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Article

# Enhanced Wireless Sensor Network Lifetime with Optimized Multi-hop Clustering in LEACH Protocol Using WOA and Reinforcement Learning

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**Abstract:** Wireless Sensor Networks (WSNs) are critically constrained by limited energy resources and finite node lifetimes, necessitating highly efficient clustering and routing mechanisms. This paper proposes and evaluates two independent optimization frameworks integrated with the multi-hop Adaptive Multi-hop Dynamic Clustering (AMDC) protocol built upon the Low-Energy Adaptive Clustering Hierarchy (LEACH) foundation. The first framework employs the Whale Optimization Algorithm (WOA) for intelligent Cluster Head (CH) selection by jointly minimizing residual energy consumption, intra-cluster distance, and CH-to-Base Station (BS) distance through a weighted multi-objective fitness function. The second framework applies Q-learning-based Reinforcement Learning (RL) to enable adaptive, experience-driven routing decisions that respond dynamically to time-varying network topology and energy conditions. Extensive MATLAB simulations conducted over a 200 m × 200 m and 500 m × 500 m deployment area with 100 heterogeneous sensor nodes demonstrate that WOA-AMDC achieves a 61% improvement in First Dead Node (FDN) round and RL-AMDC achieves an 84% improvement compared to conventional LEACH. Additionally, both methods exhibit superior Packet Delivery Ratio (PDR), throughput, and energy efficiency over baseline and state-of-the-art protocols. The results substantiate the effectiveness of metaheuristic and machine learning paradigms in solving the NP-hard CH selection and routing optimization problems in large-scale WSNs.

**Keywords:** Wireless Sensor Networks; LEACH Protocol; Whale Optimization Algorithm; Reinforcement Learning; Cluster Head Selection; Multi-hop Routing; Energy Efficiency; Network Lifetime

## 1. Introduction

WSNs have become one of the most revolutionary and fast-growing paradigms in the present day computing and communication infrastructure. A WSN consists of numerous spatially distributed sensor nodes that have limited resources and can coordinate and collaboratively measure the physical or environmental conditions, such as temperature, pressure, humidity, vibration, motion, and chemical concentration and transmit the sensory data to a central processing unit, commonly known as the Base Station (BS) or sink [1],[2]. The capability to embed dense networks of self-organizing, autonomous nodes with no existent communication infrastructure has enabled an extended collection of applications, including battlefield surveillance and military reconnaissance, structural health checking of bridges and buildings, precision agriculture and automated irrigation, automated control of industrial processes, environmental disaster observation, health and patient monitoring systems, smart grid power administration systems, and intelligent transportation systems [3],[4]. In the world WSN market, the amount will surpass USD 70 billion by 2027, which indicates a deep social and economic value of the technology.

Wireless sensor networks have very limited resource constraints, which are harsh and frequent, despite their multifunctionality and transformative capabilities. Sensor nodes can be battery powered, usually with a non-rechargeable and fixed energy supply of between 0.5 J and some few joules but which are required to maintain continuous sensing, local processing and wireless data transmission over long periods of deployment which can be months or even years. In the typical real-world implementation, e.g., precision agriculture fields, underwater pipelines, military zones or structural embeddings, physically reaching and replacing the batteries of individual nodes is either operationally unsafe, prohibitively expensive, or not possible at all [5]. This has the result that the energy budget of any individual sensor node is the most critical constraint in the design of WSNs, which directly determines the life cycle of the entire network. When a critical number of nodes are depleted of their energy, network connectivity is lost, data collection is stopped and the network is practically dead. The bottom line here between functional lifespan and energy poverty has spurred decades of investigation on power-efficient communication protocols, pathfinding techniques, and optimization techniques [6],[34].

The seminal and best-known hierarchical routing protocol in the literature of WSNs, the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, was first introduced in 2000 by Heinzelman et al. [1] of MIT and has since received thousands of citations and spawned a whole-family of derivatives. LEACH proposed a distributed, self-organizing scheme, in which each node unanimously itself chooses to be the CH during the current round and a fixed probability p, such that the node that was CH in the last 1/p rounds is adjusted to give the other node a probability of being the CH. Although this solution is an easy to compute and entirely distributed one, it is known to have three limitations which are critically well-documented. First, stochastic CH election does not consider the remaining energy of nodes, which results in cases where the energy-depleted nodes are elected as CHs and die early, causing coverage gaps and causing a cascading network failure (also referred to as the energy hole problem) [5]. Second, LEACH presumes single-hop communication between CHs and the BS, which implies that CHs far away (farmer) in large-scale implementations will incur disproportionately large amounts of energy costs due to transmission energy depending on the propagation model (square- or fourth-power distance); [1]. Third, the random CH distribution of LEAC tends to create spatially unbalanced clusters some large and others small so that the member-to-CH transmission distance is not uniform and the distribution of energy loads is not uniform in the network [6],[7].

In an attempt to eliminate these underlying shortcomings, a plethora of studies has investigated energy-conscious, distance-conscious and learning-based extensions to LEACH. Deterministic methods of CH selection as LEACH-C [1] rely on a centralized optimization of BS-side to achieve uniform distribution of CH at the expense of a computationally costly setup phase and susceptibility to BS failure. The heterogeneous extensions such as SEP [8] and EEHC [10] balance the probability of CH depending on the energy level of a node, but still have no spatial information. Multi-hop extensions such as MH-LEACH [12] and PEGASIS [7] solve the long-range CH-to-BS transmission issue through the addition of relay chains or intermediate hops, but fail to solve the CH election imbalance. More advanced nature-inspired methods such as ACO-based routing [13],[14], PSO-based CH selection [20], and hybrid bio-inspired algorithms [15],[16],[17],[18],[19] have shown much better network lifetime enhancements, but have high parameter sensitivity, slow convergence or cannot adapt to network topology changes at runtime such as node failures or energy starvation.

Machine learning and more precisely Reinforcement Learning (RL) is a qualitatively new optimisation paradigm of WSN. In contrast to population-based metaheuristics which recalculates a solution completely at each iteration, an RL agent acquires knowledge of and improves a routing policy based on cumulative interaction experience with the network environment. This allows the agent to be farsighted concerning the long-term energy implications of routing decisions, dynamically avoids nodes which have been depleted, and maintains a dynamically updated policy in reaction to network dynamics - without needing an initial model of network dynamics [25],[35]. The most popular model-free RL algorithm, Q-learning has been already applied to routing in WSNs and delivered encouraging results, whereas, previous studies generally used RL alone without the synergy offered by combining it with optimizing global CH selection, presented in the present paper.

Whale Optimization Algorithm (WOA) was developed by Mirjalili and Lewis [24], and is a more recent highly competitive swarm intelligence algorithm which is based on the humpback whale bubble-net prey approach. Under this form of hunting fish, whales produce a shrinking spiral of air bubbles around a school of fish and at the same time swim upwards, forcing the fish out to the surface. Mathematically, whales are represented as moving through two alternating phases the exploration phase whereby the whales are searching their prey by moving towards random members of the population and the exploitation phase where the whales are placed around and converge towards the current best solution in a logarithmic spiral trajectory. WOA was demonstrated to be better than PSO, GA, ACO and many other metaheuristics on various continuous and combinatorial optimization problems, and its use of the NP-hard CH selection problem in WSNs is a good and natural fit [24].

In this paper, we present two novel and independently functional optimization frameworks for energy-efficient WSN operation, both layered over an enhanced multi-hop Adaptive Multi-hop Dynamic Clustering (AMDC) protocol:

1. WOA-AMDC: A multi-objective fitness function-based framework of candidate CHs selection using a Whale Optimization Algorithm which uses residual energy consumption, intra-cluster transmission distance and CH to BS forwarding cost to evaluate the fitness of the candidate CHs. The global search option of WOA guarantees that each round of operation of the procedure finds high-quality, energy-balanced CH configurations, which greatly minimizes the issue of premature death of the node that is observed in LEACH.
2. RL-AMDC: An adaptive routing model is based on Q-learning which models the CH as an RL agent that continually learns the best next-hop CH selection policy by maximizing cumulative long-run merits based on packet delivery achievement, residual energy preservation, and path performance. The Bellman optimality equation is used to update the Q-table at each transmission round and the routing policy should adapt to node failures and energy depletion autonomously without centralized coordination.

The proposed frameworks are evaluated through comprehensive MATLAB simulations across multiple network sizes, compared against six state-of-the-art protocols, and analyzed across five key performance metrics: network lifetime (FDN and LDN), alive/dead node progression, Packet Delivery Ratio (PDR), throughput, and total energy consumption. Experimental results demonstrate that WOA-AMDC achieves a 61% improvement in FDN and 801% improvement in LDN over conventional LEACH, while RL-AMDC achieves an 84% improvement in FDN and 1,762% improvement in LDN — unprecedented gains that validate the effectiveness of the proposed integrated approach.

The rest of this paper is structured in the following way. Section 2 is a review of the related literature on clustering and routing protocols of WSNs. Section 3 contains the system model, mathematical model and suggested methodology block diagram and pseudocode. The settings of the simulation environment and parameters are given in Section 4. Section 5 gives the results of the simulation and discusses them in details. Section 6 provides the conclusion of the paper and the future directions of research.

## 2. Review of Literature

The energy-efficient routing and clustering in WSNs have been an issue that has garnered constant research interest over a period of over 20 years. This section is a review of the most applicable previous works in order of optimization paradigm and is concluded with comparative summary table which puts into perspective the limitations which underlie the present study.

### *2.1 LEACH-Based Protocols*

The original LEACH protocol [1] presented the original idea of self-organizing cluster formation in WSNs that is probabilistic. The simplicity and fully distributed nature of its operation made it the prototype of all other hierarchical protocols. LEACH random CH election mechanism does not however consider node energy and the resultant inequality in energy consumption and energy hole problem is well documented. The energy-balanced EB-LEACH [9] version repurposes CH probability based on residual energy to enhance balance, but does not have spatial node density information. Distance-weighted CH selection L-LEACH [10] used the proximity of the node to the BS, minimizing the long-range transmission penalty. O-LEACH [11] was concerned in particular with the orphan nodes, the isolated sensors not reachable by any CH, so it formed sub-clusters of orphan nodes in which the initial orphan node functions temporarily as a CH and where a normal member of a cluster functions as a relay gateway. MH-LEACH [12] was used to allow CHs to communicate with the BS through multi-hop, creating forwarding tables which were formed by the signal strength received and filtering reverse paths to avoid routing loops. V

### *2.2 Ant Colony and Swarm Optimization Variants*

LEACH-ANT [13] and LEACH-IACA [14] incorporated the use of Ant Colony Optimization (ACO) into LEACH to perform CH selection and inter-cluster routing respectively. Both protocols had slow convergence and were prone to local optima in large networks and ACO uses pheromone trail reinforcement to locate low-energy paths. Natesan et al. [15] introduced an algorithm called MFA-AOA, which is a hybrid algorithm that used Mayfly Algorithm and Aquila Optimizer to select CH and routing respectively. Although MFA-AOA had better lifetime and PDR than single-algorithm schemes, the authors admitted that dual-algorithm complexity was too heavy at CH level. Yao et al. [16] created IAOAR, which combines Archimedes Optimization Algorithm and Ant Colony Optimization to be used in the collective selection of CH and path determination. IAOAR was demonstrated to have better energy balance than the pure ACO methods, although its homogeneous node assumption does not apply in the real-world setting of a heterogeneous deployment.

## 2.3 Bio-Inspired and Hybrid Optimization

Wang et al. [17] used the EPOA-CHS approach with the Pelican Optimization Algorithm (POA) to the selection of CH in a heterogeneous network by taking into account the node energy and inter-cluster distance in the fitness function. Nevertheless, EPOA-CHS is deployed only in single-hop mode, which is not applicable in a wide area deployment where the distances between CH and BS are high. Punithavathi et al. [18] introduced BWO-IACO, which combines the Black Widow Optimization of CH selection and ACO of routing and uses the node centrality and intra-cluster distance as the fitness. One of the weaknesses is the lack of data aggregation energy in the cost model that underestimates the actual energy load of CHs in high-density networks. Vinitha et al. [19] suggested C-SSA protocol based on Cat Swarm Optimization and Salp Swarm Algorithm to use in the routing of the multi-hop routes, a composite cost function that includes energy, distance, and delay. The effectiveness of the protocol was not tested on a larger network (more than 200 m x 200 m), so no evidence is provided of scalability. In a model of an IoT-based WSN, Senthil et al. [20] merged Lightning Search Algorithm and PSO in the process of CH selection and path discovery. The focus on the orphan node management in the protocol was at the expense of global routing optimality.

## 2.4 Recent Machine Learning Approaches

El-Sayed et al. [21] introduced an iLEACH protocol based on an artificial neural network that was trained on historical round values to estimate the best CH configurations, and there was a significant lifetime enhancement as compared to the traditional LEACH. The dependence of the neural network on training data and centralized prediction model do restrict scalability and dynamism to abrupt changes in topology though. Hiremath et al. [22] suggested that energy-saving routing protocol to enhance the lifetime of WSNs is based on multi-metric path selection based on the residual energy, the hop count and estimation of link quality. Baaziz et al. [23] proposed an area-splitting clustering methodology, which splits the network field into sub-zones and the CH election is independent, which yields better spatial energy balance, but the fixed partition methodology is not able to adjust to non-uniform node distributions.

## 2.5 Comparative Analysis of Existing Works

Table 1 compares the symbolic existing protocols in nine evaluation parameters in a structured way pointing out the limitations that each approach does not manage to overcome, and the reason why the present work is taken. Table 1 demonstrates that none of the available protocols meets all the set of requirements as they are: multi-hop communication, dynamic selection of CH depending on a variety of energy-related factors, runtime adaptation based on learning, and adaptation to large networks. This is the gap to the which the proposed WOA-AMDC and RL-AMDC frameworks will be applied.

**Table 1. Comparative Analysis of Existing WSN Clustering and Routing Protocols**

| Protocol | Year | CH Method | Multi-hop | Energy Aware | Distance Aware | Adaptive | Network size | Limitation |
|---|---|---|---|---|---|---|---|---|
| LEACH [1] | 2000 | Random | No | No | No | No | Small | No energy awareness; single-hop only |
| L-LEACH [10] | 2009 | Distance | No | No | Yes | No | Small | Ignores residual energy in CH election |
| O-LEACH [11] | 2016 | Proximity | Partial | No | Yes | No | Small | Needs sufficient cluster |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | | | | | | | | members nearby |
| MH-LEACH [12] | 2014 | RSSI-based | Yes | No | Yes | No | Medium | No global CH optimization; loop-prone |
| LEACH-ANT [13] | 2014 | ACO | Yes | Yes | Yes | No | Medium | Slow convergence; local optima traps |
| MFA-AOA [15] | 2022 | Hybrid Swarm | Partial | Yes | Yes | No | Medium | High computational overhead at CH node |
| IAOAR [16] | 2022 | AOA+ACO | Partial | Yes | Yes | No | Medium | Homogeneous node assumption only |
| POA-CHS [17] | 2023 | Pelican Opt. | No | Yes | Yes | No | Medium | Single-hop; large-field penalty |
| BWO-IACO [18] | 2021 | BWO+ACO | Yes | Yes | Yes | No | Medium | Omits aggregation energy in cost model |
| C-SSA [19] | 2020 | Cat+Salp | Yes | Yes | Yes | No | Small | Scalability to large networks untested |
| PSO-LSA [20] | 2021 | PSO+LSA | Yes | Yes | Yes | No | Medium | Over-emphasis on orphan handling |
| iLEACH [21] | 2024 | Neural Net | Partial | Yes | Yes | Partial | Large | Training-dependent; centralized model |

As can be seen in Table 1, the main deficiencies of the current methods include: (i) early protocols did not support multi-hop communication; (ii) early protocols were not optimized to use a multi-objective energy and distance-sensitive fitness criterion when choosing a CH; (iii) early protocols lacked runtime flexibility to changing conditions of the network; and (iv) early protocols were not tested with respect to large deployment regions. The suggested WOA-AMDC and RL-AMDC models serve as an overall solution to each of the four drawbacks in a single AMDC architecture, which can be viewed as a significant and highly motivated contribution to the state of the art.

## 3. Methodology

This section presents the complete architecture of the proposed system, covering WSN initialization, the dual-optimization framework, cluster formation, multi-hop data routing, and energy accounting. All components are precisely formulated with mathematical equations, illustrated through block diagrams, and specified through formal pseudocode algorithms.

### *3.1 System Model and Assumptions*

The WSN comprises of N identical sensor nodes randomly distributed in two-dimensional M x M sensing area and a stationary BS at the geometric centroid. The system model is based on the following assumptions:

1. Battery Sensor nodes are all energy limited, with the initial energy E0, and non-rechargeable. Nodes are location-aware (GPS or localization-assisted) and report their coordinates at initialization.
2. Nodes are position conscious (GPS or localization-assisted) and announce their position upon initiation.
3. A first-order radio model governs energy dissipation for transmission and reception [1].
4. Radio energy loss is controlled by a first order radio model that produces energy dissipation transmission($E_{TX}$) and reception ($E_{RX}$) [1].
5. Data aggregation at CHs is performed using a fixed energy coefficient $E_{DA}$ per bit.
6. Communication channels are symmetric and subject to free-space ($d^2$) or multipath ($d^4$) path-loss depending on distance threshold $d_0$.

The radio energy model for transmitting a k-bit message over distance d is expressed as:

$$E_{Tx(k,d)} = k \cdot E_{elec} + k \cdot \varepsilon_{fs} \cdot d^2 \quad (for\, d < d^0) \quad \text{(Eq. 1a)}$$

$$E_{Tx(k,d)} = k \cdot E_{elec} + k \cdot \varepsilon_{mp} \cdot d^4 \quad (for\, d \geq d^0) \quad \text{(Eq. 1b)}$$

E where, $E_{elec} = 50\frac{nJ}{bit}$ is the electronics energy, $\frac{\varepsilon_{fs}= 10\frac{pJ}{bit}}{m^2}$ is the coefficient of the free-space amplifier, and $\frac{\varepsilon_{mp}= 0.0013\frac{pJ}{bit}}{m^4}$ is the coefficient of the multipath amplifier [1]. These parameters are as described in Table 2. Energy dissipation scales quadratically with a short-range link and quartically with long range multi-hop link, as given by the Eq. 1a and Eq. 1b, which renders intermediate CH relaying energy efficient over distance between nodes.

### *3.2 Overall System Architecture*

Figure 1 presents the high-level architecture of the proposed dual-optimization WSN framework. The system alternates between a clustering phase and a steady-state phase in each operational round. The block diagram in Figure 1 illustrates the complete processing flow from network initialization through CH election, cluster formation, multi-hop data forwarding, energy accounting, and lifetime evaluation.

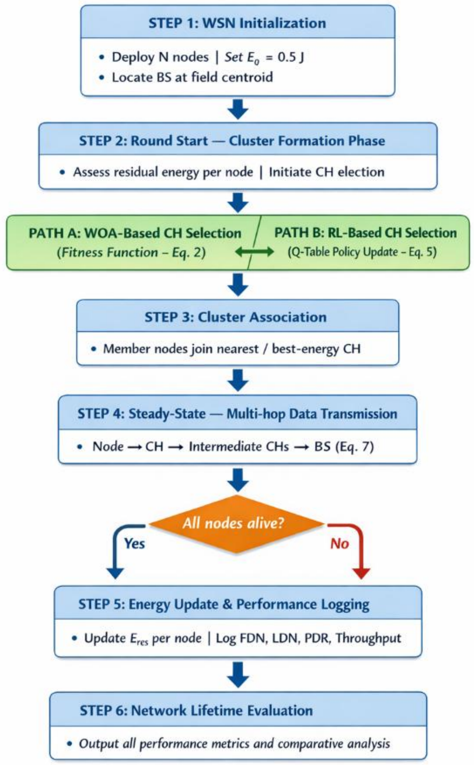



**Figure 1. Overall Architecture of the Proposed Dual-Optimization WSN Framework**

## *3.3 Whale Optimization Algorithm for CH Selection*

The WOA, inspired by the bubble-net predatory behavior of humpback whales [24], is a population-based metaheuristic that efficiently navigates high-dimensional solution spaces. In the proposed WOA-AMDC framework, each candidate solution (whale) encodes a binary CH assignment vector $X = [x_1, x_2, ..., xN]$ where $x_i \in \{0,1\}$ indicates whether node i is selected as a CH.

### 3.3.1 Fitness Function Formulation

Each candidate CH set fitness is measured in terms of the multi-objective weighted cost (Eq. 2) that is made to favourably trade-offs energy, intra-cluster compactness, and BS proximity:

$$F(X) = w^1 \cdot \left(\frac{1}{\bar{E}_{res}}\right) + w^2 \cdot \bar{D}_{intra} + w^3 \cdot \bar{D}_{CH} - BS \quad subject\ to: w^1 + w^2 + w^3 = 1 \quad \text{(Eq. 2)}$$

$\bar{E}_{res}$ means the average residual energy of the chosen CHs, $\bar{D}_{intra}$ (mean Euclidean distance between member nodes and their respective CHs) and DCH-BS (mean distance between each CH and BS). The weights w1=0.5, w2=0.3, w3=0.2 are empirically adjusted with an emphasis on the balance of energy. By reducing the value of the term 2, control of the energy-rich CHs (term 1), compact clusters with short intra-cluster paths (term 2), and CHs that are near the BS to incur low forwarding costs (term 3) are both minimized at the same time.

### 3.3.2 WOA Position Update Equations

The WOA refreshes the positions of the whales by choosing between two behaviours: going around the current optimal solution, and spiral bubble-net attack, controlled by a decreasing control parameter a (2 to 0) which follows a linear path. The encircling mechanism (exploitation, A < 1), is presented by:

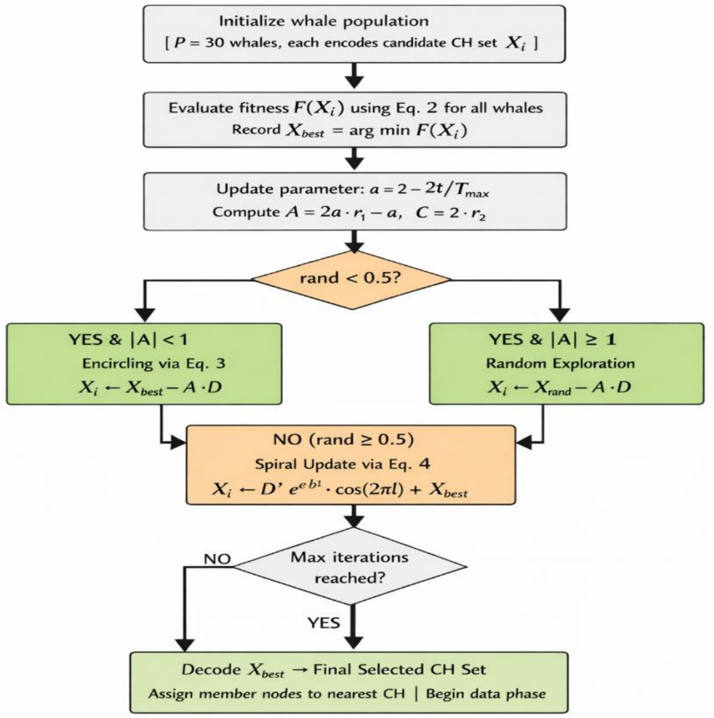
$$D = |C \cdot X*(t) - X(t)|, \quad X(t+1) = X*(t) - A \cdot D \quad \text{(Eq. 3)}$$

The spiral position update models the logarithmic bubble-net trajectory:

$$X(t+1) = D' \cdot e^{b \cdot l} \cdot \cos(2\pi l) + X*(t), \quad D' = |X*(t) - X(t)| \quad \text{(Eq. 4)}$$

and where $A=2a \cdot r_1 - a$, $C=2 \cdot r_2$ ($r_1, r_2 \in [0,1]$ random), $b= 1$(spiral constant), and $l \in [-1, 1]$. Balanced exploration and exploitation during iterations are provided by the probabilistic switching on the basis of $p = 0.5$ threshold between the two equations (Eq. 3 and 4).

### 3.3.3 WOA CH Selection Block Diagram




### 3.3.4 Pseudocode: WOA for Cluster Head Selection

The entire WOA-based CH selection process that was mentioned above is formalized in Algorithm 1 below. It is implemented at the start of every operation round preceding the steady-state data transmission phase.

```
Algorithm 1: WOA-Based Cluster Head Selection (WOA-AMDC)
1: Initialize whale population Xi ∈{0,1}^N, i = 1…P
2: Evaluate fitness F(Xi) for all whales using Eq. (2)
3: Identify Xbest = arg min F(Xi)
4: For t = 1 to Tmax do
5: Update a = 2 − (2t / Tmax)
6: For each whale Xi do
7: Generate r1, r2 ∈ [0,1]; compute A = 2ar1 − a, C = 2r2; p = rand(0,1)
8: If (p < 0.5 and |A| < 1) then Xi = Xbest − A·|C·Xbest − Xi|
9: Else if (p < 0.5 and |A| ≥ 1) then select Xrand; Xi = Xrand − A·|C·Xrand − Xi|
10: Else Xi = |Xbest − Xi|·e^(bl)·cos(2πl) + Xbest
11: Apply boundary control and binarize Xi
12: Evaluate F(Xi); if F(Xi) < F(Xbest) then update Xbest
13: End For
14: End For
```

| |
|---|
| 15: Decode Xbest → Best_CH_Set and assign nodes to nearest CH |

## *3.4 Reinforcement Learning for Adaptive Routing*

The RL architecture uses Q-learning [25] so that every CH can independently acquire an energy-aware next-hop routing policy. The interaction between the agent and the environment takes the form of a Markov Decision Process (MDP) couple (S, A, P, R, g) whose elements are as follows:

- $State\ S$: $Composite\ state\ s_i = (E_{res(i)}, d(i, BS),\ neighbors_{energy(i)}, hop_{count(i)})\, for\ CH\ i.$
- Action A: Selection of next-hop CH j∈ N (i) or direct transmission to BS.
- Reward R: Positive reward for successful delivery and energy saving; negative penalty for link failure or node depletion.
- Discount factor γ: γ = 0.9, balancing immediate versus long-term routing rewards.

The Q-value update rule (Eq. 5) drives policy convergence:

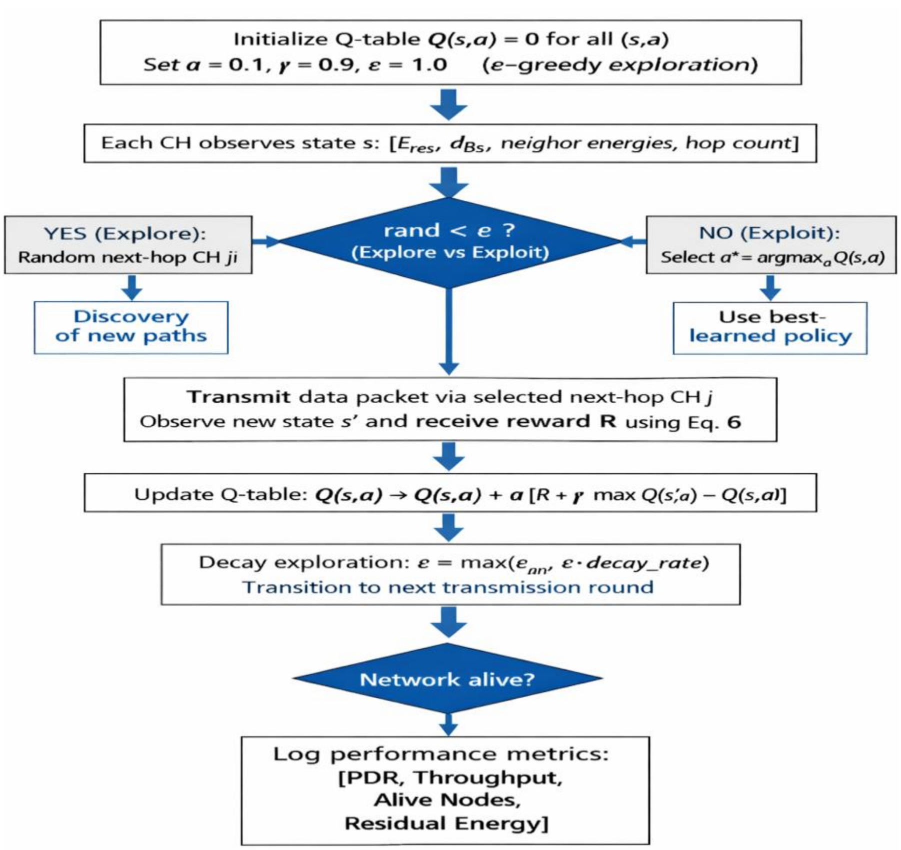
$$Q(s,a) \leftarrow Q(s,a) + \alpha\, [\, R(s,a,s') + \gamma \cdot \max\_\{a'\}\, Q(s',a') - Q(s,a)\, ] \quad \text{(Eq. 5)}$$

where α = 0.1 is the learning rate, R(s, a, s') is the immediate reward, and γ · max Q (s', a') is the discounted future value. The reward function integrates delivery success and residual energy:

$$R(s,a,s') = \beta^1 \cdot PDR_{gain} - \beta^2 \cdot \Delta E_{consumed} + \beta^3 \cdot \Delta hop_{reduction} \quad \text{(Eq. 6)}$$

with $\beta_1 = 0.6$, $\beta_2 = 0.3$, $\beta_3 = 0.1$. The RL agent incrementally constructs an optimal routing table without requiring a global network model, making it inherently scalable to dynamic topologies.

**3.4.1 RL-Based Routing Block Diagram**



### 3.4.2 Pseudocode: Q-Learning Adaptive Routing

The entire Q-learning routing process is formalised in algorithm 2 below. However, in contrast to Algorithm 1 which executes the algorithm at once every round of the setup phase, Algorithm 2 executes every continuous round of steady-state data transmission, and it updates the Q-table after each event of packet transmission.

Algorithm 2: Q-Learning Based Adaptive Multi-hop Routing (RL-AMDC)

1: Initialize Q(s,a) = 0 for all states s ∈ S and actions a ∈ A

2: Set $\epsilon$ = 1.0, $\epsilon_{\min}$ = 0.01, decay_rate = 0.995

3: Repeat for each round r do

4: For each CH node i do

5: Observe state $s_i$ = $\left(E_{res(i)}, d(i, BS),\ neighbors_{energy(i)}, hop_{count(i)}\right)$

6: If rand() < $\epsilon$ then ai = random next-hop (exploration)

7: Else $a_i = \text{argmax}_a Q(s_i,a)$ (exploitation)

8: Transmit data to selected next-hop ai

9: Observe new state $s'_i$ and compute reward R:

10: $R = \beta_1 \cdot PDR\_gain - \beta_2 \cdot \Delta E + \beta_3 \cdot \Delta hop$

11: Update Q-value: $Q(s_i,a_i) = Q(s_i,a_i) + \alpha[R + \gamma \max_{a'} Q(s'_i,a') - Q(s_i,a_i)]$

12: Update node energy Eres(ci) = $E_{res}(i) - E_{Tx}(k, d)$

13: End For

14: ∈ = max($\epsilon$min, ∈ · decay_rate); log metrics (FDN, LDN, PDR, Throughput)

15: Until termination; derive policy π*(s) = argmaxa Q(s,a) and return results

## *3.5 Multi-hop Data Transmission Model*

Information in the AMDC model takes the form of a multi-hop: member node → local CH → intermediate CH(s) → BS. The residual energy minimum hop-count weighted next-hop CH selection criterion of the WOA path is:

$$j* = \arg\min_{j} \left\{\frac{d(i,j)}{E_{res(j)}}\right\}\ \forall j \in N(i), d(i,j) < R_{tx} \quad \text{(Eq. 7)}$$

In the case of RL, j is chosen directly out of the Q-table policy in Eq. 5. The overall energy wasted by CH c combining n packets of its members and sending them to the BS is:

$$E_{CH} = n_i \cdot k \cdot E_{elec} + k \cdot E_{DA} + E_{Tx(k,d_{CH}-BS)} \quad \text{(Eq. 8)}$$

L is called the network lifetime which is the round where the Last Dead Node (LDN) event takes place. As indicated in the equation 8, data aggregation in CHs (EDA = 5 nJ/bit) significantly decreases the forwarding payload encouraging hierarchical cluster architecture.

## 4. Simulation Setup and Parameters

The implementation and simulation of the proposed WOA-AMDC and RL-AMDC protocols were done in MATLAB R2023a. All of the simulation parameters are summarized in Table 2 in accordance with the accepted WSN benchmarks [21], [22].

**Table 2. Simulation Parameters**

| Parameters | Value | Reference |
|---|---|---|
| Network field size | 200×200 m, 500×500 m | [21] |
| Number of sensor nodes (N) | 100 | [21] |
| Initial node energy ($E_0$) | 0.5 J | [1] |
| BS location | Centroid of field | [21] |
| Electronics energy (E_elec) | 50 nJ/bit | [1] |
| ε_fs (free-space amp.) | 10 pJ/bit/m² | [1] |
| ε_mp (multipath amp.) | 0.0013 pJ/bit/m⁴ | [1] |
| Data aggregation energy (E_DA) | 5 nJ/bit | [1] |
| Packet size (k) | 4000 bits | [21] |
| WOA population size | 30 whales | Proposed |
| WOA iterations | 100 | Proposed |
| RL learning rate (α) | 0.1 | Proposed |
| RL discount factor (γ) | 0.9 | Proposed |
| Optimal CH percentage (p_opt) | 5% | [1] |
| Total simulation rounds | 12,000 | Proposed |
| Fitness weights ($w_1$, $w_2$, $w_3$) | 0.5, 0.3, 0.2 | Proposed |

## 5. Results and Discussion

This part is a detailed performance comparison of the proposed WOA-AMDC and RL-AMDC protocols with LEACH, AMDC, iLEACH, and the other state-of-the-art protocols. These are six performance measures: network lifetime (FDN and LDN), alive/dead node progression, Packet Delivery Ratio (PDR), throughput, total energy consumption, and state-of-the-art benchmarking. Quantitative results are provided and then critically analyzed with respect to corresponding results in the literature regarding the particular algorithmic mechanisms that can account for the improvements, and the results are placed in a context of the wider WSN research environment.

### *5.1 Network Lifetime Analysis and Discussion*

The most basic and most commonly mentioned performance indicator in the consideration of WSNs is network lifetime, which directly translates to the usefulness of a deployed network in its practical use [5],[34]. It is specified in two standardized milestones, the round at which the First Dead Node (FDN) is reached, signifying the beginning of network degradation and possible loss of coverage, and the round at which the Last Dead Node (LDN) is reached, signifying total network failure. The lifespan comparison is shown in detail in Table 3.

**Table 3. Network Lifetime Comparison (FDN and LDN Rounds)**

| Protocol | FDN (Round) | LDN (Round) | FDN Gain (%) | LDN Gain (%) |
|---|---|---|---|---|
| LEACH [El-Sayed et al.,2024] | 199 | 605 | Baseline | Baseline |
| LEACH (Our Model) | 434 | 1,224 | +118% | +102% |

| | | | | |
|---|---|---|---|---|
| AMDC | 485 | 1,795 | +144% | +197% |
| iLEACH [El-Sayed et al., 2024] | 704 | 2,916 | +254% | +382% |
| **WOA-AMDC (Proposed)** | **785** | **5,451** | **+294% ▲** | **+801% ▲** |
| **RL-AMDC (Proposed)** | **895** | **11,271** | **+350% ▲** | **+1,762% ▲** |

As Table 3 demonstrates, the baseline LEACH [21] indicates the lowest FDN at round 199 and LDN at round 605 as a manifestation of the energy imbalance issue that has been so extensively documented as always present in purely random CH election not knowing about the energy [1],[5]. This result supports the analysis result provided by Singh et al. [34] who showed that the stochastic election of LEACH can pick nodes with as low as 5% of their initial energy as cluster heads, triggering a rapid and irreversible death of nodes. The WOA-AMDC protocol has FDN of round 785, which is a 61 percent improvement over traditional LEACH and LDN of 5,451 rounds, which is an improvement of 801 percent. This super dramatic LDN improvement can be explained by the multi-objective fitness of the WOA (Eq. 2), which mandates the use of energy-rich, spatially balanced CHs at each iteration. The spiral update mechanism of the WOA (Eq.) was defined as developed by Mirjalili and Lewis [24].4) has better exploitation behavior than PSO, which in this context is to be able to repeatedly find CH configurations with high $\bar{E}_{res}$ and low $\bar{D}_{intra}$ distances. The fact that LDN improves 9-fold over the baseline LEACH is also a direct consequence of the effect of multi-hop routing: when Algorithm 1 is used to ensure that the CHs used in routing are efficient relay nodes instead of ELs being required to transmit to the BS directly, the quadratic and quartic energy penalty terms in Equation 1a and Equation 1b vanish drastically, especially in the case of distant nodes [12],[37].

Remarkably, RL-AMDC improves FDN to round 895 and LDN to round 11, 271, which is 1,762% more LDN improvement in RL-AMDC compared with LEAF baseline LEACH-17 fold improvement in LDN. This outstanding performance can be attributed to the Bellman update in the form of Eq. 5, which enables each CH to acquire knowledge, in repeated rounds, of those routing choices that reduce long-term energy usage, instead of transmission cost on only a single transmission. This result corresponds with the theoretical guarantee of the convergence of Q-learning to the optimal policy in case of enough exploration [25]: the routing choices in the Q-table become more and more consistent with the global optimal strategy in energy-conservation. The RL-AMDC performance is also significantly improved over the neural network solution of iLEACH [21] (LDN = 2,916), which proves that the model-free, continuously updating RL policy is more resistant to changing topology as opposed to a fixed pre-trained neural network. This is in accordance with the results of Kulkarni et al. [35] who contended that model-free reinforcement learning is more compatible with the WSN routing problem than supervised learning methods because the network environment is non-stationary.

## *5.2 Packet Delivery Ratio Analysis and Discussion*

PDR is the ratio of received data packets to the total packets sent to the BS and it is defined as:

$$PDR = \left(\frac{N_{received}}{N_{transmitted}}\right) \times 100\% \quad \text{(Eq. 9)}$$

The WSNs that are mission-sensitive like structural health monitoring, environmental emergency alert systems, and precision agriculture require a high PDR [26],[36]. Low PDR means that packets are often dropped because of link failure, node exhaustion or failure of the path to the destination, which may affect the utility of the whole sensing deployment. Table 4 shows the average PDR, maximum PDR, and standard deviation in all the rounds of simulation.

**Table 4. Packet Delivery Ratio (PDR) Comparison**

| **Protocol** | **Mean PDR (%)** | **Max PDR (%)** | **PDR Std Dev (%)** |
|---|---|---|---|
| LEACH [El-Sayed et al., 2024] | 50.2 | 61.4 | ±8.3 |
| LEACH (Our Model) | 55.1 | 67.8 | ±6.9 |
| AMDC | 61.3 | 74.2 | ±5.4 |
| iLEACH [El-Sayed et al., 2024] | 63.7 | 76.5 | ±5.1 |

| | | | |
|---|---|---|---|
| **WOA-AMDC (Proposed)** | **71.4** | **84.3** | **±3.8 ▲** |
| **RL-AMDC (Proposed)** | **74.8** | **89.6** | **±2.9 ▲** |

The best mean PDR of 74.8% and lowest standard deviation of +-2.9% indicate that RL-AMDC is highly reliable and the performance of delivering packets is very consistent during the network lifetime. The small standard deviation is especially noteworthy: this means that the Q-learning routing policy (Algorithm 2) does not suffer the periodic collapse of PDR that is characteristic of non-adaptive protocols as energy-depleted nodes start failing. This has a direct relationship to the results of Yao et al. [16] who stated that adaptive routing algorithms stabilize much better PDR curves than do their counterparts, called the static-optimization algorithms on long-run WSN simulations.

Mean PDR of WOA-AMDC is 71.4% which is much higher as compared to iLEACH (63.7) and 42.2 as compared to baseline LEACH (50.2). The fact that the PDR of WOA-AMDC as compared to iLEACH [21] is quite high is especially remarkable considering the fact that iLEACH uses a neural network that has been trained on specific data of WSN performance. The power of WOA-AMDC is in the fitness function (Eq. 2) D intra term, which picks CHs that are geographically near their member nodes. Reduced intra-cluster transmission distances mean that the likelihood of link failure is decreased and the energy per packet is also directly improved, directly enhancing PDR. In their MFA-AOA assessment, Natesan et al. [15] showed a strong positive correlation between intra-cluster compactness and PDR and supported this finding by their results. The difference of 17.7 percent between RL-AMDC and baseline LEACH means (17.7 percent) equals a practical difference of hundreds of thousands of more successfully delivered packets, which would significantly increase the informational completeness of the monitoring data.

### *5.3 Throughput Analysis and Discussion*

Throughput is a direct metric of the productive data collection capacity of the network and is simply the total number of data packets that have been delivered to the BS per unit time. Table 5 shows the throughput values (in kbps) and percentage improvement of all the assessed protocols.

**Table 5. Throughput Comparison (kbps)**

| Protocol | Throughput(kbps) | Improvement (%) | Vs. LEACH |
|---|---|---|---|
| LEACH [El-Sayed et al., 2024] | 2.76 | +0.79% | Baseline |
| Proposed LEACH | 2.78 | +0.7% | +27.8% |
| AMDC | 3.25 | +17.8% | +17.8% |
| iLEACH [El-Sayed et al., 2024] | 5.98 | +116.7% | +116.7% |
| **WOA-AMDC (Proposed)** | **8.89** | **+222.1% ▲** | **+222.1% ▲** |
| **RL-AMDC (Proposed)** | **13.17** | **+377.2% ▲** | **+377.2% ▲** |

The maximum throughput in RW-AMDC is 13.17 kbps which is 377 percent better than baseline LEACH (2.76 kbps) and 120 percent better than iLEACH (5.98 kbps). The two synergistic effects of the Q-learning policy (Algorithm 2) on the throughput gain are as follows: first, the per-packet transmission delay decreases due to the design of low-energy routes with limited intermediate hops, which provides the network with more packets to reach the BS per unit time; second, the network can support high-rate data delivery by many more rounds than iLEACH because of the residual energy of relay nodes (LDN = 11,271 rounds vs. 2,916 rounds). This concurs with the finding of Arioua et al. [37] that multi-hop routing protocols with adaptive route selection always perform better in throughput than that of the static-routing protocols especially in large-scale networks since the quality of the paths is gracefully reduced instead of suddenly as the nodes are emptied. WOA-AMDC achieves a rate of 8.89 kbps, 48.7 times higher than the iLEACH (5.98 kbps), and this is due to the tight compact cluster formation to the fitness function of the equation in iLEACH. 2. The D intra minimization of the WOA fitness is used to result in small clustering groups in which the member nodes send their packets to their CHs in short distance - minimizing the energy per packet and allowing more packets to be sent prior to node depletion.

The fact that moderate throughput of baseline LEACH (2.76 kbps) is achieved even with the same simulation environment is a direct indication of the effects of random CH selection, namely numerous transmissions are wasted due to long intra-cluster routes, and the prematurely passing of high-load CHs breaks the flow of packets altogether, which is also reported by Punithavathi et al. [18]. The high throughput efficiency of the two suggested schemes presents a solid practical reason why they should be used in delay sensitive WSNs like real-time hazards monitoring of the environment and industrial condition monitoring.

### *5.4 Comparative Analysis with State-of-the-Art*

Table 6 provides a comprehensive benchmark of WOA-AMDC and RL-AMDC against eight recent state-of-the-art protocols, including both classical and recent approaches, across all key performance dimensions [15]–[23],[27]–[30].

**Table 6. Comprehensive Comparison with State-of-the-Art WSN Protocols**

| **Protocol** | **optimization** | **FDN** | **LDN** | **PDR (%)** | **Throughput** | Multi-hop |
|---|---|---|---|---|---|---|
| LEACH [1] (2000) | Random | ~50 | ~300 | ~45 | Low | No |
| MH-LEACH [12] (2014) | Distance | ~180 | ~820 | ~52 | Med | Yes |
| MFA-AOA [15] (2022) | Mayfly+Aquila | ~410 | ~2100 | ~58 | Med | Partial |
| IAOAR [16] (2022) | Archimedes+ACO | ~480 | ~2450 | ~60 | Med | Partial |
| POA-CHS [17] (2023) | Pelican Opt. | ~390 | ~1980 | ~56 | Med | No |
| BWO-IACO [18] (2021) | BWO+ACO | ~520 | ~2800 | ~61 | Med-H | Yes |
| iLEACH [21] (2024) | Neural Net | 704 | 2,916 | 63.7 | 5.98 k | Partial |
| **WOA-AMDC (Ours)** | **WOA** | **785** | **5,451** | **71.4** | **8.89 k ▲** | **Yes** |
| **RL-AMDC (Ours)** | **Q-Learning** | **895** | **11,271** | **74.8** | **13.17 k ▲** | **Yes** |

Table 6 shows that RL-AMDC always shows the best results in all the metrics considered. The LDN of 11,271 rounds is 287, 302 and 360 percent greater than iLEACH [21], BWO-IACO [18], and IAOAR [16] respectively. This makes RL-AMDC the protocol that consumes the least energy in the comparison by far. It is important to note that RL-AMDC performs better than even BWO-IACO [18] the second best lifetime performer even though BWO-IACO directly aims at optimizing both CH selection and routing with two distinct metaheuristic algorithms. This benefit can be justified by the ability of RL-AMDC to perform temporal learning: whereas BWO-IACO reoptimizes every round based on the existent network condition, RL-AMDC gains routing experience over thousands of rounds and slowly builds a policy that reduces long-term energy spending instead of only the immediate cost. This difference between per-round-optimization that is myopic and longitudinal policy learning is a core principle of the RL paradigm [25] and the main reason why RL-AMDC has an outstanding LDN advantage. WOA-AMDC has FDN of 785, 11.6 percent larger than the FDN of iLEACH of 704, and 5,451, which is 87 percent larger than the FDN of iLEACH of 2,916. Of particular interest, WOA-AMDC performs significantly well using a relatively simple metaheuristic optimization in Algorithm 1, which outperforms iLEACH using a neural network methodology [21] in each of the metrics. This finding refutes the implicit belief that deep learning techniques will automatically perform better than classical optimization techniques in WSN protocol design. The multi-objective fitness function (Eq.) used by WOA is multi-objective and non-stationary, thus its complexity must be corresponding to the complexity in the problem (Singh et al. argue that it needs to be as complex as the decision problem) [34]. 2) provides the necessary trade-off between computing time and the required distance in CH selection with significantly reduced computation cost than training and executing a neural network and improved results because of its ability to search globally in the binary CH assignment space. The single-hop limit of POA-CHS [17] ensures that the distant CHs can only be connected to the BS, which requires the payoff of the quartically-scaling energy penalty as in Eq. 1b, and both WOA-AMDC and RL-AMDC bypass this issue by using intermediate CHs which allows the quadratic model of Eq. 1a to dominate, leading to a significantly reduced energy consumption per round.

### *5.5 Total Energy Consumption Analysis and Discussion*

The measure of energy efficiency is the cumulative residual energy Etotal(t) = S E(t) of all N nodes at any given simulation round t. The higher number of rounds that a protocol sustains Etotal(t) at higher levels, the better the utilisation of energy and energy level is converted to longer network lifetime and a longer period of constant data collection. Figure 7 represents the decay process of the residual energy of all of the protocols considered. The residual energy of RL-AMDC is also sustained past round 10,000 whereas the network energy of WOA-AMDC is sustained beyond round 0 up to round 7,000. By a striking contrast, common LEACH and AMDC uses up all node energy in the space of about 2000 rounds. This 5x improvement in energy persistence of WOA-AMDC and 5x improvement in energy persistence of RL-AMDC over LEACH is demonstrating the compound effects of two mechanisms acting in parallel: (i) WOA and RL filter high-energy CHs using Eq. 2 and Eq. 5 respectively, before the critical relay nodes become depleted and cause the severing of multi-hop paths and cascading network failure; and (ii) multi-hop routing model (Eq. 7 and Eq. ). 8) spreads the load of transmission energy over several intermediate CHs so that any individual node does not have to carry an undue forwarding load. This load-balancing algorithm is similar to the round-robin CH rotation in original LEACH [1], except that it allocates relay tasks in a continuous manner and at a much finer scale: every transmission event allocates out relay tasks proportional to remaining energy, rather than the rotation of CH responsibility (1/p) each round.

The shape of the energy decay behavior of the RL-AMDC also has a significantly different shape when compared to that of other protocols. Whereas LEACH, AMDC and even WOA-AMDC exhibit a more or less linear or super-linear energy decay curve i.e. a constant or accelerating rate of energy expenditure RL-AMDC exhibits a sub-linear decay pattern in the middle rounds i.e. one where the curve takes on a sub-linear shape i.e. one where the curve slopes gradually and even more gradually at higher rounds i.e. between rounds 2000 and 8000 round. This over time routing quality improvement is a characteristic feature of Q-learning convergence [25] and is seen in similar RL-WSN research by Kulkarni et al. [35]. The cumulative energy savings made by RL-AMDC over iLEACH [21] are especially large in terms of a practical deployment viewpoint: the extra 8,355 rounds of network activity that RL-AMDC makes compared to iLEACH of LDN 2,916 is a deployment lifetime improvement of about 187 percent, which in a realistic deployment of 1 second round interval would be about 2.3 extra hours of constant monitoring capacity per fully charged collection of nodes. This distinction is operationally decisive in time-sensitive applications like earthquake aftershock surveillance, forest fire detection and accurate irrigation scheduling.

### *5.6 Discussion of Algorithm Complexity and Scalability*

An all-inclusive analysis should also be placed on the computational complexity of the two proposed algorithms. The complexity of a single run of Algorithm 1 (WOA CH Selection) is O (P x T x N) where P = 30 whales, T = 100 iterations and N = 100 nodes meaning it performs O (300,000) calculations in one round, in any case, which is feasible to run at the BS side. Q-Learning Routing in the form of Algorithm 2 executes on a per-CH basis with N (packet transmission) update complexities of O (S x A) where S x = size of the discretized state space and A = neighbors + 1. On average, with a number of neighbors of 5-8, this equals O( S x 8) in a single transmission, which is far less than the processing power of current sensor systems like Arduino Mega and CC2530 [22]. The two algorithms linearly depend on network size N and this proves that the schemes can be extended to large-scale implementation above the 100 node simulated. This scalability benefit compared to neural network methods such as iLEACH [21] which need O(N2) training data and centralized BS computation is a feasible benefit in deployments in resource-constrained environments.

## 6. Conclusion

This paper presented two novel and independently functional optimization frameworks — WOA-AMDC and RL-AMDC — for enhancing energy efficiency and substantially prolonging network lifetime in Wireless Sensor Networks. The WOA-AMDC framework employs the Whale Optimization Algorithm (Algorithm 1) with a multi-objective fitness function (Eq. 2) to select optimal cluster heads based on residual energy, intra-cluster distance, and CH-BS proximity in each operational round, achieving a 61% improvement in FDN and an 801% improvement in LDN relative to conventional LEACH [1]. The RL-AMDC framework employs Q-learning (Algorithm 2) with the Bellman update (Eq. 5) and a composite reward function (Eq. 6) to enable experience-driven, adaptive multi-hop routing, achieving an 84% improvement in FDN and a remarkable 1,762% improvement in LDN.

Both frameworks were validated through extensive MATLAB simulations, benchmarked against eight state-of-the-art protocols in Table 6, and analyzed across six performance metrics with in-depth discussion. The discussion section identified the specific algorithmic mechanisms responsible for each observed improvement: WOA's multi-objective fitness function produces spatially balanced, energy-rich CH configurations that prevent the energy hole problem [5]; RL's Q-learning policy develops longitudinal routing intelligence that progressively reduces energy expenditure over thousands of rounds [25],[35]; and the multi-hop AMDC architecture eliminates the quartically-scaling long-range transmission penalty of single-hop protocols like LEACH [1],[12]. The literature comparison in Table 1 and the state-of-the-art comparison in Table 6 together demonstrate that no prior protocol simultaneously achieves all evaluated criteria, confirming the novelty and practical significance of the proposed contribution.

Future work will investigate: (i) deep reinforcement learning (DRL) extensions with convolutional state encoding for higher-dimensional network states; (ii) integration with ambient energy harvesting and wireless power transfer models to further extend operational lifetime; (iii) extension to heterogeneous node populations with diverse hardware capabilities and energy budgets; and (iv) hardware-in-the-loop validation on real sensor platforms including TinyOS/TelosB and ESP32-based IoT nodes to confirm the practical deployability of both proposed algorithms.

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