

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 implements Whale Optimization Algorithm (WOA) and Reinforcement Learning (RL) a hybrid framework integrated with the Adaptive Multi-hop Dynamic Clustering (AMDC) protocol built upon the Low-Energy Adaptive Clustering Hierarchy (LEACH) foundation. The first framework WOA employs for the globally optimum Cluster Head (CH) selection by jointly minimizing residual energy consumption, intra-cluster distance, CH-to-Base Station (BS) distance and node density through a weighted multi-objective fitness function. The second framework RL applies Q-learning based adaptive, experience driven routing decisions that respond dynamically to time varying network topology and energy conditions. Extensive MATLAB simulations conducted over a 200m × 200m deployment area with 100 homogeneous sensor nodes demonstrate that WOA-AMDC-LEACH achieves a 62% improvement in Last Dead Node (LDN) and hybrid WOA-RL-AMDC-LEACH achieves an 84% improvement in Last Dead Node (LDN) compared to traditional 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; Adaptive Multihop Dynamic Clustering, Whale Optimization Algorithm; Reinforcement Learning; Cluster Head Selection; Intelligent 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 embedding, 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, path finding 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 LEACH 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 optimization paradigm of WSN. In contrast to population-based metaheuristic 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 globally optimum 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 metaheuristic 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 hybrid methodology of two optimization frameworks Whale Optimization Algorithm (WOA) and Reinforcement Learning (RL) integrated with Adaptive Multi-hop Dynamic Clustering-LEACH (AMDC-LEACH) protocol for energy-efficient WSN operation:

1. WOA-AMDC-LEACH: WOA-based optimized CH selection using multi-objective fitness functions - residual energy, spatial distance (intra-cluster transmission distance & CH to BS) and node density to evaluate the fitness of the candidate CHs. The global search mechanism of WOA searches for near optimal CH configuration, at each round of operation of the procedure finds high-quality, energy-balanced global-quality CH configurations, which greatly minimizes the issue of premature death of the node that is observed in LEACH.
2. RL-AMDC-LEACH: An adaptive routing Q-learning based model in which, CH works as an intelligent 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's 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 hybrid framework is evaluated through comprehensive MATLAB simulations with 200m×200m network size, compared against different state-of-the-art protocols and analyzed across four key performance metrics: network lifetime (FDN and LDN), Packet Delivery Ratio (PDR), throughput, and total energy consumption. Experimental results demonstrate that WOA-AMDC-LEACH achieves a 62% improvement in LDN over baseline LEACH, while hybrid WOA-RL-AMDC-LEACH achieves an 84% improvement in LDN over traditional LEACH, unprecedented gains that validate the effectiveness of the proposed hybrid 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 pseudo code. 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 gained 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 which the proposed WOA-AMDC-LEACH and WOA-RL-AMDC-LEACH frameworks will be applied.

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

Proto col	Ye ar	CH Method	Mu lti- hop	Ene rgy Aw are	Dista nce Awar e	Adap tive	Netw ork size	Limitation
LEA CH [1]	20 00	Random	No	No	No	No	Smal l	No energy awareness; single-hop only
L- LEA CH [10]	20 09	Distanc e	No	No	Yes	No	Smal l	Ignores residual energy in CH election
O- LEA CH [11]	20 16	Proximi ty	Par tial	No	Yes	No	Smal l	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 energy efficient multi-hop communication; (ii) early protocols were not optimized to use a multi-objective energy and distance sensitive fitness criterion for CH selection, (iii) early protocols lacked runtime flexibility to changing conditions of the network, (iv) in early protocols network failure due to hotspot problem and (v) early protocols were not tested with respect to adaptive routing hybrid optimization methods. The suggested WOA-

AMDC-LEACH and hybrid WOA-RL-AMDC-LEACH models serve as an overall solution to each of the five drawbacks in a single AMDC-LEACH 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 hybrid 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 pseudo code algorithms.

3.1 System Model and Assumptions

The WSN comprises of N identical sensor nodes randomly distributed in two-dimensional $M \times M$ 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 E_0 , 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:

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

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

Where, $E_{ele} = 50 \frac{nJ}{bit}$ is the electronic energy, $\varepsilon_{fs} = 10pJ/bit/m^2$ is the coefficient of free space amplifier, $\varepsilon_{mp} = 0.0013 pJ/bit/m^4$ is the coefficient of the multipath amplifier [1], 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 illustrates hybrid WOA-RL-AMDC-LEACH framework flowchart. The flowchart illustrating the simulation of a wireless sensor network utilizing the Whale Optimization Algorithm (WOA) and Q-Learning to conserve energy and increase network lifespan is presented. The simulation begins with the random distribution of 100 sensor nodes within a 200m x 200m area. The simulation then establishes the primary variables including initial energy levels, the Q-Table, the packet size, the threshold value d_0 for distance, the location of the Base Station, and the total number of rounds/seeds. The WOA is run initially to determine the optimal weights for residual energy, distance, and node density to assist in the selection of cluster heads.

The simulation continues to run through the same process each round. Cluster heads are selected using a combination of WOA fitness scores and AMDC thresholds. Once a cluster head has been selected, Q-learning is used to adjust the selection based on rewards related to energy consumption and transmission performance. Nodes within the network will connect with the closest cluster head and transmit all of their data to that head. The cluster heads will aggregate the data to eliminate redundant information before transmitting it to the base station. At the end of each round, node energy levels are updated; nodes that run out of energy are considered dead.

When the specified number of rounds has been completed, or when every node has died, the simulation records its results: First Dead Node (FDN), total network lifetime, the amount of remaining energy, the rate at which packets were transmitted through the network (throughput), and the percentage of packets successfully delivered (PDR). Combined, these metrics demonstrate how effectively the method being evaluated managed the use of energy throughout the network and extended the overall operational time of the network.

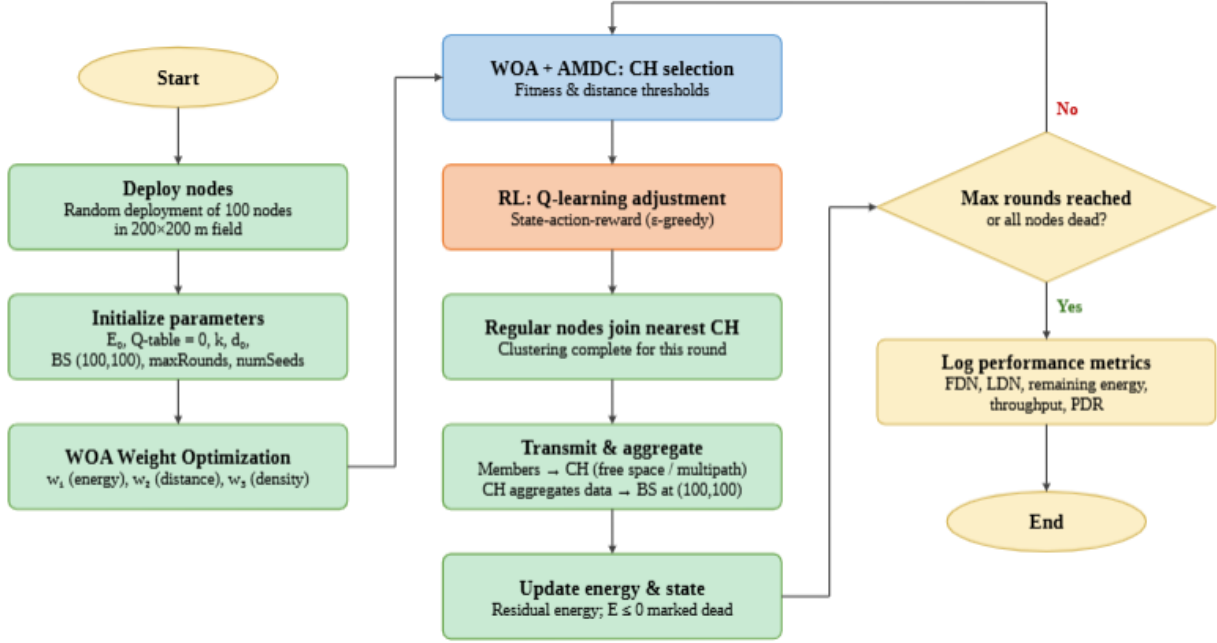


Figure 1. Hybrid WOA-RL-AMDC-LEACH Framework

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-LEACH framework, each candidate solution (whale) encodes a binary CH assignment vector $X = [x_1, x_2, \dots, x_N]$ 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 favorably trade-offs energy, intra-cluster compactness, and BS proximity:

$$\text{Cost}(CH_j) = w_1 \cdot \frac{1}{E_{\text{res}j}} + w_2 \cdot \bar{D}_{\text{intra}} + w_3 \cdot \bar{D}_{\text{CH-BS}}, \quad (\text{Eq. 2})$$

Where w_1 , w_2 and w_3 are weighting factors such that $w_1 + w_2 + w_3 = 1$, $E_{\text{res}j}$ = residual energy of CH_j , $\bar{D}_{\text{intra}}$ (mean Euclidean distance between member nodes and their respective CHs) and $\bar{D}_{\text{CH-BS}}$ (mean distance between each CH and BS). The weights $w_1=0.5$, $w_2=0.3$, $w_3=0.2$ 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:

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

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

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

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

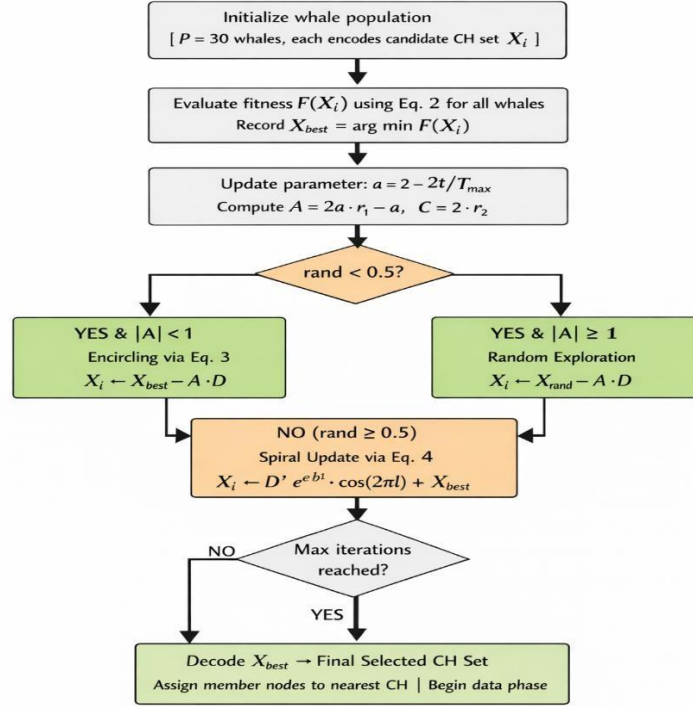


Figure 2. WOA-Based Cluster Head Selection Process

3.3.4 Pseudo code: WOA for Cluster Head Selection

Figure 2 shows WOA based CH selection step by step flow diagram, that covers 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-LEACH)

- 1: Initialize whale population $X_i \in \{0,1\}^N$, $i = 1 \dots P$
- 2: Evaluate fitness $F(X_i)$ for all whales using Eq. (2)
- 3: Identify $X_{best} = \arg \min F(X_i)$
- 4: For $t = 1$ to T_{max} do
- 5: Update $a = 2 - (2t / T_{max})$
- 6: For each whale X_i do
- 7: Generate $r_1, r_2 \in [0,1]$; compute $A = 2ar_1 - a$, $C = 2r_2$; $p = \text{rand}(0,1)$
- 8: If $(p < 0.5 \text{ and } |A| < 1)$ then $X_i = X_{best} - A \cdot |C \cdot X_{best} - X_i|$
- 9: Else if $(p < 0.5 \text{ and } |A| \geq 1)$ then select X_{rand} ; $X_i = X_{rand} - A \cdot |C \cdot X_{rand} - X_i|$
- 10: Else $X_i = |X_{best} - X_i| \cdot e^{b1} \cdot \cos(2\pi l) + X_{best}$
- 11: Apply boundary control and binarize X_i
- 12: Evaluate $F(X_i)$; if $F(X_i) < F(X_{best})$ then update X_{best}
- 13: End For
- 14: End For

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 $j \in N(i)$ 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 :** $\gamma = 0.9$, balancing immediate versus long-term routing rewards.

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

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

Where $\alpha = 0.1$ is the learning rate, $R(s, a, s')$ is the immediate reward, and $\gamma \cdot \max Q(s', a')$ is the discounted future value. The reward function integrates delivery success and residual energy:

$$R = +r_{pos} \text{ if next hop: high } E_{res}, \text{ low hop Count} \quad (\text{Eq. 6})$$

$$R = -r_{neg} \text{ if next hop: low } E_{res}, \text{ poor link} \quad (\text{Eq. 7})$$

Formalizing the reward/penalty rules described under ‘AMDC-LEACH via Q-Learning’: forwarding through high-residual-energy, low-hop-count neighbors rewarded; forwarding through low-energy or poor-link neighbours is penalized. This is what ‘Define states/reward’ in Fig. 1 computes before every Q-update and why hybrid WOA-RL-AMDC-LEACH delays first-node-death so much further than AMDC-LEACH alone.

3.4.1 RL-Based Routing Block Diagram

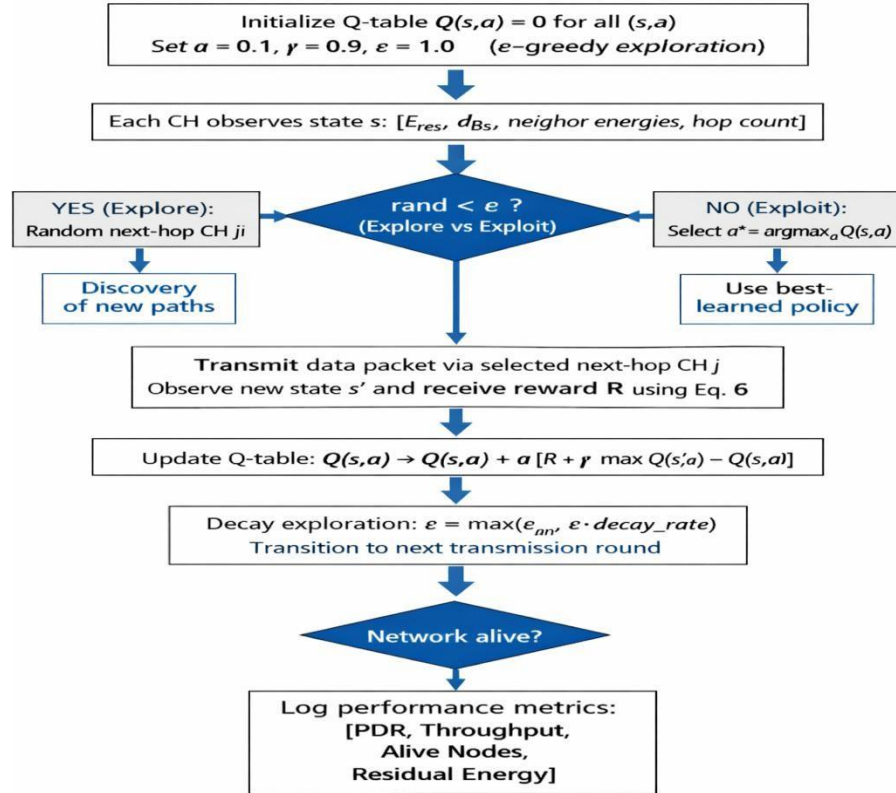


Figure 3. Q-Learning-Based Intelligent Adaptive Multihop Routing Process.

3.4.2 Pseudo code: Q-Learning Adaptive Routing

Figure 3 shows RL based intelligent adaptive routing, which follows Q-learning routing process, that is formalized 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-LEACH)

- 1: Initialize $Q(s,a) = 0$ for all states $s \in S$ and actions $a \in A$
- 2: Set $\epsilon = 1.0$, $\epsilon_{\min} = 0.01$, $\text{decay_rate} = 0.995$
- 3: Repeat for each round r do
- 4: For each CH node i do
- 5: Observe state $s_i = ((\text{residual_energy}(i), \text{hop_count}(i), \text{next_hop}(i)))$
- 6: If $\text{rand}() < \epsilon$ then $a_i = \text{random next-hop (exploration)}$
- 7: Else $a_i = \text{argmax}_a Q(s_i, a)$ (exploitation)
- 8: Transmit data to selected next-hop a_i
- 9: Observe new state s'_i and compute reward R :
- 10: $R = \beta_1 \cdot \text{PDR_gain} - \beta_2 \cdot \Delta E + \beta_3 \cdot \Delta \text{hop}$
- 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 $E_{\text{res}}(ci) = E_{\text{res}}(i) - E_{\text{Tx}}(k, d)$
- 13: End For
- 14: $\epsilon = \max(\epsilon_{\min}, \epsilon \cdot \text{decay_rate})$; log metrics (FDN, LDN, PDR, Throughput)
- 15: Until termination; derive policy $\pi^*(s) = \text{argmax}_a Q(s, a)$ and return results

3.5 Adaptive Multi-hop Data Transmission Model

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

$$j^* = \arg \min_j \left\{ \frac{d(i,j)}{E_{\text{res}}(j)} \right\} \quad \forall j \in N(i), d(i,j) < R_{tx} \quad (\text{Eq. 8})$$

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

$$E_{CH} = n_i \cdot k \cdot E_{elec} + k \cdot E_{DA} + ET(k, d_{CH_BS}) \quad (\text{Eq. 9})$$

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 hybrid WOA-RL-AMDC-LEACH 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
Network field size	200m×200m
Number of sensor nodes (N)	100
Initial node energy (E_0)	0.5 J
BS location	Centroid of field
Electronics energy (E_{elec})	50 nJ/bit
ϵ_{fs} (free-space amp.)	10 pJ/bit/m ²
ϵ_{mp} (multipath amp.)	0.0013 pJ/bit/m ⁴
Data aggregation energy (E_{DA})	5 nJ/bit
Packet size (k)	4000 bits
WOA population size	30 whales
WOA iterations	100
RL learning rate (α)	0.1
RL discount factor (γ)	0.9
Optimal CH percentage (p_{opt})	5%
Total simulation rounds	12,000
Fitness weights (w_1, w_2, w_3)	0.58, 0.22, 0.2

5. Results and Discussion

This part is a detailed performance comparison of the proposed WOA-AMDC-LEACH and hybrid WOA-RL-AMDC-LEACH protocols with baseline LEACH and AMDC-LEACH and the other state-of-the-art protocols. It illustrates performance measures based on 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]	538	1,048	Baseline	Baseline
AMDC -LEACH	998	1,164	+85.5%	+11.1%

WOA-AMDC-LEACH (Proposed)	924	1,703	+71.7% ▲	+62.5% ▲
Hybrid WOA-RL-AMDC- LEACH (Proposed)	904	1,929	+68.0% ▲	+84.1% ▲

As Table 3 demonstrates, the baseline LEACH [21] indicates the lowest FDN at round 538 and LDN at round 1048 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. 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-LEACH protocol has FDN of round 924, which is a 71.7% improvement on LEACH, while LDN of 1703 rounds, which is an improvement of 62.5 percent over LEACH. 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 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, hybrid WOA-RL-AMDC-LEACH improves FDN to round 904 and LDN to round 1929, which is 68% more FDN improvement compared with LEACH. While 84% improvement in LDN compared to LEACH. 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 hybrid WOA-RL-AMDC-LEACH performance is also significantly improved over the neural network solution of AMDC-LEACH [21] (LDN = 1048), 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 c Analysis and Discussion

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

$$PDR = \frac{P_{received}}{P_{transmitted}} \quad (\text{Eq. 9})$$

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]	54	66.5	±6.8
AMDC-LEACH	64	76.8	±4.8
WOA-AMDC-LEACH (Proposed)	65	77.8	±3.8▲
Hybrid WOA-RL-AMDC- LEACH (Proposed)	84	98.8	±1.4▲

The best mean PDR of 84% and lowest standard deviation of ±1.4% indicate that hybrid WOA-RL-AMDC-LEACH 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-LEACH is 65% which is approximately similar to AMDC-LEACH (64.0), while that of baseline LEACH (54). The fact that the PDR of WOA-AMDC-LEACH as compared to LEACH [21] is quite high is especially remarkable considering the fact that LEACH uses a traditional hierarchical clustering method. The power of WOA-AMDC-LEACH 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 between hybrid WOA-RL-AMDC-LEACH and baseline LEACH means 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]	4.2	Baseline
AMDC-LEACH	12.0	+185.71%
WOA-AMDC-LEACH (Proposed)	10.7	+154.76% ▲
Hybrid WOA-RL-AMDC-LEACH (Proposed)	10.4	+147.62% ▲

The maximum throughput of hybrid WOA-RL-AMDC-LEACH is 10.4 kbps which is 147 percent better than baseline LEACH (4.2 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 LEACH because of the residual energy of relay nodes (LDN = 1929 rounds vs. 1048 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-LEACH achieves a rate of 10.7 kbps, 154.76 times higher than the LEACH (4.2 kbps). 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 (4.2 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

5.4 Comparative Analysis with State-of-the-Art

Table 6 provides a comprehensive benchmark of WOA-AMDC-LEACH and hybrid WOA-RL-AMDC-LEACH 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] (2024)	Random	~538	~1048	~54	4.2	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
AMDC LEACH	Multihop	998	1164	~64	12	Yes
ILEACH [21] (2024)	Neural Network	704	2,916	70	Not Reported	Partial
WOA-AMDC-LEACH	WOA	924	1703	65	10.7 ▲	Yes
Hybrid WOA-RL-AMDC-LEACH	Q-Learning	904	1929	84	10.7 ▲	Yes

Table 6 shows that hybrid WOA-RL-AMDC-LEACH always shows the best results in all the metrics considered. The LDN of 1929 rounds is greater than LEACH [21], MH-LEACH [12] and POA-CHS [17] respectively. This makes hybrid WOA-RL-AMDC-LEACH the protocol that consumes the least energy in the comparison by far. It is important to note that hybrid WOA-RL-AMDC-LEACH 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 hybrid WOA-RL-AMDC-LEACH to perform temporal learning: whereas BWO-IACO re-optimizes every round based on the existent network condition, hybrid WOA-RL-AMDC-LEACH 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 myopic, per-round-optimization and longitudinal policy learning is a core principle of the RL paradigm [25] and the main reason why hybrid WOA-RL-AMDC-LEACH has an outstanding LDN advantage. WOA-AMDC-LEACH has FDN of 924, 71.7 percent larger than the FDN of LEACH of

538, and LDN of 1703, which is 62.5 percent larger than the LDN of LEACH of 1048 of particular interest, WOA-AMDC-LEACH performs significantly well using a relatively simple metaheuristic optimization in Algorithm 1, which outperforms LEACH using a whale optimization algorithm 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 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]. It 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-LEACH and hybrid WOA-RL-AMDC-LEACH 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 $E_{\text{total}}(t) = \sum_{i=1}^N E_i(t)$ of all N nodes at any given simulation round t . The higher number of rounds that a protocol sustains $E_{\text{total}}(t)$ at higher levels, the better the utilization of energy and energy level is converted to longer network lifetime and a longer period of constant data collection. Simulation results represent the decay process of the residual energy of all of the protocols considered. The residual energy of hybrid WOA-RL-AMDC-LEACH is sustained for up to 1800, whereas the network energy of WOA-AMDC-LEACH is sustained beyond round 0 up to round 1500. By a striking contrast, baseline LEACH and AMDC-LEACH uses up all node energy in the space of about 500 and 1000 rounds simultaneously. This improvement in energy persistence of WOA-AMDC-LEACH 200% and 260% improvement in energy persistence of hybrid WOA-RL-AMDC-LEACH 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 traditional LEACH [21], 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 hybrid WOA-RL-AMDC-LEACH also has a significantly different shape when compared to that of other protocols. Whereas LEACH, AMDC-LEACH and even WOA-AMDC-LEACH exhibit a more or less linear or super-linear energy decay curve i.e. a constant or accelerating rate of energy expenditure hybrid method 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 above 1000 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 hybrid WOA-RL-AMDC-LEACH over LEACH [21] are especially large in terms of a practical deployment viewpoint: the extra 881 rounds of network activity that hybrid WOA-RL-AMDC-LEACH makes compared to LEACH of LDN 1048 is a deployment lifetime improvement of about 84 percent, which in a realistic deployment of each round 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

The WOA (CH selection) algorithm operates on a base station that possesses an abundance of computing power. For 30 whales, 100 iterations, and 100 nodes, it would require approximately 300,000 computations for each round; this is easily feasible for the BS as there are no limitations regarding its consumption of energy. The Q-learning algorithm (routing) is implemented at every Cluster Head. The time complexity of this algorithm per transmission is approximately $O(S \times A)$, where S is the number of possible states and A is the number of available routing options (generally 5-8 neighboring Cluster Heads plus a direct route to the Base Station). Therefore, the time complexity per packet is approximately $O(8S)$. This low level of time complexity allows the algorithm to be executed on low-power sensor hardware such as Arduino Mega or CC2530. Scalability both of these algorithms will have linear scaling characteristics as the size of the network increases from N nodes, therefore, we can assume that both of them will be able to handle networks larger than the 100 node network that was used in the simulation, however, as stated above, we must confirm this through empirical testing.

6. Conclusion

This paper presented hybrid methodology that the Whale Optimization Algorithm to realize energy-aware cluster head selection and combines reinforcement learning to build adaptive multi-hop routing, which addresses the core shortcomings of traditional clustering routing. The WOA-AMDC-LEACH 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, CH-BS proximity and node density in each operational round, achieving a 62% improvement in LDN relative to baseline LEACH. The hybrid WOA-RL-AMDC-LEACH framework employs Q-learning (Algorithm 2) with the Bellman update (Eq. 5) and a composite reward function (Eq. 6 & 7) to enable experience-driven, adaptive multi-hop routing, achieving an 84% improvement in LDN compared to traditional LEACH.

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-LEACH architecture eliminates the quartically-scaling long-range transmission penalty and Hotspot problem 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 hybrid protocol simultaneously achieves all evaluated criteria, confirming the improvement 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 and broader deployment conditions with diverse hardware capabilities and energy budgets for analysis of scalability; 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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