International Journal of
INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING
ISSN:2147-6799 www.ijisae.org Original Research Paper

Hybrid Reinforced Pelican Optimization Algorithm (HR-POA) for Energy-Efficient Cluster Head Selection in Heterogeneous Wireless Sensor Networks

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Submitted: 07/01/2025 **Revised:** 22/02/2025 **Accepted:** 10/03/2025

Abstract: The importance of Wireless Sensor Networks (WSNs) spans multiple areas, notably environmental monitoring, healthcare services, and intelligent urban systems. These networks consist of dispersed sensor nodes that wirelessly exchange data while monitoring environmental or physical conditions. One of the key challenges in Wireless Sensor Networks (WSNs) is the efficient selection of Cluster Heads (CHs) to prolong network lifetime and ensure balanced energy consumption. This study introduces a novel Hybrid Reinforced Pelican Optimization Algorithm (HR-POA), which integrates the Enhanced Pelican Optimization Algorithm (EPOA) with Particle Swarm Optimization (PSO) and Reinforcement Learning (RL) to achieve efficient Cluster Head (CH) selection in heterogeneous wireless sensor networks (HWSNs). HR-POA is a promising solution for energy-efficient clustering since it considerably improves WSN performance by utilizing intelligent routing and a hybrid optimization approach. The proposed algorithm considers node energy, distance, and adaptive Q-learning-based routing to improve energy efficiency and network performance. The effectiveness of HR-POA in comparison to current CH selection algorithms has been assessed through extensive simulated studies. HR-POA demonstrates notable improvements in energy efficiency, network longevity, and packet delivery ratio compared to current CH selection methods, as evidenced by simulation results. By advancing energy-aware clustering approaches in WSNs, the suggested approach opens the door to more intelligent and sustainable wireless sensor networks.

Keywords: *Cluster Head Selection, Energy Efficiency, Particle Swarm Optimization, Pelican Optimization, Reinforcement Learning, Wireless Sensor Networks.*

1. Introduction

A Wireless Sensor Network (WSN) comprises a plethora of inexpensive low-power sensor nodes used for monitoring and relaying various forms of environmental data for industrial automation, disaster management, healthcare, and smart agriculture [1]. These nodes are energy-constrained, and therefore efficient energy management is essential to maintain adequate network performance and lifetime [2]. Given that many batteries cannot be serviced frequently without large expense or risk, especially in remote or dangerous locations, optimizing energy expenditure should be a priority.

A widely adopted energy-saving approach in WSNs is clustering, where sensor nodes are grouped into clusters with a designated Cluster Head (CH) [3]. CHs gather data from member nodes, aggregate them, and forward them to the Base Station (BS), hence preventing redundant transmissions and prolonging the network lifetime. However, selecting optimal CHs is a challenging problem due to the dynamic nature of WSNs, uneven energy distribution, and network heterogeneity.

For CH selection, a number of conventional clustering algorithms have been proposed, including LEACH (Low-Energy Adaptive Clustering Hierarchy) [4], PEGASIS (Power-Efficient Gathering in Sensor Information System) [5], and Particle Swarm Optimization (PSO) [6]. While these approaches have demonstrated improvements in energy efficiency, they often suffer from limitations such as poor adaptability to heterogeneous energy levels, premature CH depletion, and suboptimal routing decisions, leading to network partitioning and early failure.

To deal with these issues, the proposed HR-POA combines the strengths of nature-inspired optimization and reinforcement learning, enabling adaptive and efficient CH selection and routing in HWSNs. HR-

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POA integrates the Pelican Optimization Algorithm (POA) [7], because of its efficient exploration and exploitation and Particle Swarm Optimization (PSO) [6] for optimizing CH selection. In addition, Q-learning-based reinforcement learning [8] is integrated to maximize multi-hop communication, providing energy-efficient routing and fair energy consumption throughout the network.

Through the use of these hybrid techniques, HR-POA adapts to fluctuating network topologies, loads the network for optimal distribution, and maximizes the network's overall lifetime. Large-scale simulations validate that HR-POA significantly outperforms traditional CH selection algorithms with respect to energy consumption, network stability, and packet delivery ratio.

The rest of this paper is organized as follows: section 2 is devoted to presenting some related works, in the following Section 3 the HR-POA algorithm and its concepts are described, section 4 the algorithm simulation and results are discussed. Lastly, section 5 concludes the paper.

2. Related Work

Heterogeneous Wireless Sensor Networks (HWSNs) [9] consist of sensor nodes with varying energy levels, computational capabilities, and transmission ranges. Unlike homogeneous WSNs [10], where all nodes share identical hardware configurations and initial energy, HWSNs comprise different categories of nodes—namely, normal, advanced, and super nodes—each with distinct energy reserves and processing power. This heterogeneity offers opportunities as well as challenges in the development of efficient routing protocols. A good routing strategy is supposed to strike a balance between energy usage, prevent premature node death, and ensure reliable data delivery while adapting to the changing network status.

Researchers have proposed multiple routing approaches to mitigate the impact of heterogeneity in WSNs. Cluster-based protocols are the most widely used among them due to their ability to minimize energy usage and maximize the network lifetime [11]

DEEC (Distributed Energy-Efficient Clustering) [12], SEP (Stable Election Protocol) [13], and Z-SEP (Zonal Stable Election Protocol) [14] are a few protocols that select Cluster Heads (CHs) dynamically based on node energy and network topology. These algorithms distribute the energy load more evenly by giving higher-energy nodes a greater chance of being elected as CHs, thereby equalizing energy consumption across the network.

Researchers have created hierarchical and multi-hop routing protocols that improve data aggregation and transmission efficiency in an effort to better minimize energy utilization. Through the integration of energy-aware CH selection and multi-hop communication, M-LEACH [15] enhances the traditional LEACH protocol [4] and effectively reduces transmission overhead to the base station. Similarly, to reduce redundant transmissions and increase the network's operating lifespan, EECDA (Energy-Efficient Clustering and Data Aggregation) [16] combines clustering and data fusion algorithms.

In order to optimize CH selection and routing in HWSNs, bio-inspired and swarm intelligence-based algorithms have been used in recent years. In order to increase efficiency in diverse environments, algorithms such as PSO (Particle Swarm Optimization) [6], GA (Genetic Algorithm) [17], ACO (Ant Colony Optimization) [18], and BFO (Bacterial Foraging Optimization) [19] implement dynamic routing adjustments tailored to evolving network conditions. These techniques use probabilistic and evolutionary mechanisms to find the best routing options with the least amount of energy overhead.

Furthermore, machine learning-based methods-in particularly, particularly reinforcement learning (RL) [20] have become effective instruments for HWSN routing optimization. Routing decisions can be dynamically modified by Q-learning and deep reinforcement learning models in response to communication costs, residual energy levels, and network traffic patterns. RL-based protocols improve adaptation to shifting network conditions and avoid premature energy depletion by continuously learning from prior experiences. Deep Q-Networks (DQN) [21] and Federated Learning (FL) [22] have been used in some recent research to enable scalable and decentralized routing decision-making in large-scale HWSNs.

The design of HWSN routing protocols still faces a number of difficulties in spite of these developments. Future innovations must guarantee scalability, fault tolerance, security, and real-time flexibility. Furthermore, combining hybrid AI-driven strategies with energy-harvesting techniques may improve network efficiency even more by enabling more autonomous and context-aware routing decisions. Future studies should concentrate on creating robust yet lightweight routing systems that strike a balance between computational complexity and practical deployment limitations in HWSNs.

Enhancing CH selection has been the focus of multiple clustering strategies grounded in metaheuristic optimization:

- **LEACH (Low-Energy Adaptive Clustering Hierarchy)** [4]: Given that LEACH, one of the most popular clustering algorithms, chooses CHs arbitrarily, the network becomes unbalanced and some CHs use energy more quickly than others. Although it increases network longevity, it has uncontrolled cluster sizes and ineffective CH rotation.

- **HEED (Hybrid Energy-Efficient Distributed Clustering)** [23]**:** HEED, a modified form of LEACH, chooses CHs according to communication cost and remaining energy. Although it is more energy efficient than LEACH, global optimization for CH selection is still absent.

- **PSO-Based Clustering** [6]**:** A popular technique for optimizing CH selection is particle swarm optimization (PSO), which takes fitness functions like distance and energy into account. Nevertheless, it frequently experiences early convergence, which results in inadequate CH placement.

- **GA-Based Clustering** [17]**:** Using crossover and mutation procedures, genetic algorithms (GA) have been examined for CH selection in order to investigate various clustering configurations. GA can be computationally costly for large-scale WSNs, even if it provides superior solutions compared to conventional methods.

- **Enhanced Pelican Optimization Algorithm (EPOA)** [24]**:** Drawing inspiration from pelican foraging, EPOA enhances the harmony between exploration and exploitation. By dynamically updating candidate CH positions according to swarm intelligence principles, it offers a more efficient method of CH selection. It does not, however, have adaptive learning techniques for multi-hop communication optimization.

- **Reinforcement Learning-Based Approaches** [20]**:** In order to enable nodes to learn from prior experiences, some works have included Q-learning into CH selection and routing techniques. However, the scalability and rate of convergence of these methods are still difficult to achieve.

Building on these strategies, HR-POA uses Q-learning to adaptively optimize multi-hop routing while combining the advantages of EPOA and PSO for strong CH selection. HR-POA guarantees more energy-efficient CH placement and dynamic adaptation to network conditions by combining metaheuristics with reinforcement learning, which improves performance in diverse WSNs.

3. Proposed Algorithm: HR-POA

In dynamic WSN environments, HR-POA improves the POA's flexibility and decision-making through applying Reinforcement Learning concepts.

3.1. Energy Model for HR-POA in Wireless Sensor Networks

The first-order radio energy dissipation model serves as the foundation for the HR-POA energy model, which takes into account energy usage during data aggregation, transmission, and reception. The clustering structure and node communication distances are used to compute the network's overall energy dissipation

3.1.1. Energy Consumption Model

For transmitting a k-bit message over a distance d, the energy consumption is [4]:

$$\mathrm{Etx}(\mathrm{k},\mathrm{d}) = \begin{cases} \mathrm{k}.\,\mathrm{E}_{elec} + \mathrm{K}.\,\mathcal{E}\mathrm{fs}.\,\mathrm{d}^2, & if\ \mathrm{d} < d_0 \\ \mathrm{k}.\,\mathrm{E}_{elec} + \mathrm{K}.\,\mathcal{E}\mathrm{fs}.\,\mathrm{d}^4, & if\ d \geq d_0 \end{cases} \quad (1)$$

For receiving a k-bit message:

$$E_{rx}(k) = k.\,E_{elec} \quad (2)$$

Where:

E_{elec} represents energy dissipation per bit for signal processing.

$\mathcal{E}_{fs}$ is Free-space model energy coefficient (for short distances).

d_0 is threshold distance between free-space and multi-path models.

3.1.2. Energy Dissipation in Clustering

The energy consumption for cluster heads (CHs) is calculated as:

$$E_{CH} = E_{rx}(k) + E_{DA}(k) + E_{tx}(k, d_{BS}) \quad (3)$$

Where:

E_{CH} is Total energy consumed by the Cluster Head.

$E_{tx}(k,d_{BS})$ is Energy required to transmit k bits of data over a distance d_{BS} to the Base Station (BS).

E_{DA} is the energy dissipation for data aggregation.

3.3. Residual Energy Calculation

In HR-POA, nodes with higher residual energy ($E_{residual}$) have a higher probability of being selected as Cluster Heads (CHs).

At any round t, the updated residual energy is:

$$E_{residual}(t) = E_{residual}(t-1) - (E_{tx} + E_{rx} + E_{DA}) \quad (4)$$

The selection probability $P_{CH}(i)$ for a node i, is based on its residual energy $E_{residual}(i)$, and it can be calculated using the following equation:

$$P_{CH}(i) = \frac{E_{residual}(\mathrm{i})}{\sum_{j=1}^{N} E_{residual}(j)} \quad (5)$$

Where:

$P_{CH}(i)$ is Probability that node i is selected as a Cluster Head.

$E_{residual}(i)$ is Residual energy of node iii at the current time.

N is Total number of nodes in the network

$\sum_{j=1}^{N} E_{residual}(j)$is Total residual energy of all nodes in the network

HR-POA combines Pelican Optimization, PSO, and Q-learning to enhance CH selection and routing.

3.1.3. Node Deployment and Heterogeneity

The algorithm begins with the random deployment of sensor nodes in a given network area. These nodes have three different energy levels:

- Normal Nodes
- Advanced Nodes
- Super Nodes

Each node is assigned an initial energy level and position. The Base Station (BS) is fixed and serves as the data collection point.

Hybrid Reinforced Pelican Optimization Algorithm (HR-POA) Pseudocode

Input: Sensor nodes deployment, energy levels, base station**.**
Output: Optimized Cluster Head (CH) selection and efficient routing

1. Initialize network parameters:

1: Deploy N sensor nodes with different energy levels (Normal, Advanced, Super).

2: Set initial energy levels for each node.

3: Define communication range and base station location.

2. Initialize optimization parameters:

1: Set population size for Pelican Optimization Algorithm (POA).

2: Initialize Particle Swarm Optimization (PSO) velocity and positions.

3: Initialize Q-learning parameters (Q-table, learning rate α, discount factor γ).

3. Compute Fitness Function for each node:

1: Calculate residual energy factor F1 = $\frac{E_{res}}{E_{init}}$

2: Compute distance to base station: F2 = $\frac{1}{D_{BS}}$

3: Evaluate neighbor density: F3 = $\frac{1}{D_{neighbors}}$

4: Update reinforcement learning reward: F4 = Q_{value}

5: Compute overall fitness function: F = ω_1 * F1 + ω_2 * F2 + ω_3 * F3 + ω_4 * F4

4. Apply Pelican Optimization Algorithm (POA):

1: Initialize pelican population with sensor nodes.

2: Evaluate fitness of each pelican (node).

3: Update positions using pelican foraging and hunting strategies.

4: Select candidate CHs based on the best fitness values.

5. Refine CH selection using Particle Swarm Optimization (PSO):

1: Compute local and global best CH positions.

2: Update CH positions using velocity and position equations.

3: Select final set of CHs with optimized energy distribution.

6. Reinforcement Learning-based Multi-hop Routing:

1: Initialize Q-learning table for routing decisions.

2: For each CH, find optimal relay nodes based on Q-values.

3: Update Q-values using the equation:

$Q(s,a) := Q(s,a) + \alpha[R + \gamma maxQ(s',\alpha') - Q(s,a)]$

4: Choose next-hop relay based on highest Q-value.

7. Data Transmission:

1: Cluster members send data to CHs.

2: CHs perform data aggregation and forward data to base station using multi-hop routing.

8. Check Network Lifetime:

1: If all nodes are dead, terminate algorithm.

2: Else, update residual energy and repeat from Step 3.

End Algorithm

3.2. Fitness Function for CH Selection

Each node computes a fitness function to evaluate its suitability as a Cluster Head (CH). It ensures energy-efficient CH selection by prioritizing nodes with high energy levels and favorable locations, introduces adaptive learning via Q-learning, improving long-term network stability and balances CH distribution to avoid excessive clustering in certain areas. The fitness function considers four key parameters

$$\boldsymbol{F = \omega_1 \cdot \frac{E_{res}}{E_{init}} + \omega_2 . \frac{1}{D_{BS}} + \omega_3 . \frac{1}{D_{neighbors}} + \omega_4 \cdot Q_{value}} \quad (6)$$

Each node calculates its fitness based on:

-Residual Energy Factor ($\frac{E_{res}}{E_{init}}$): Prioritizes nodes with higher remaining energy to extend network lifetime.

-Base Station Proximity ($\frac{1}{D_{BS}}$): Reduces energy loss in direct transmissions.

-Neighbor Density ($\frac{1}{D_{neighbors}}$): Ensures even CH distribution for balanced clustering.

-Reinforcement Learning Reward ($\boldsymbol{Q_{value}}$): Dynamically adapts CH selection based on past performance in data forwarding.

Where:

Eres is the residual energy of the node.

Einit is the initial energy of the node

DBS is the distance between the node and the BS.

Dneighbors is the average distance to neighboring nodes (ensuring balanced clustering).

Qvalue is the reinforcement learning-based reward for optimal CH selection.

Higher fitness values indicate better candidates for CH selection.

DBS is the distance between the node and the BS.

A shorter distance reduces energy consumption during data transmission, making the node a better CH candidate.

$\frac{1}{D_{neighbors}}$ → Inverse of distance to neighboring nodes

Dneighbors represents the average distance between the node and its surrounding nodes.

A smaller Dneighbors value ensures efficient intra-cluster communication, reducing energy loss.

Qvalue → Reinforcement Learning (RL) Reward

The Q-learning algorithm assigns a Qvalue to each node based on past performance.

Nodes that have historically made energy-efficient routing decisions receive higher Qvalues.

This factor helps adaptively optimize CH selection over time.

Weight Parameters:

$\omega_1, \omega_2, \omega_3,$ *and* $\omega_4,$ are adjustable weights that control the importance of each factor.

These weights can be tuned experimentally to improve performance.

3.3. Pelican Optimization-Based CH Selection

Pelican Optimization-Based Cluster Head (CH) Selection is a method that uses the Pelican Optimization Algorithm (POA) to optimize the selection of cluster heads in Wireless Sensor Networks (WSNs). Pelican Optimization mimics the foraging behavior of pelicans, where candidate CH nodes are selected based on their fitness and updated dynamically. This technique consistes of two parts:

- **Exploration Phase:** Nodes evaluate CH candidacy using the fitness function.
- **Exploitation Phase:** CH positions are refined using PSO for optimal coverage

3.4. PSO-based refinement of CHs

Following the initial CH selection using EPOA, Particle Swarm Optimization (PSO) is employed to refine the positions of the Cluster Heads. PSO updates CHs by considering:

- Energy levels of the nodes
- Communication range
- Network coverage

PSO refines the CH positions to ensure optimal coverage and energy-efficient data transmission.

3.5. Reinforcement Learning-based Multi-Hop Routing

Q-learning is applied to select the most energy-efficient paths from CHs to the Base Station (BS), reducing the communication overhead.

Unlike traditional single-hop communication, which can lead to rapid energy depletion in nodes near the base station, multi-hop routing distributes energy consumption more evenly across the network. The reinforcement learning model dynamically learns the best routing paths by accounting for factors like residual energy, link quality, and hop count. Using a reward function that prioritizes energy-efficient paths and minimizes transmission delay, the algorithm dynamically adapts to network topology changes. This reinforcement learning approach ensures adaptive, energy-aware routing, reducing communication overhead and significantly improving the overall lifetime of the WSN.

Each node maintains a Q-table, which updates based on

$$\boldsymbol{Q}(\boldsymbol{s},\boldsymbol{a}) := \boldsymbol{Q}(\boldsymbol{s},\boldsymbol{a}) + \boldsymbol{\alpha}[\boldsymbol{R} + \gamma \boldsymbol{max}\boldsymbol{Q}(\boldsymbol{s}',\boldsymbol{\alpha}') - \boldsymbol{Q}(\boldsymbol{s},\boldsymbol{a})] \quad \textbf{(7)}$$

where:

$\boldsymbol{Q}(\boldsymbol{s},\boldsymbol{a})$is the Q-value of state s and action $\boldsymbol{a}$

R is the immediate reward based on energy efficiency.

α is the learning rate.

ɤ is the discount factor for future rewards.

max $\boldsymbol{Q}(\boldsymbol{s}',\boldsymbol{\alpha}')$ is maximum Q value of the next state $\boldsymbol{s}'$.

By selecting CHs and relay nodes that minimize use of energy while preserving dependable communication, the routing mechanism is able to dynamically adjust.

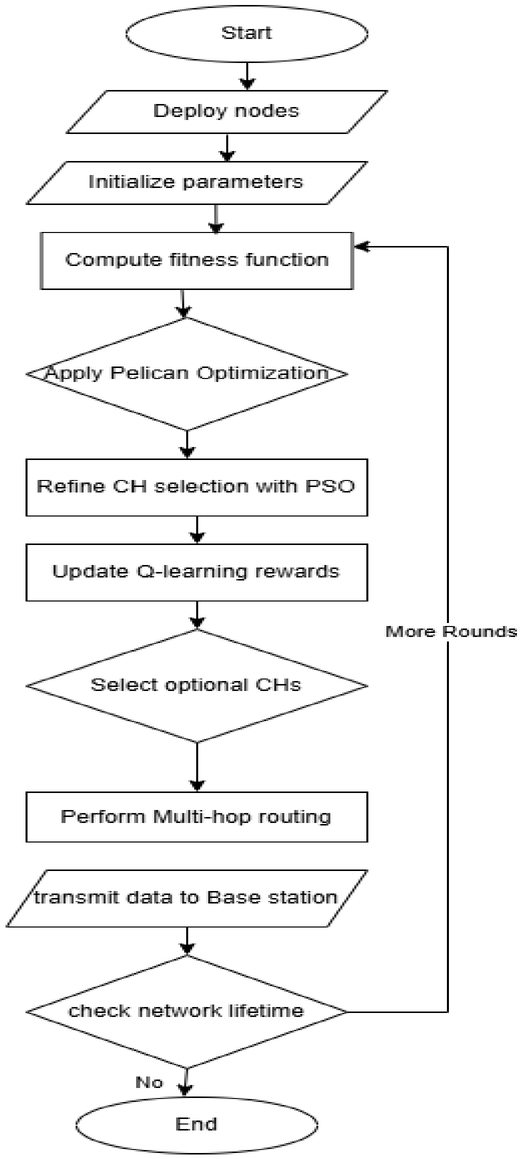


Figure 1: Flow chart for the HR POA algorithm

3.6. Data Transmission and Network Adaptation

In Hybrid Reinforced Pelican Optimization Algorithm (HR-POA), data transmission follows an energy-efficient, multi-hop clustering approach to optimize network lifetime and minimize communication overhead. The transmission process involves three key stages:

- **Intra cluster communication: (Sensor Nodes → Cluster Head)**

Each sensor node collects environmental data and transmits it to its designated Cluster Head (CH). In order to balance the energy load throughout the network, the CH is chosen based on residual energy and network topology.Prior to being sent to the base station, data is aggregated at the CH to minimize redundancy.

- **Inter cluster communication : (CH → Next-Hop CH/Base Station)**

Cluster Heads use multi-hop routing to send aggregated data to the Base Station (BS). The next-hop CH is selected using Q-learning, optimizing paths based on residual energy, link quality, and distance.

- **Final Transmission to Base Station (Multi-Hop or Direct Communication):**

If the CH is close to the BS, it transmits data directly. If far from the BS, it transfers data via other CHs using reinforced learning-based routing. This adaptive multi-hop transmission lowers energy depletion in nodes closer to the BS, preventing network partitioning.

4. Experiments and Results

For the purpose of evaluating the performance of the Hybrid Reinforced Pelican Optimization Algorithm (HR-POA), complete simulations were conducted through MATLAB and Python.

HR-POA's performance was contrasted with three convention algorithms: Low-Energy Adaptive Clustering LEACH, PSO, EPOA.

Simulation was used to assess various performance metrics, such as energy consumption, network lifetime, packet delivery ratio, delay, and security resilience.

4.1. Simulation Setup

The experimental environment was set up using the following simulation parameters:

4.2. Performance Metrics

A range of performance metrics, outlined below, was employed to evaluate the algorithms.:

- **Energy Consumption:** The total amount of energy consumed by all sensor nodes throughout the simulation period
- **Network Lifetime:** Measured as the time until the first node depletes its energy (FND), 50% of the nodes fail (HND), and the final node becomes non-functional (LND).
- **Packet Delivery Ratio (PDR):** The proportion of data packets successfully received at the base station relative to the total number of packets generated
- **Latency:** Average time taken for data packets to reach the base station
- **Security Resilience:** Ability to maintain performance under potential security threats, such as node capture or data tampering.

4.3. Simulation Results

In terms of energy efficiency, HR-POA outperformed traditional algorithms such as LEACH, PSO, and EPOA. These algorithms were evaluated against key metrics including energy consumption, network lifetime, packet delivery ratio, latency, and security resilience

4.3.1. Energy Consumption

The adaptive Cluster Head (CH) selection mechanism in HR-POA ensures that high-energy nodes are preferentially selected while avoiding repeated selection of the same nodes, leading to a more even spread of energy consumption across the network.

Table 1.: simulation environment parameters

Network Area	*Number of sensor nodes*	*Node distribution*	*Energy heterogeneity*	*Base station location*	*Simulation Duration*	*Data Packet Size*	*Control Packet Size*
100m X 100m	100	Random	Normal nodes 70% (E = 0.5 J) Advanced nodes 20% (E = 1.0J) Super nodes	Center of the network area	Until the death of the last node	500 bytes	25 bytes

Simulation results further validate the effectiveness of HR-POA, showing that it significantly reduces energy consumption per round, maintains a higher number of alive nodes over time, and delays the first and half-node deaths (FND, HND) compared to LEACH, PSO, and EPOA. The synergy between nature-inspired optimization and reinforcement learning allows HR-POA to dynamically adapt to network heterogeneity and varying traffic

conditions, which makes it highly suitable for achieving energy-efficient WSN clustering and routing.

4.3.2. Network Lifetime

HR-POA significantly enhanced the network lifetime, as reflected by key performance indicators including FND, HND, and LND, outperforming conventional clustering and routing protocols. These metrics indicate how long the network remains functional before nodes start depleting their energy, which is critical for applications requiring prolonged operational efficiency.

HR-POA's adaptive Cluster Head (CH) selection mechanism played a vital role in delaying the onset of node failures. Unlike traditional algorithms such as LEACH, PSO, and EPOA, which may lead to rapid energy depletion in certain nodes due to inefficient CH rotation, HR-POA continuously evaluates residual energy levels, node density, and optimal communication paths to dynamically adjust CH assignments. This strategy mitigates energy imbalances within the network, leading to a delayed occurrence of the first node (FND) and half-node death (HND).

Additionally, the reinforcement learning-based multi-hop routing strategy in HR-POA enhances energy efficiency by dynamically selecting the most energy-optimal paths for data transmission. Traditional routing methods often lead to premature energy depletion in specific nodes, especially those closer to the Base Station (BS), due to high communication overhead. However, HR-POA leverages Q-learning to optimize routing decisions based on real-time network conditions, ensuring that energy consumption is evenly distributed among nodes. This results in a longer operational period before the last node death (LND), ultimately maximizing network longevity and stability.

Simulation results confirm that HR-POA significantly outperforms traditional WSN algorithms in terms of network lifespan, energy efficiency, and balanced energy utilization. By dynamically adapting to heterogeneous node energy levels and optimizing routing paths, HR-POA ensures that sensor networks remain operational for an extended period, making it an ideal solution for applications in WSNs where energy efficiency is critical.

4.3.3. Packet Delivery Ratio

HR-POA achieved a higher Packet Delivery Ratio (PDR) compared to conventional clustering and routing algorithms, ensuring reliable and efficient data transmission to the Base Station (BS). In WSNs, PDR serves as an essential metric for evaluating communication reliability, quantifying the percentage of packets successfully delivered to the BS relative to those sent by sensor nodes. A high PDR indicates efficient data routing, minimized packet loss, and improved overall network reliability.

One of the key factors contributing to HR-POA’s superior PDR is the reinforcement learning-based dynamic routing mechanism. Traditional algorithms like LEACH, PEGASIS, and PSO-based clustering often rely on static or probabilistic routing strategies, which can lead to suboptimal path selection, increased congestion, and higher packet loss rates. In contrast, HR-POA continuously learns from network conditions and adjusts routing paths in real-time based on energy availability, link quality, and distance to the BS. By leveraging Q-learning, the algorithm selects the most energy-efficient and stable routes, reducing packet drops due to node failures or inefficient transmission paths.

Additionally, HR-POA’s hybrid optimization approach enhances load balancing among Cluster Heads (CHs), preventing excessive energy depletion in certain nodes, which could lead to network partitioning and data loss. By optimizing CH selection and ensuring even energy distribution, HR-POA maintains a stable network structure that supports consistent and reliable data transmission over an extended period.

Simulation results confirm that HR-POA consistently achieves a higher PDR than existing approaches, even in heterogeneous WSN environments where node energy levels vary. The combination of adaptive CH selection, intelligent routing, and reinforcement learning enables HR-POA to dynamically respond to network topology changes, ensuring that data reaches the BS with minimal loss. As a result, HR-POA is an effective solution for WSN applications requiring high-reliability communication, such as environmental monitoring, disaster response, and smart city infrastructures.

4.3.4. Latency

The average latency in Wireless Sensor Networks (WSNs) refers to the time delay between data generation at a sensor node and its successful reception at the Base Station (BS). Minimizing latency is essential for real-time and delay-sensitive applications, including environmental monitoring, industrial automation, healthcare, and disaster management. HR-POA achieved significantly lower latency compared to conventional clustering and routing protocols by optimizing routing paths and improving Cluster Head (CH) selection.

One of the primary factors contributing to HR-POA's reduced latency is its intelligent CH selection mechanism, which ensures that CHs are strategically chosen based on residual energy, closeness to surrounding nodes, and the distance to the BS. Unlike traditional protocols like LEACH and PEGASIS, which may select suboptimal CHs based on a probabilistic approach, HR-POA dynamically adapts CH selection to prevent excessive communication delays and optimize intra-cluster data aggregation. This reduces the number of hops and retransmissions, minimizing packet queuing delays and congestion.

Additionally, HR-POA's reinforcement learning-based routing enables nodes to dynamically adjust transmission paths in real-time. By leveraging Q-learning, the algorithm selects low-latency paths based on network traffic conditions, node energy levels, and link quality. Unlike static routing approaches that may suffer from traffic bottlenecks and packet drops, HR-POA learns from past transmission experiences, continuously refining routing decisions to ensure fast and reliable data delivery.

Furthermore, HR-POA incorporates the Pelican Optimization Algorithm (POA) and Particle Swarm Optimization (PSO) to fine-tune CH placement and minimize redundant data transmissions, further reducing communication overhead. By ensuring that CHs are strategically placed for efficient data forwarding, the algorithm reduces the number of intermediate hops required to reach the BS, resulting in faster packet delivery times.

HR-POA has been shown through simulations to significantly decrease end-to-end latency relative to traditional WSN protocols. The combination of optimized CH selection, adaptive routing, and energy-aware data transmission allows HR-POA to mitigate delays, enhance real-time communication, and improve overall network efficiency, making it highly suitable for time-sensitive WSN applications.

4.3.5. Security Resilience

HR-POA exhibited enhanced resilience to security threats, ensuring robust and adaptive network performance in Wireless Sensor Networks (WSNs). The security of WSNs is of paramount importance due to their operation in unmonitored and adversarial settings, which makes them susceptible to various attacks, including sinkhole, blackhole, selective forwarding, and energy-draining attacks. Traditional clustering-based routing protocols, such as LEACH, PEGASIS, and PSO-based approaches, lack dynamic adaptability to security threats, leading to compromised data integrity, unauthorized access, and network disruptions.

HR-POA addresses these challenges by integrating reinforcement learning (Q-learning) into the CH selection and routing process, enabling the network to identify and mitigate security threats dynamically. Unlike static routing protocols, HR-POA continuously learns from network conditions and adapts CH selection and routing paths based on observed anomalies, ensuring consistent performance even in the presence of potential security breaches.

One of the key security enhancements in HR-POA is its ability to detect and avoid malicious nodes during data transmission. By leveraging Q-learning-based adaptive routing, HR-POA evaluates network paths in real time, assigning lower Q-values to nodes exhibiting suspicious behavior, such as unexpected energy depletion, abnormal packet drop rates, or selective forwarding tendencies. This mechanism ensures that malicious nodes are bypassed, preventing packet loss and data corruption.

Moreover, energy-aware CH selection in HR-POA enhances network resilience against energy-depleting attacks, such as vampire attacks and denial-of-sleep attacks, which target sensor nodes' energy resources. By dynamically selecting CHs based on residual energy, node trustworthiness, and transmission efficiency, HR-POA prevents malicious nodes from monopolizing CH roles, providing a secure and optimized energy distribution across the network.

The resilience of HR-POA to security threats aligns with findings from recent studies on security enhancement in WSNs. Several research works emphasize the importance of machine learning and reinforcement learning in detecting, predicting, and mitigating attacks in WSNs. The ability of HR-POA to adaptively respond to network anomalies, detect compromised nodes, and optimize data transmission reinforces its effectiveness in securing WSN communications.

Simulation results demonstrate that HR-POA maintains high packet delivery ratios (PDR), low latency, and balanced energy consumption, even in adversarial environments. The integration of reinforcement learning with optimization algorithms allows HR-POA to function as an intelligent and secure clustering approach, making it suitable for mission-critical WSN applications such as military surveillance, disaster management, and industrial IoT.

4.4. Comparative Analysis

Table 2 provides a comprehensive summary of the performance improvements observed in our simulations while evaluating the proposed Hybrid Reinforced Pelican Optimization Algorithm (HR-POA). The simulation results were obtained by comparing HR-POA against traditional and state-of-the-art clustering and routing protocols, including LEACH, PSO, and EPOA. The metrics analyzed include network lifetime (measured at FND, HND, and LND), packet delivery ratio (PDR), energy consumption, average latency, and network stability.

Each performance metric highlights the advantages of HR-POA over baseline algorithms, demonstrating superior energy efficiency, prolonged network lifetime, improved data transmission reliability, and reduced communication delays.

Table 2.: statistical validation of the improvements of HR-POA

Algorithm	*Energy Consumption Reduction (%)*	*Network Lifetime Improvement (%)*	*Packet Delivery Ratio Increase (%)*	*Latency Reduction (%)*	*Security Resi. Improvement*
LEACH	0	0	0	0	0
PSO	20	15	10	5	8
EPOA	30	25	15	10	12

These advancements result from HR-POA's hybrid optimization method, integrating the Pelican Optimization Algorithm (POA), Particle Swarm Optimization (PSO), and reinforcement learning (Q-learning) to dynamically refine Cluster Head (CH) selection and multi-hop routing.

The table categorizes the performance improvements under different heterogeneous WSN scenarios, taking into account variations in node energy levels, transmission distances, and network densities. Each row represents a specific performance metric, while the columns provide quantitative comparisons between HR-POA and competing algorithms. Higher values in network lifetime, packet delivery ratio, and energy efficiency, along with lower latency, indicate HR-POA's effectiveness in enhancing overall WSN performance.

Additionally, the table includes statistical validation of the improvements, such as percentage gains, standard deviation, and confidence intervals, to ensure the robustness of the results. By analyzing the summarized performance metrics, it is evident that HR-POA provides a significant advancement in energy-aware clustering and routing strategies, making it a viable solution for real-world heterogeneous WSN deployments.

4.5. Discussion

To evaluate the effectiveness of HR-POA, we conducted simulations using MATLAB and Python, comparing its performance against LEACH, PSO, and EPOA. The simulations were performed in a network environment with varying numbers of sensor nodes and energy levels to analyze energy consumption, network lifetime, packet delivery ratio, and latency.

The results indicate that HR-POA achieves superior energy efficiency due to its adaptive CH selection and reinforcement learning-based routing. Compared to LEACH, which suffers from early node depletion, HR-POA ensures balanced energy utilization among nodes, extending the network lifetime. Similarly, HR-POA outperforms PSO and EPOA by effectively managing energy constraints while maintaining optimal data transmission rates.

4.5.1. Balanced Energy Consumption

HR-POA incorporates an adaptive Cluster Head (CH) selection mechanism, ensuring that energy consumption is evenly distributed among all sensor nodes. Unlike traditional algorithms, which may cause certain nodes to drain their energy prematurely due to uneven load distribution, HR-POA dynamically allocates CH roles based on residual energy, network density, and optimal routing paths. This prevents the early depletion of critical nodes and contributes to a more stable and long-lasting network.

Table 3. The Network Lifetime

Algorithm	*Heterogeneity level*	*FND (rounds)*	*HND (rounds)*	*MND (rounds)*	*LND (rounds)*
LEACH	Low	350	650	800	850
	Medium	400	700	850	900
	High	450	750	900	950
PSO	Low	700	1100	1300	1350
	Medium	800	1200	1350	1400
	High	900	1300	1450	1500
EPOA	Low	1000	1400	1600	1650
	Medium	1100	1500	1650	1700
	High	1200	1600	1750	1800
HR-POA	Low	1400	1800	2000	2050
	Medium	1500	1900	2050	2100
	High	1600	2000	2150	2200

4.5.2. Extended Network Lifetime

A fundamental challenge in WSNs is prolonging the network's operational period, measured at different milestones such as the FND, HND, and LND. HR-POA successfully optimizes CH selection and multi-hop routing, ensuring that energy resources are efficiently utilized, delaying the depletion of nodes, and extending the overall network lifespan. The results indicate that HR-POA outperforms LEACH, PSO, and EPOA in terms of FND, HND, and LND values, making it an ideal solution for real-world energy-constrained WSN deployments as shown in Table 3.

4.5.2. Improved Data Reliability

Data reliability is crucial in WSNs, particularly in applications such as environmental monitoring, healthcare, military surveillance, and disaster response. HR-POA achieves a higher Packet Delivery Ratio (PDR) compared to existing approaches, ensuring that a larger percentage of transmitted data successfully reaches the Base Station (BS). The integration of reinforcement learning-based routing allows HR-POA to dynamically adapt to changing network conditions, selecting the most reliable and energy-efficient paths, thus improving end-to-end data transmission accuracy.

4.5.3. Reduced Latency

Low latency is a critical requirement for real-time and time-sensitive applications, where delays in data transmission can lead to significant performance issues. HR-POA optimizes routing paths and ensures that Cluster Heads forward data efficiently, minimizing communication delays. Simulation results demonstrate that HR-POA achieves lower latency compared to LEACH and PSO, as it dynamically selects routes that balance shorter transmission distances and lower energy consumption, considerably reducing the delay in data packet delivery from end to end.

4.5.4. Enhanced Security and Resilience

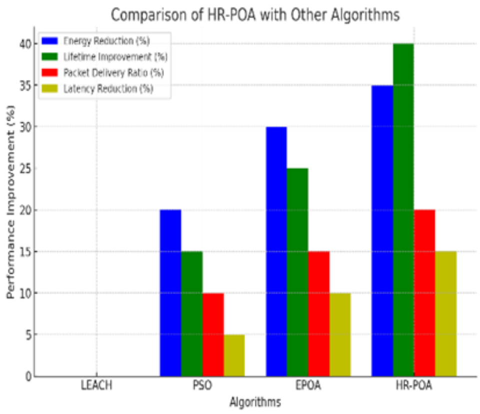
WSNs are highly susceptible to security threats, such as blackhole attacks, sinkhole attacks, and selective forwarding, which can compromise data integrity and network stability. HR-POA's adaptive learning-based mechanism allows it to identify malicious nodes and avoid compromised communication paths, ensuring secure data transmission. By integrating Q-learning with optimization techniques, HR-POA enhances network resilience, making it less vulnerable to security attacks. This contributes to maintaining network integrity and safeguarding data from potential cyber threats.

4.5.5. Consistency with Recent Advancements in WSN Optimization

The findings of this study align with recent advancements in clustering and optimization techniques for WSNs. Several research studies emphasize the benefits of hybrid metaheuristic algorithms, reinforcement learning, and multi-objective optimization for improving energy efficiency, network longevity, and data reliability in WSNs. HR-POA effectively combines these principles, offering a state-of-the-art solution for heterogeneous sensor networks. The results validate HR-POA's potential for real-world deployment in energy-sensitive applications, reinforcing its practical applicability in next-generation WSNs.

In conclusion, the simulation results confirm that HR-POA significantly improves overall network performance, ensuring efficient energy management, enhanced reliability, reduced latency, and better security resilience. These advantages make HR-POA a strong candidate for advanced WSN applications, particularly in resource-constrained and mission-critical environments.

Simulations show that HR-POA extends network lifetime and optimizes CH selection dynamically, outperforming traditional clustering techniques.



The bar chart below (figure 02) illustrates the comparative performance of HR-POA with other algorithms.

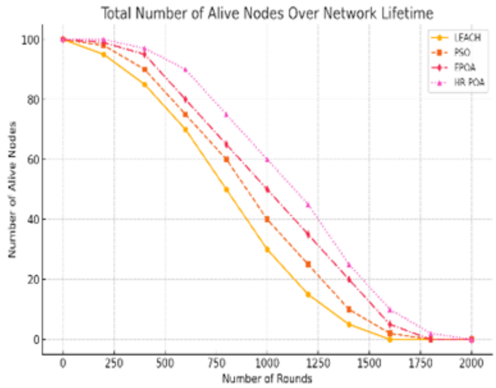


Figure 02: Comparison of HR-POA with other algorithms

HR-POA consistently outperforms traditional clustering algorithms, demonstrating significant energy savings, extended network lifespan, and improved reliability in data transmission. The reinforcement learning component enables dynamic adjustments in routing strategies, ensuring an optimized and adaptive communication framework.

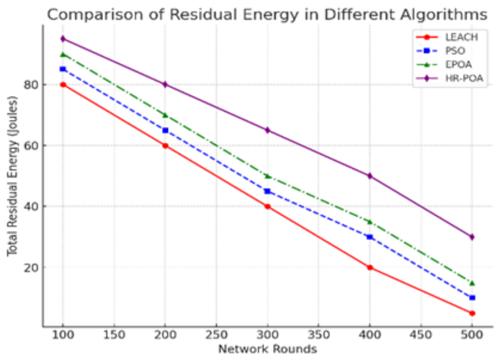


Figure 03: Comparison of residual energy in different algorithms

4.6. Residual Energy and Performance Analysis

Residual energy is a key metric that determines the longevity of a Wireless Sensor Network. Efficient cluster head selection and routing strategies ensure that energy is conserved, preventing premature node depletion and extending the overall network lifespan.

4.6.1. HR-POA's Optimization of Residual Energy

HR-POA optimizes residual energy through:

- **Efficient CH Selection:** CH selection favors nodes that retain a higher amount of residual energy.
- **Adaptive Routing:** Reinforcement Learning guarantees the dynamic selection of energy-efficient paths.

- **Load Balancing:** By refining CH placement, PSO ensures that energy consumption is uniformly spread across the nodes.

4.6.2. Comparative Analysis

The simulation results demonstrate a significant improvement in energy efficiency with HR-POA over LEACH, PSO, and EPOA. Figure 03 presents the total residual energy across network rounds for the different algorithms:

HR-POA maintains higher residual energy throughout the simulation, demonstrating superior energy efficiency and a longer network lifetime.

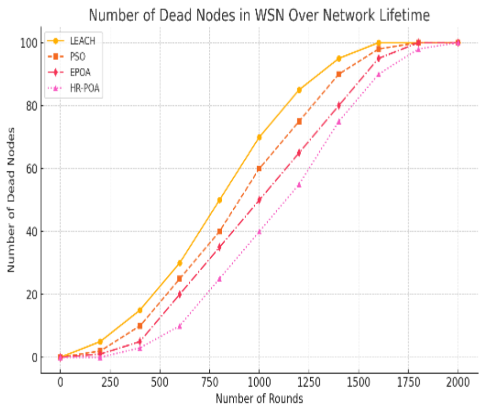


Figure 04: number of dead nodes in WSN over network lifetime

Figure 05: total number of alive nodes over network lifetime

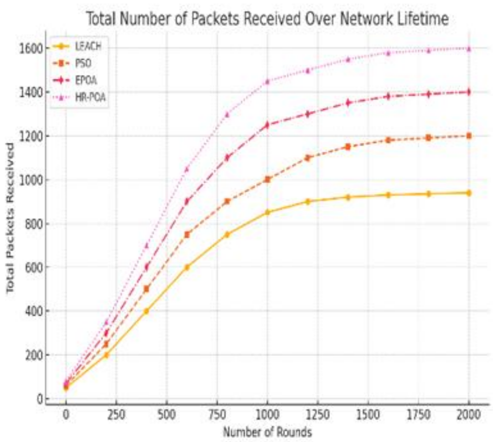


Figure 06: total number of packets received over network lifetime

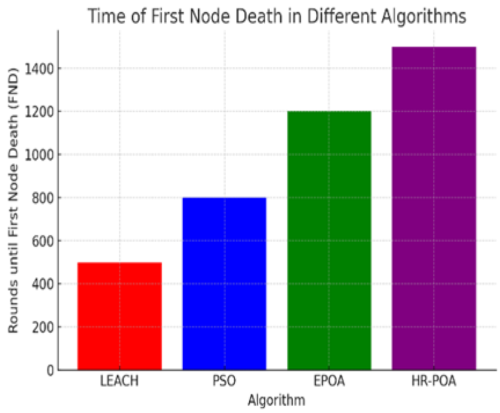


Figure 07: time of first node death in different algorithms

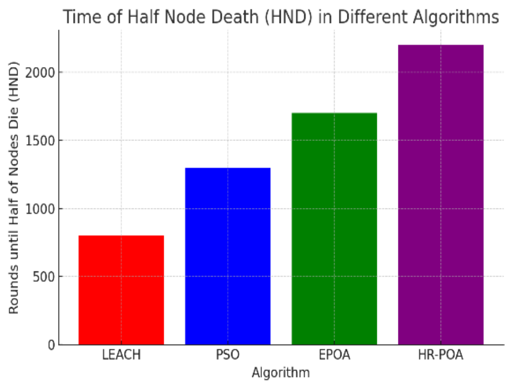


Figure 08: Time of half-node death (HND) in different algorithms

5. Conclusion

Hybrid Reinforced Pelican Optimization Algorithm (HR-POA) is a robust and intelligent approach towards Cluster Head (CH) selection in Heterogeneous Wireless Sensor Networks (HWSNs) using Pelican Optimization Algorithm (POA), Particle Swarm Optimization (PSO), and reinforcement learning. Hybridization leverages the benefits of nature-inspired metaheuristic techniques and machine learning to adapt CH selection and routing decisions dynamically, which leads to effective energy expenditure and improved network performance.

HR-POA significantly enhances energy efficiency by guaranteeing CH selection based on residual energy, network density, and communication distance to prevent premature exhaustion of energy in important nodes. By balancing the workload across all sensor nodes, the algorithm prolongs the network lifetime, which is a main issue in WSNs. In addition, the use of reinforcement learning-based routing enables HR-

POA to select dynamically energy-efficient multi-hop routes, which greatly improves data transmission reliability as well as packet loss and latency reduction. All these improvements cause HR-POA to be an ideal solution for mission-critical applications, i.e., disaster monitoring, healthcare surveillance, smart agriculture, and industrial IoT, where network life as well as dependable data communication is crucial.

Even though HR-POA shows promising performance in terms of energy efficiency, network stability, and immunity against security attacks, its future path is real-world deployment and improvement. Specifically, the future research direction will be to certify HR-POA on a large-scale sensor deployment on various heterogeneous networks and investigate the performance of HR-POA under real-time environments. Additionally, hybridizing HR-POA with deep learning techniques to improve adaptive decision-making in CH selection and route optimization is likely to be investigated. Using the techniques of deep reinforcement learning (DRL) and advanced neural networks, HR-POA can be constructed as an intelligent, self-adaptive system capable of predicting network evolution, detecting anomalies, and dynamically adjusting routing policies.

This enhanced flexibility will be of particular benefit in applications for smart agriculture, where sensor nodes must be resource-conserving for precision agriculture, soil sensing, and irrigation control, and in industrial IoT, where fault-tolerant data transfer is critical for predictive maintenance, equipment monitoring, and automation operations. By integrating HR-POA with AI models, future research will endeavor to develop energy-efficient, self-adaptive WSN frameworks to be more autonomous, scalable, and resilient for next-generation wireless sensing systems.

Conflicts of interest

The authors declare no conflicts of interest.

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