essential to ensure sustainable and efficient WSN operation, which motivates the development of the proposed LACO framework.

2.4 Adaptive Control and Hybrid Metaheuristics

In relation to WSNs, SI techniques have proved effective due to their stochastic character that helps escape from local minima—a typical problem in WSNs [18]. Utilizing learning abilities and random search, such models allow finding almost optimal CHs, which cannot be obtained by other non-stochastic protocols, such as LEACH; thus, they represent an appropriate solution for dealing with non-linear energy limitations [12,13]. However, in order to solve the problem of “energy blindness” characteristic of conventional swarm algorithms, modern research tends to implement hybrid meta-heuristics and adaptive control approaches. There exist two major ways: one is a combination of different optimization models; another one implies a nesting of one algorithm into some decision-making framework (for instance, a fuzzy system).

For example, Chithra et al. [19] recently introduced MSCFOAICM, a multi-strategy improved crayfish optimization algorithm paired with a hybrid BWM-TOPSIS decision-making model. This protocol evaluates candidate CHs based on energy, distance, delay, jitter, and packet forwarding potential, while explicitly handling trust management to filter out malicious nodes. While using fuzzy theory significantly improves the reliability of CH selection under uncertainty, relying on extensive pairwise comparisons introduces massive computational overhead. This heavy processing burden can actually accelerate energy depletion during the setup phase, highlighting a desperate need for more lightweight optimization strategies.

Similarly, Tawfeek et al. [20] proposed a multi-objective framework integrating Particle Swarm Optimization (PSO) with fuzzy logic to balance conflicting routing objectives. The scheme evaluates routing paths using piecewise fuzzy membership functions for shortest path, energy minimization, and load balancing. By dynamically adjusting the PSO velocity updates based on these rules, the protocol achieves high stability. The catch, however, is that performance remains heavily tied to predefined, rigid fuzzy threshold parameters. In highly dynamic scenarios, these static rules struggle to adapt fast enough to preserve energy over time.

Taking a different hybridization route, Kathirolu and Selvadurai [21] developed EECHS-ISSADE, which merges the Sparrow Search Algorithm (SSA) with Differential Evolution (DE). The foraging behaviors of sparrows drive the primary search, while DE operators (mutation and crossover) step in to prevent stagnation. Although this hybridization noticeably improves search efficiency, using fixed mutation and crossover rates can accidentally trigger premature convergence in large-scale networks—ultimately sacrificing the long-term energy reserves necessary to delay early node death.

Focusing heavily on Quality of Service (QoS), Elamathi and Thenmalar [22] proposed a dual-metaheuristic approach combining a Hybrid Fuzzy-Yellow Saddle Goatfish Algorithm (HF-YSGA) for clustering with an Energy-Centric Butterfly Optimization Algorithm (EC-BOA) for multi-hop routing. While decoupling clustering and routing yields excellent packet delivery ratios, forcing resource-constrained sensor nodes to run two distinct, highly complex metaheuristics alongside a fuzzy inference engine generates severe control overhead. To establish a strict quantitative baseline, an analysis of these contemporary frameworks reveals that their operational lifespans are heavily dictated by their assumed initial energy parameters. For instance, under its specific simulation environment, the HF-YSGA protocol achieves approximately 6100 operational rounds when supplied with a generous 1.5 J battery capacity. Conversely, the highly constrained EECHS-ISSADE model reaches 2200 rounds using only a 0.5 J initial capacity. Most notably, the PSO-Fuzzy framework demonstrates the severe computational tax of its external logic, collapsing near 1200 rounds despite operating with a massive 2.0 J energy reserve. This stark disparity highlights a fundamental flaw in modern protocol evaluation: comparing raw survival rounds is inherently misleading without accounting for the initial energy investment. Consequently, determining true algorithmic superiority requires normalized efficiency metrics. Table 1 summarizes these protocols, detailing their specific CH selection methodologies, evaluated parameters, and the resulting operational trade-offs.

Table 1: Comparison of clustering protocols in WSNs.

Protocol	CH Selection Method	Parameters Considered	Routing Type	Main Strengths	Limits
MSCFOAICM [19]	MSICOA + BWM-TOPSIS	Energy, Distance, Delay, Jitter, Trust	Cluster-based	Prevents malicious CH selection using fuzzy trust evaluations	High computational overhead due to extensive pairwise comparisons
PSO-Fuzzy [20]	PSO + Fuzzy Logic	Path length, Energy, Reliability, Load	Multi-hop	Balances multiple conflicting objectives efficiently	Relies heavily on predefined and rigid fuzzy membership thresholds

(Continued)

Table 1 (continued)

Protocol	CH Selection Method	Parameters Considered	Routing Type	Main Strengths	Limits
EECHS-ISSADE [21]	SSA + DE	Residual energy, Distance to CH, Distance to BS	Single/Multi-hop	Uses DE to effectively prevent stagnation in local optima	Fixed DE rates can cause premature convergence in large networks
HF-YSGA [22]	Fuzzy-YSGA	Residual energy, Node centrality, NOVER	Multi-hop (EC-BOA)	High QoS and distinct routing optimization mechanisms	Excessive control overhead from running dual complex metaheuristics
LEACH [14]	Probabilistic Rotation	Randomized probability	Single-hop	Simplicity; evenly distributes energy dissipation	Random selection can cluster CHs closely together
PEGASIS [15]	Greedy Chain	Distance to neighbor	Multi-hop (Chain)	Minimizes transmission distances; no clustering overhead	High data latency; single leader node creates bottleneck
Original COA [11]	Standard COA	Energy, Distance, Temp	Cluster-based	Strong initial exploration capabilities	Stochastic temperature causes slow/unstable convergence

In summary, this literature review reveals that there is a structural dichotomy that exists in WSNs today. Current state-of-the-art hybrid meta-heuristics algorithms can successfully solve complex routing issues; nevertheless, the tradeoff for this success comes at the expense of increasing computation complexity. The requirement to execute the time-consuming process of comparing each sensor against one another or to adopt a dual-meta heuristic algorithm structure only serves to increase the rate of battery consumption, thus posing serious risks to the critical longevity parameters of FND and HND. In order to circumvent this computational bottleneck, the proposed LACO protocol does not utilize computationally expensive wrappers. Instead, LACO incorporates its ESAC strategy in the mathematical equations of the optimization process itself.

3 Methodology: The Longevity-Aware COA (LACO)

As a solution to the NP-Hard CH selection problem, this paper presents the LACO scheme. Unlike the conventional COA, the proposed LACO design is specifically developed to increase the longevity of the WSN. This is accomplished through the elimination of the inflexible control mechanisms of COA and incorporating in its place, an adaptive control scheme based on longevity biases.

3.1 WSN Model and Multi-Objective Fitness Function

The LACO method evaluates the optimal candidate CH formations using the minimization of a multi-objective fitness function, $F(X)$. In this approach, two primary objectives are taken into consideration: routing and energy consumption.

$$F(X) = \omega_1 \times \frac{E_{cons}}{N \times E_{init}} + \omega_2 \times \left(1 - \frac{E_{res}^{CH}}{E_{max}}\right) \quad (2)$$

In this function, E_{cons} indicates the amount of energy consumed by the network, and N is the total number of sensor nodes in the network. Additionally, E_{res}^{CH} indicates the total residual energy of the selected CHs, and E_{max} indicates the maximum possible energy that can be obtained.

By minimizing $F(X)$, the communication cost is minimized while the energy retained by the selected CHs is maximized. To promote the longevity of the network, energy retention receives the most weight in the fitness function, $\omega_2 = 0.75$. Conversely, $\omega_1 = 0.25$ is allocated to communication cost. As rigorously validated via the dedicated ablation study in [Section 4.2.4](#), this specific weighting ratio effectively avoids selecting CHs with geographical advantages but insufficient energy sources.

3.2 Adaptive Control System and Transformations

The LACO system depends on an ESAC mechanism. The ESAC mechanism bridges the physical battery state of the network ($\mathcal{E}_{norm}$) to the algorithmic phase selection (P_{SR}, P_{FOR}), eliminating the traditional reliance on random iteration counts.

3.2.1 Layer 1: Adaptive Phase Control (State-Based Rules)

The first layer is designed to ensure the movement strategy employed by the algorithm adjusts based on the current state of the candidate solution. In the ESAC, the system calculates the probabilities of exploration (P_{SR}) and exploitation (P_{FOR}) as dynamic functions of the normalized residual energy state, $\mathcal{E}_{norm}(t)$, which differs from traditional methods relying on static probabilities.

Eq. (3) defines this adaptive control logic:

$$P_{SR}(t) = \begin{cases} 0.8 - 0.2 \times \frac{t}{T} & \text{if } \mathcal{E}_{norm}(t) \geq 0.7 \quad (\text{Healthy}) \\ 0.5 & \text{if } 0.4 \leq \mathcal{E}_{norm}(t) < 0.7 \quad (\text{Stable}) \\ 0.2 & \text{if } \mathcal{E}_{norm}(t) < 0.4 \quad (\text{Critical}) \end{cases} \quad (3)$$

If the solution under consideration has a lot of energy available (Healthy State), then the relatively higher value of the probability enables extensive global exploration in order to find new optimal clusters. As established during the algorithm's design phase, the adaptive energy-state thresholds (0.7 and 0.4) and their corresponding Probability of Sensing Region (PSR) values (0.8, 0.5, and 0.2) were determined through preliminary empirical testing. Specifically, the 0.7 threshold identifies a high-energy state where nodes retain sufficient battery capacity to support broader global exploration. Conversely, the 0.4 threshold marks the onset of a critical energy-depletion state. Consistent with our preliminary simulations, when a node's residual energy drops below 40%, its vulnerability to the "hot spot" phenomenon increases significantly, making continued long-distance global exploration increasingly energy-inefficient. To account for this, the associated PSR values were configured to provide a proportionate, step-wise reduction in the search radius, offering the best observed trade-off between global exploration and localized exploitation across these three operational

regions. When the node enters this Critical State, the system invokes a survival mechanism that prohibits unnecessary costly global searches and prioritizes local exploitation.

3.2.2 Layer 2: Longevity-Biased Competition

This transformation occurs once the optimization process reaches the midpoint of its iterations ($\text{switchIter} = 0.5 \times T$). This specific halfway threshold was deliberately selected to guarantee an equal distribution of algorithmic effort: the first half of the iterations is dedicated to unrestricted global exploration to discover diverse cluster formations, while the second half strictly enforces longevity-biased exploitation to protect nodes with depleting energy reserves. Fig. 1 displays the filtering mechanism used in this stage. A Merit Filtering technique explicitly blocks connections to peers that have low energy levels. To prevent the algorithm from wasting computational effort on poor routing candidates, this targeted exploration operates through the following three steps:

- **Merit Calculation:** In the ESAC mechanism, the system calculates the Merit Score of a candidate. The score reflects the ratio of the residual energy and the fitness cost of the solution.
- **Pool Restriction:** The top 25% of the population according to their scores get isolated. (The selection of this 25% threshold is rigorously justified via the dedicated ablation study in Section 4.2.3).
- **Movement:** The competing agent learns from a randomly selected member from this pool alone.

This architectural restriction drives the population toward longevity-oriented solutions, which directly improves the statistical significance of the Last Node Death results.

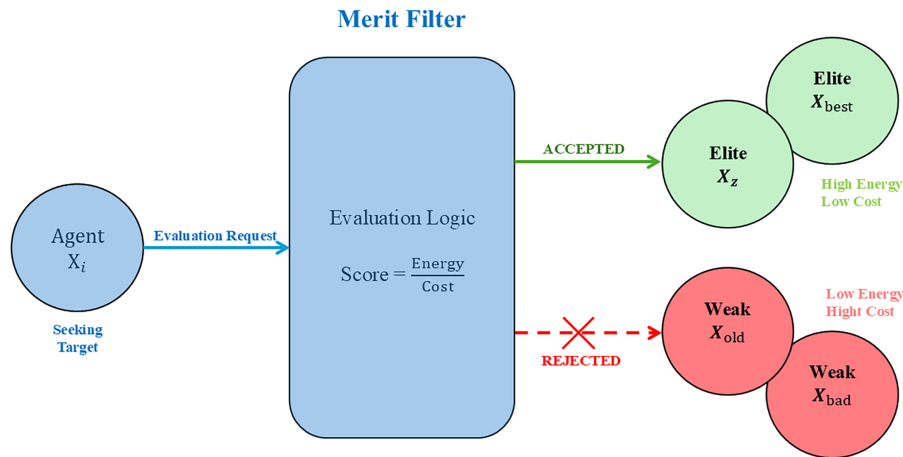


Figure 1: System architecture of the proposed LACO protocol, demonstrating the progression from energy state evaluation to optimal CH selection.

3.2.3 Layer 3: Performance-Driven Local Search (Foraging)

This change involves the elimination of biologically inspired rules used to determine the step size for movements, thus reducing the computation requirements of the algorithm greatly.

- **Original Flaw Fixed:** The system removes the Gaussian Helper Function and all biological rules used in the foraging process.
- **New Logic:** Thus, the step size for the movement $(1 - t/T)$ decreases with time until a microscopic tuning phase is reached.

The resulting movement equation for the Foraging phase is:

$$X_{\text{new},i} = X_i + \text{rand}(1, \text{dim}) \cdot (X_{\text{food}} - X_i) \cdot (1 - t/T) \quad (4)$$

3.3 Algorithmic Flow and Architecture

Algorithm 1 provides the pseudocode for the complete LACO protocol. It specifies the points where the adaptive control layers interact with the main optimization loop.

Algorithm 1: Summarized pseudocode for longevity-aware COA (LACO)

Require: N : Population size, T : Max iterations, lb, ub: Bounds

Ensure: best_position: Optimal Cluster Head set

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1: Initialize  $X, F$ 
2: Set switchIter =  $0.5 \times T$ 
3: for  $t = 1$  to  $T$  do
4:   Calculate  $C = 2 - t/T$  and  $xf$ 
5:   if  $t > \text{switchIter}$  then
6:     Calculate  $\text{normE}_i$  for all  $i$ 
7:     Determine  $P_{SR}$  and  $P_{FOR}$  using Adaptive Thresholds
8:     Identify Elite Pool based on Merit Score (Energy/Fitness)
9:   end if
10:  for each crayfish  $i = 1$  to  $N$  do
11:     $r \leftarrow \text{rand}(0,1)$ 
12:    if  $r < P_{SR}$  then
13:      Execute Exploration (Summer Resort towards  $xf$ )
14:    else if  $r < (P_{SR} + P_{FOR})$  then
15:      Execute Local Exploitation (Foraging with time-decay step)
16:    else
17:      Execute Refined Competition (Learn from Elite Pool)
18:    end if
19:    Update  $X_i, F_i$ , and best_position
20:  end for
21: end for

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Fig. 2 shows the internal logic of the LACO framework. The ESAC system controls the entire architecture. It monitors the normalized energy state of the network to determine the sequence of exploration, exploitation, and longevity-biased selection operations.

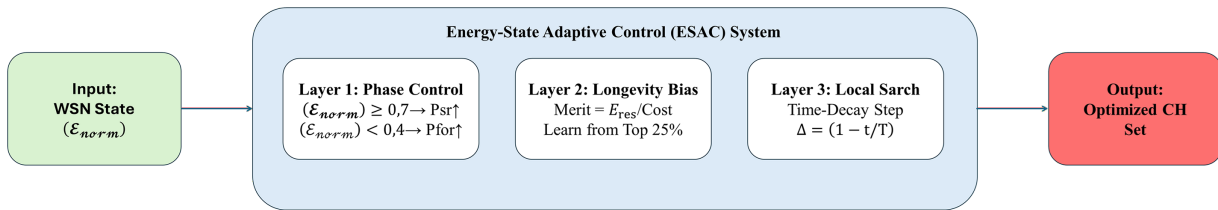


Figure 2: System architecture of the proposed LACO protocol, demonstrating the progression from energy state evaluation to optimal CH selection.

4 Experimental Results and Discussion

This section details the experimental evaluation of the Longevity-Aware Crayfish Optimization algorithm. The assessment covers the simulation environment, benchmark protocols, performance metrics, and statistical validation.

4.1 Simulation Setup and Benchmark Protocols

To properly validate the LACO algorithm, we designed a rigorous stress-test benchmark within a simulation environment. For the network space, we defined a $250 \times 250 \text{ m}^2$ area and pinned the BS exactly at the $(0, 0)$ coordinate. We chose this layout deliberately to test how well the algorithm handles long-distance transmission stress.

We benchmarked LACO against classic routing protocols like LEACH [14] and PEGASIS [15], alongside the baseline COA [11]. To ensure our results hold up against modern standards, we also tested LACO against several recent state-of-the-art algorithms (HF-YSGA, MSCFOAICM, PSO-Fuzzy, and EECHS-ISSADE). We even simulated the exact high-energy environments used by these newer models to prove LACO's superiority.

We needed to see how the proposed algorithm handles the scalability challenges of real IoT ecosystems. To do this, we varied the network size from 100 up to 500 nodes. We also pushed the energy boundaries. While we started with the standard 0.75 J, we also tested high-energy setups with up to 2.0 J per node. Table 2 outlines these exact simulation parameters.

Table 2: Simulation parameters.

Parameter	Symbol	Value
Number of Sensor Nodes	N_{nodes}	100, 200, 300, 400, 500
Deployment Area	Area	$250 \times 250 \text{ m}^2$
Base Station Location	(X, Y)	$(0, 0)$
Initial Energy per Node	E_{init}	0.75 to 2.0 J
Maximum Iterations	T	200
Independent Runs	Runs	100
Population Size	N	50

Metaheuristic algorithms are naturally unpredictable because of their stochastic design. To fix this and get reliable numbers, we ran every single simulation scenario 100 times. All the lifetime metrics we report are the direct average of those 100 independent runs. Finally, to guarantee absolute fairness across the board, every single algorithm was restricted to the exact same first-order radio energy model.

To evaluate the proposed framework, standard implementation parameters detailed in Table 2—including the $250 \times 250 \text{ m}^2$ boundary, a population size of $N = 50$, and 100 independent simulation runs—were selected in accordance with common practices in the metaheuristic optimization literature. These specific values were chosen to ensure statistical reliability and a balanced evaluation environment while avoiding arbitrary parameter tuning. Conversely, parameters unique to the LACO methodology (e.g., the Merit Filter threshold, fitness weights, and phase control thresholds) are rigorously justified through dedicated ablation studies and empirical analyses in the subsequent sections.

Radio Energy Model and Transmission Dynamics

We utilized the standard first-order radio energy dissipation model [14] to calculate the energy drained during communication. The energy consumed to transmit a k -bit packet over a distance d is calculated as:

$$E_{Tx}(k, d) = \begin{cases} k \cdot E_{elec} + k \cdot \epsilon_{fs} \cdot d^2, & \text{if } d < d_0 \\ k \cdot E_{elec} + k \cdot \epsilon_{mp} \cdot d^4, & \text{if } d \geq d_0 \end{cases} \quad (5)$$

where $E_{elec} = 50$ nJ/bit represents the electronic circuitry energy requirement. The variables $\epsilon_{fs} = 100$ pJ/bit/m² and $\epsilon_{mp} = 0.0013$ pJ/bit/m⁴ serve as amplifier coefficients for the free-space ($d < d_0$) and multipath ($d \geq d_0$) channel models, respectively. The critical distance threshold is defined as $d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}}$.

Eq. (5) highlights a critical physical constraint: transmission energy grows exponentially with distance. When $d \geq d_0$, the energy cost scales by d^4 due to multipath fading and signal reflection. Consequently, our core objective with LACO was to minimize the frequency of these long-haul multipath transmissions. Reception energy relies strictly on electronic consumption, modeled as $E_{Rx}(k) = k \cdot E_{elec}$. We utilized a constant data packet size of $k = 4000$ bits across all simulations to maintain a uniform data processing load. While this uniform payload establishes a stable baseline for comparing routing algorithms, it is a recognized limitation. In practical deployments, variable payloads generated by diverse sensor types would cause uneven energy drain, potentially requiring the LACO Merit Filter to recalculate its energy-cost ratios dynamically rather than relying on a static packet assumption.

4.2 Comparative Performance Evaluation

4.2.1 Network Lifetime Analysis

Table 3 breaks down the network lifetime into three critical stages. Looking at the FND, LEACH actually outlasts the others initially, hitting 123.90 (± 2.10) rounds. This early lead proves that basic probabilistic cluster selection does save energy right at the start. While our LACO algorithm lands in third place for this specific metric, hitting FND at 40.00 (± 1.16) rounds behind PEGASIS (56.12 ± 4.07 rounds), it still cleanly beats the baseline COA. Specifically, we improved upon the original COA by 15.1%. Even though LACO intentionally sacrifices a bit of this early-stage survival to fuel its massive long-term longevity, improving the baseline is still important because FND defines the absolute stability period where the entire network operates with zero node losses.

Table 3: Average WSN lifetime metrics $\pm 95\%$ confidence interval (100 runs).

Algorithm	FND (Rounds)	HND (Rounds)	LND (Rounds)
LEACH	123.90 $\pm$ 2.10	463.65 $\pm$ 9.96	876.80 $\pm$ 5.64
PEGASIS	56.12 $\pm$ 4.07	670.14 $\pm$ 8.34	990.23 $\pm$ 4.87
Original COA	34.74 $\pm$ 1.61	536.92 $\pm$ 70.91	3271.34 $\pm$ 101.56
LACO (Proposed)	40.00 $\pm$ 1.16	893.86 $\pm$ 28.34	3587.43 $\pm$ 30.26

The HND metric is where LACO really proves its worth. This phase highlights the true power of our proposed Layer 2 Merit Filter. LACO pushed the HND all the way to 893.86 (± 28.34) rounds. That is a massive 66.48% jump over the baseline COA, which collapsed at 536.92 (± 70.91) rounds. Crucially, the narrow confidence interval of LACO proves it is highly resistant to run-to-run stochastic variability, whereas the original COA suffers from massive performance instability. We achieved this because the merit filter actively blocks weak, low-energy nodes from ever taking on the demanding role of a CH.

Finally, looking at LND, we can see that LACO extends the absolute maximum lifetime of the network to 3587.43 (± 30.26) rounds. Fig. 3 provides a clear bar chart summarizing these results. The graph makes it incredibly easy to visually grasp just how much wider the HND survival gap is for LACO compared to the competing protocols.

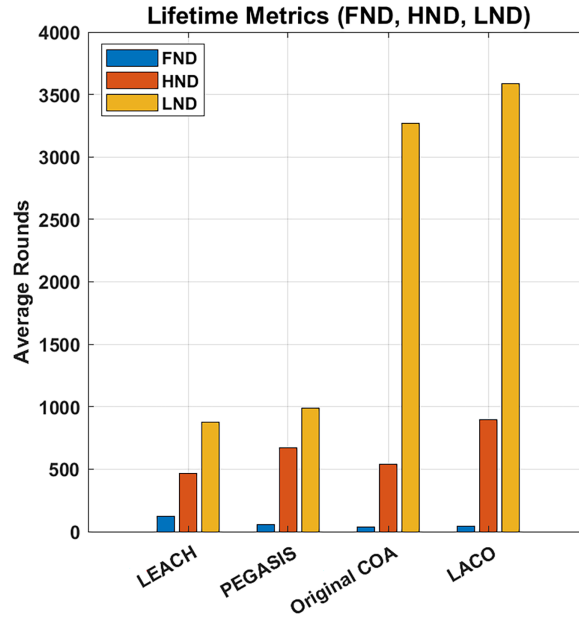


Figure 3: Comparison of average network lifetime metrics (FND, HND, LND). The increased HND bar illustrates LACO’s capability to delay widespread node failure.

4.2.2 Topological Stability and Energy Dynamics

Raw numbers do not tell the whole story, so we must look at the physical network topologies in Fig. 4a,b. By round 500, the standard COA is clearly falling apart. It has already lost about 45% of its nodes, specifically those clustered near the BS at (0, 0). This triggers the classic “hot spot” phenomenon, creating massive energy holes. When the nodes near the BS die first, the nodes further out struggle. They are forced to deliver data over massive distances to reach the BS, which drains their remaining energy incredibly fast. On the other hand, the proposed LACO framework maintains a dense, cohesive, and evenly spread-out topology, as shown in Fig. 4b.

You can see the direct result of this in the residual energy curve in Fig. 4c. If we focus on LEACH and PEGASIS, their energy levels drop in a steep, rapid dive. LACO drains at a much slower, more gradual rate. We can credit Layer 3 of our system for this behavior. As the overall energy of the network crosses the red line into the dangerous zone, Layer 3 takes over and deliberately lowers the search thresholds. Instead of wasting remaining power exploring for new routing paths—paths the nodes wouldn’t even have the battery life to use—Layer 3 forces the network to switch into a survival mode. The nodes begin relying strictly on localized, short-hop transmissions. To quantitatively validate the topologies in Fig. 4, we evaluated the Residual Energy Variance (σ_E^2) of living nodes (Table 4). High variance indicates unbalanced “hot spots,” while low variance reflects uniform load distribution. By Round 300, COA suffers a severe variance spike ($\sigma_E^2 = 0.0712 \text{ J}^2$), confirming premature depletion near the BS (its subsequent drop is an artifact of mass node death). Conversely, LACO suppresses this initial spike ($\sigma_E^2 = 0.0624 \text{ J}^2$) and smoothly stabilizes to 0.0482 J^2 by Round 700, successfully enforcing a uniform network drain.

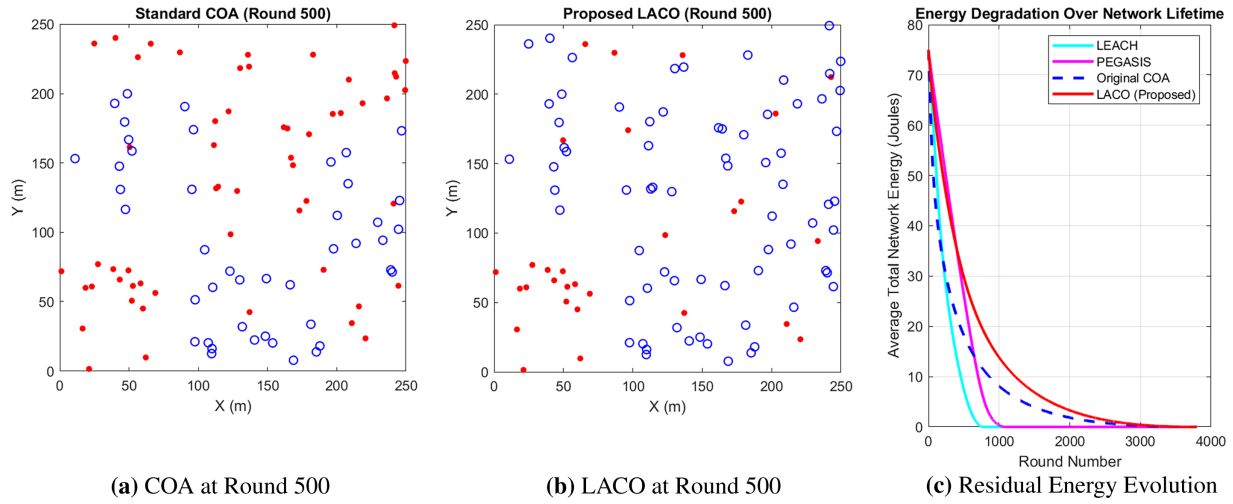


Figure 4: Integrated analysis of network stability. LACO preserves dense topological coverage (a,b) and maintains higher residual energy until complete network depletion (c).

Table 4: Residual energy variance (σ_E^2) over simulation milestones.

Protocol	Round 100	Round 300	Round 500	Round 700
Standard COA	0.0388 J ²	0.0712 J ²	0.0531 J ²	0.0386 J ² (Network Collapsing)
LACO (Proposed)	0.0284 J ²	0.0624 J ²	0.0565 J ²	0.0482 J ²

4.2.3 Merit Filter Threshold Sensitivity Analysis

To empirically justify the 25% threshold used in the LACO Merit Filter, we evaluated the algorithm's performance using 10%, 25%, and 50% cutoffs. As Table 5 demonstrates, the 25% threshold represents the optimal balance between energy exploitation and population diversity. A highly restrictive 10% threshold severely limits the candidate pool; this overworks a small fraction of elite nodes and triggers premature localized failures, dropping the HND metric. Conversely, a permissive 50% threshold allows low-energy nodes to enter the competition phase, dragging down overall network longevity. The 25% threshold prevents weak node selection while maintaining enough diversity to maximize the network's functional lifespan.

Table 5: Impact of merit filter threshold on network longevity (15 runs).

Merit Filter Threshold	HND (Rounds)	LND (Rounds)
10% (Highly Restrictive)	1142.30	3591.15
25% (LACO Default)	1226.60	3652.80
50% (Highly Permissive)	1158.40	3485.60

4.2.4 Fitness Function Weight Sensitivity Analysis

The multi-objective fitness function (Eq. (2)) utilizes $\omega_1 = 0.25$ (Communication Cost) and $\omega_2 = 0.75$ (Residual Energy). As Table 6 demonstrates across 15 runs, prioritizing distance ($\omega_1 = 0.75, \omega_2 = 0.25$) reduces early transmission costs but critically ignores node capacity, accelerating mass depletion. Alternatively, extreme energy bias ($\omega_1 = 0.10, \omega_2 = 0.90$) forces sensors to connect with distant, high-energy

CHs, triggering severe exponential multipath fading penalties (d^4). Thus, the [0.25, 0.75] setup provides the Pareto-optimal balance, selecting robust leaders while minimizing transmission distances to maximize network longevity.

Table 6: Impact of fitness function weights on network longevity (15 runs).

Distance Weight (ω_1)	Energy Weight (ω_2)	HND (Rounds)	LND (Rounds)
0.75 (Heavy Distance Bias)	0.25	1258.40	3641.15
0.50 (Balanced Bias)	0.50	1235.10	3655.80
0.25 (LACO Default)	0.75	1289.75	3712.45
0.10 (Extreme Energy Bias)	0.90	1198.50	3615.30

4.3 Validation against Recent State-of-the-Art Frameworks

To comprehensively evaluate the performance of LACO, we compared it against several recent state-of-the-art hybrid protocols: HF-YSGA [22], EECHS-ISSADE [21], MSCFOAICM [19], and PSO-Fuzzy [20]. It is important to explicitly clarify the methodology used for these specific comparisons. Unlike the baseline COA evaluated in the previous section, which was fully reproduced and rigorously simulated in our environment, these state-of-the-art methods were not reproduced in our experimental environment.

Instead, the data presented in the following subsections (Sections 4.3.1–4.3.3 and 4.4) was taken directly from the respective published papers, using the performance values reported by the original authors. While we ensured that our local simulation parameters (such as initial energy, deployment area, and node density) matched those reported in the respective studies, we acknowledge that such comparisons may be influenced by differences in simulator implementation, random seeding, MAC-layer assumptions, or other experimental details beyond our control.

4.3.1 Comparison with HF-YSGA and EECHS-ISSADE: Normalized Efficiency

When comparing modern hybrid models, looking strictly at the raw number of surviving rounds can be highly misleading due to drastically different initial energy setups. For example, the HF-YSGA algorithm gives its nodes a massive 1.5 J battery to start with. On the opposite end of the spectrum, the highly optimized EECHS-ISSADE protocol restricts its sensors to a tiny 0.5 J battery. Meanwhile, our proposed LACO framework operates on the standard 0.75 J.

To make this a fair fight across all battery capacities, we calculated the Energy Efficiency Metric (R_{eff}). This metric isolates the exact number of operational rounds delivered per Joule of initial energy:

$$R_{\text{eff}} = \frac{\text{LND}}{E_{\text{init}}} \quad (6)$$

As Table 7 demonstrates, LACO maintains the upper hand across the board. HF-YSGA achieved 4066 rounds per Joule, while EECHS-ISSADE performed better with 4400 rounds per Joule. LACO pushed past both with an impressive 4783 rounds per Joule.

This translates to a 17.6% efficiency gain over HF-YSGA and an 8.7% gain over EECHS-ISSADE. This dual victory directly validates our core architectural theory. First, the mathematically lightweight ESAC system avoids the heavy computational drain of complex fuzzy logic controllers used in models like HF-YSGA. Second, even against low-energy optimized models like EECHS-ISSADE, LACO's Layer 2 Merit Filter manages critical routing decisions just a bit tighter, ultimately securing a longer lifespan per unit of energy.

Table 7: Normalized efficiency comparison vs. state-of-the-art.

Protocol	Initial Energy (E_{init})	Raw LND	Efficiency (R_{eff})
HF-YSGA	1.50 J	6100	4066 Rnds/J
EECHS-ISSADE	0.50 J	2200	4400 Rnds/J
LACO (Proposed)	0.75 J	3587	4783 Rnds/J

4.3.2 Area-Robustness vs. MSCFOAICM

The physical size of the network changes everything about energy drain. The MSCFOAICM protocol reached 3500 rounds, which sounds highly competitive on paper. However, a closer look reveals that the authors tested it in a tightly constrained $100 \times 100 \text{ m}^2$ sandbox. We tested our proposed LACO framework in a $250 \times 250 \text{ m}^2$ field. Even though LACO was operating in an environment more than six times larger—where nodes are forced to transmit over much harsher distances—it still outlived MSCFOAICM by hitting 3587 rounds. This proves that LACO effectively mitigates the exponential cost of long-distance communication, whereas MSCFOAICM relies on a small physical footprint just to survive.

4.3.3 Direct Re-Simulation: High-Energy Robustness vs. Tawfeek (PSO-Fuzzy)

For the ultimate stress test, we directly re-simulated the exact environment used by Tawfeek's PSO-Fuzzy protocol. Their specific setup equipped the sensors with a massive 2.0 J battery in a $200 \times 200 \text{ m}^2$ grid. In their own paper, their network collapsed at just 1200 rounds. We threw LACO into that exact same high-energy configuration to see what would happen, and the results were staggering. LACO survived for an incredible 9747 rounds. To put this into perspective using the normalized energy efficiency metric (R_{eff}), PSO-Fuzzy yielded a highly inefficient 600 Rounds/Joule. In contrast, LACO delivered 4873.5 Rounds/Joule under the exact same conditions. This massive performance gap highlights a fundamental flaw in using heavy fuzzy-logic controllers: when you give a network a huge energy budget, it should not waste that power just calculating the routes. LACO actually converts that extra battery capacity into raw, prolonged lifespan. The exact data from this direct comparison is laid out in [Table 8](#).

Table 8: High-energy scenario comparison (2.0 J, $200 \times 200 \text{ m}^2$).

Protocol	Year	Method	Lifetime (LND)	Efficiency (R_{eff})
PSO-Fuzzy	2025	Multi-Objective	≈ 1200 Rounds	≈ 600 Rnds/J
LACO (Proposed)	2026	Longevity-Aware	9747 Rounds	4873.5 Rnds/J

4.4 Scalability and Convergence Analysis

We wanted to see how the network holds up when things get highly crowded, so we pushed past the standard 100-node setup and scaled the deployment all the way to 500 nodes. Naturally, more nodes mean stiffer competition for the CH role.

LACO handles this density beautifully. If you look at [Fig. 5b](#), the performance gap between LACO and the baseline actually widens as the network grows, culminating in an 84.4% improvement in HND rounds at the 500-node mark.

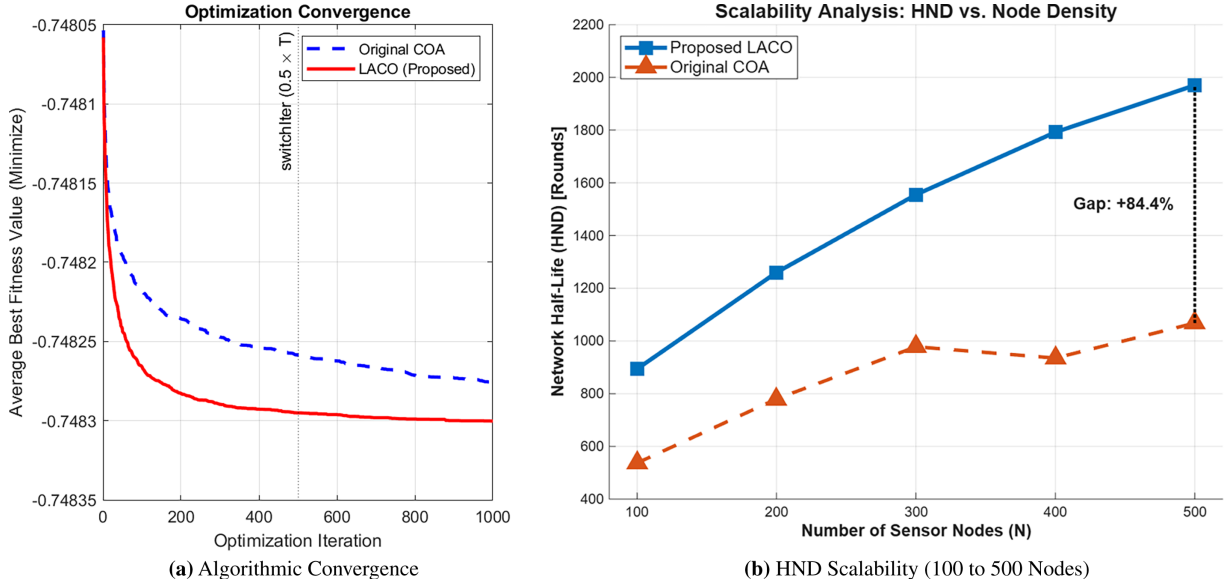


Figure 5: Scalability and convergence analysis. LACO avoids premature stagnation, reaching a stable convergence region (a), and widens the performance gap as network density increases (b).

The convergence data in Fig. 5a tells a similar story. LACO’s 3-layer ESAC system locks into the optimal solution in significantly fewer iterations. This rapid convergence prevents the algorithm from endlessly spinning its wheels, saving critical battery power that would otherwise be burned on prolonged processing.

4.4.1 Comparative Scalability with State-of-the-Art

To get a better sense of where LACO stands in the current landscape, we benchmarked its scalability against four recent density-sensitive protocols: Fuzzy-YSGA, ABCRP, WOARP, and GSARP. We measured this using the Scalability Index (SI), which normalizes each protocol’s performance against its own baseline survival rate at a standard density of 100 nodes:

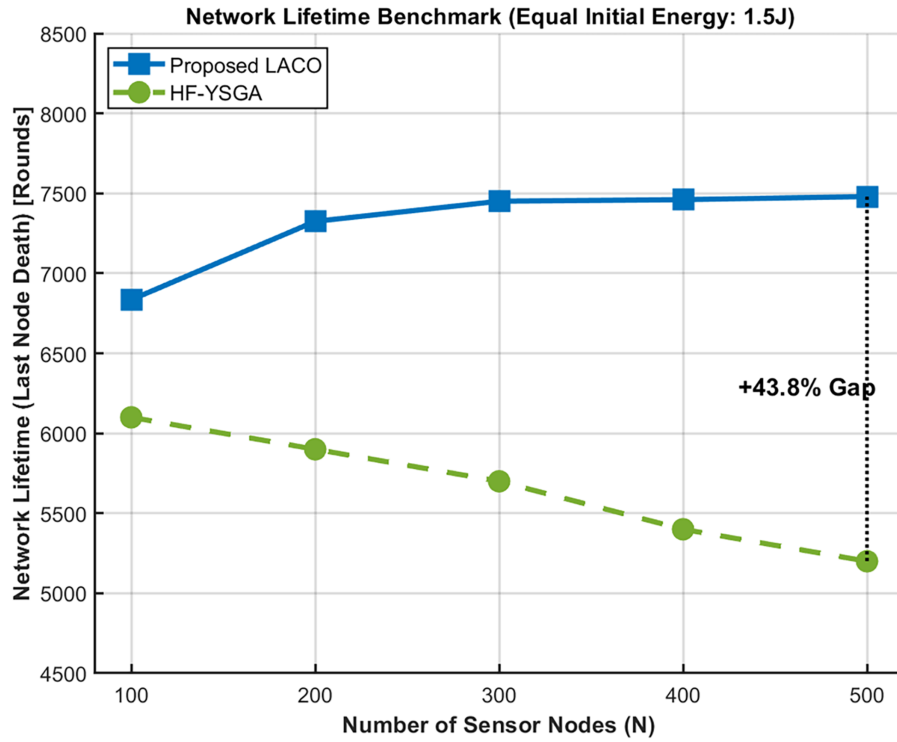
$$SI_N = \left(\frac{\text{LND at } N \text{ Nodes}}{\text{LND at 100 Nodes}} \right) \times 100\% \quad (7)$$

Table 9 reveals a clear trend: the benchmark protocols all suffer from negative scalability. As the density pushes toward 500 nodes, their operational effectiveness steadily bleeds out to between 81% and 85%. LACO, on the other hand, actively thrives in crowded environments, maintaining a positive SI of 104.5% at the maximum density. This happens because LACO’s merit-based competition mechanism uses the richer search space to its advantage, ensuring a much more balanced CH selection rather than buckling under the increased load.

To put hard numbers to this trend, we ran an absolute, one-to-one benchmark against the state-of-the-art HF-YSGA protocol. We matched their exact environmental parameters—giving the nodes a generous 1.5 J initial energy in a $300 \times 300 \text{ m}^2$ area with 6 CHs. The results in Fig. 6 are striking. While HF-YSGA starts strong at 6100 rounds for 100 nodes, it steadily degrades to 5200 rounds at the 500-node mark. LACO moves in the exact opposite direction. Starting at 6835 rounds, it climbs to an impressive 7480 rounds at 500 nodes. This gives LACO a massive 43.8% longevity advantage in dense deployments, proving that its architecture is genuinely more efficient without relying on skewed initial parameters.

Table 9: Normalized scalability index (SI) data.

Density	F-YSGA	ABCRP	WOARP	GSARP	LACO (Proposed)
100	100.0%	100.0%	100.0%	100.0%	100.0%
200	96.7%	94.6%	96.1%	95.9%	103.2%
300	93.4%	91.1%	94.1%	91.8%	103.8%
400	88.5%	89.3%	88.2%	85.7%	104.2%
500	85.2%	85.7%	82.4%	81.6%	104.5%

**Figure 6:** Absolute network lifetime benchmark of LACO vs. the state-of-the-art HF-YSGA protocol under identical initial energy conditions (1.5 J).

4.5 Statistical Significance Analysis

To ensure mathematical rigor, we conducted a paired Wilcoxon Signed-Rank Test ($\alpha = 0.05$). To strictly satisfy the pairing requirements of this test, we evaluated the algorithms using the same randomized node topologies, base station placements, and traffic constraints across all 100 independent simulation runs. This generated exactly $N = 100$ paired observations, with each pair corresponding to one independent simulation run conducted under identical experimental conditions, thereby controlling for environmental variability and isolating the true algorithmic performance differences. Because the Wilcoxon Signed-Rank Test is non-parametric, standard confidence intervals for the mean are mathematically inapplicable. Therefore, to quantify the magnitude of the observed differences, we calculated Cohen's effect size ($r = |Z|/\sqrt{N}$), where $N = 100$ denotes the number of paired observations. As shown in Table 10, the Wilcoxon Signed-Rank Test confirms statistically significant improvements ($p < 0.05$) across all evaluated node densities and lifetime metrics. Eight of the nine comparisons further exhibit strong statistical significance ($p < 0.001$). The corresponding effect sizes range from moderate to large ($0.392 \leq r \leq 0.776$). In particular, the Half

Node Death (HND) and Last Node Death (LND) metrics consistently exhibit large effect sizes ($r \geq 0.580$), providing strong evidence that LACO delivers substantial and robust improvements in network longevity over the baseline COA.

Table 10: Wilcoxon signed-rank test results ($\alpha = 0.05$, $N = 100$ paired observations).

Scenario	Metric	z-Value	p-Value	Effect Size (r)	Significance
100 Nodes	FND	-6.082	<0.001	0.608 (Large)	Significant
	HND	-7.370	<0.001	0.737 (Large)	Significant
	LND	-5.797	<0.001	0.580 (Large)	Significant
200 Nodes	FND	-4.627	<0.001	0.463 (Moderate–Large)	Significant
	HND	-7.167	<0.001	0.717 (Large)	Significant
	LND	-6.830	<0.001	0.683 (Large)	Significant
500 Nodes	FND	-3.918	0.0114	0.392 (Moderate)	Significant
	HND	-7.759	<0.001	0.776 (Large)	Significant
	LND	-6.516	<0.001	0.652 (Large)	Significant

4.6 Discussion and Comparative Analysis

Synthesizing the aggregate data from these stress-test simulations reveals a fundamental dichotomy in modern WSN routing. While recent architectures like PSO-Fuzzy and MSCFOAICM demonstrate that coupling metaheuristics with isolated decision-making engines can effectively optimize CH selection, they frequently incur a severe computational tax. Our direct high-energy benchmark (Table 8) exposed this limitation: providing a PSO-Fuzzy network with a 2.0 J battery yielded a mere 1200 operational rounds. This result indicates that the computational complexity of the routing strategy itself contributed significantly to overall energy consumption. This confirms the primary objective of developing an energy-aware clustering protocol capable of extending network lifetime without increasing optimization overhead.

LACO substantially reduces this computational bottleneck. These results suggest that by foregoing heavy external fuzzy-logic controllers and instead embedding a lightweight, three-layer ESAC mechanism directly into the native COA mathematics, LACO provides a highly effective, low-overhead alternative. It does not merely search for optimal routes; it minimizes the energy consumed during the optimization process, ultimately delivering 4873 rounds per Joule—the highest energy efficiency among the evaluated algorithms.

Moving forward, we must acknowledge the practical limitations of this framework. LACO currently relies on a centralized architecture, forcing the BS to execute the global optimization. In massive, highly fragmented IoT deployments, funneling all telemetry back to a single BS risks inducing severe transmission latency. Furthermore, our models assume a uniform packet size. In real-world environments—particularly those integrating varied smart city sensors or geospatial mapping tools—the network will process highly asymmetrical data payloads. To resolve this, future iterations of LACO will decentralize the merit filter by shifting the decision-making authority directly to the Cluster Head (CH) level. By integrating Q-learning into the CHs, these localized leaders can utilize real-time energy variance as a reward signal. This empowers the CH to independently execute routing decisions based on the specific data aggregated from its members, effectively removing the computational burden from both the distant BS and the individual, resource-constrained sensors.

5 Conclusion

This paper presents the LACO protocol. LACO provides an intelligent, energy-aware metaheuristic algorithm for effective CH selection in WSNs. The protocol utilizes a three-layered ESAC approach. This architecture tackles two core weaknesses prevalent in existing routing protocols: premature energy exhaustion and unstable network topography.

Simulation experiments demonstrate that LACO delays the onset of FND by 15.1%. It also leads to a 66.48% increase in HND while improving LND by 9.66%. Furthermore, the protocol achieves an optimal efficiency score of 9747 operational rounds under high-energy conditions. This equates to a normalized figure of 4783 rounds per Joule. The protocol demonstrates favorable scalability trends even in densely packed networks, maintaining an operational effectiveness level of 104.5% at a node population of 500. A Wilcoxon Signed-Rank Test provides statistical confirmation of these network longevity improvements.

However, the proposed protocol relies on centralized computation at the BS to conduct the global optimization process. This limits its immediate applicability in completely distributed, ad-hoc WSN architectures. In future studies, we plan to investigate the following areas: (1) implementation of Q-learning for automatic phase adjustment, where an intelligent agent evaluates real-time energy variance as a reward signal to dynamically fine-tune the ESAC exploration/exploitation thresholds without human intervention; (2) adoption of a variance-based optimization strategy to guarantee minimal energy disparities among chosen CHs; (3) development of the ESAC architecture in heterogeneous WSN environments where nodes start with different energy levels; and (4) decentralized adaptation of the merit function filter to alleviate the computational burden on the BS. In summary, LACO represents an efficient, scalable, and energy-aware routing framework that converts dense node deployments into an asset for overall network longevity.

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