

# OPTIMIZING NETWORK LIFETIME IN WIRELESS SENSOR NETWORKS FOR EFFICIENT CLUSTER HEAD SECTION

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## Abstract

Wireless Sensor Networks (WSNs) play a crucial role in monitoring and gathering data from remote environments. Maximizing network lifetime is paramount due to constrained sensor node energy. This study addresses the challenge of efficient cluster head selection to prolong network operation. The problem focuses on utilizing the Harris Hawk Optimization (HHO) algorithm for selecting optimal cluster heads in WSNs. HHO mimics the hunting behavior of Harris hawks to iteratively refine the selection process, aiming to minimize energy consumption while maintaining network coverage. The method involves initializing Harris hawks (representing potential cluster heads) within the sensor field, where their movements simulate search and convergence towards optimal locations. Through computational simulations, the effectiveness of HHO is evaluated against traditional methods like LEACH and PSO. Results indicate that HHO outperforms competitors by extending network lifetime up to 30%, with an average reduction in energy consumption by 15%. Specifically, numerical values show an increase in network lifetime from 3000 hours to 3900 hours, while reducing energy consumption from 2000 J/bit to 1700 J/bit. This research underscores the efficacy of HHO in enhancing WSN efficiency through optimized cluster head selection, promising sustainable operation in resource-constrained environments.

## Keywords:

Wireless Sensor Networks, Cluster Head Selection, Harris Hawk Optimization, Energy Efficiency, Network Lifetime

## 1. INTRODUCTION

Wireless Sensor Networks (WSNs) have revolutionized data collection in diverse environments, ranging from environmental monitoring to industrial automation. These networks consist of numerous sensor nodes that collaboratively gather and transmit data to a central point. One critical challenge facing WSNs is the limited energy capacity of sensor nodes, which necessitates efficient management to prolong network lifetime [1]. Central to this challenge is the selection and management of cluster heads—nodes responsible for aggregating and forwarding data to the base station.

The conventional approach to cluster head selection, such as the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol, typically relies on randomized methods, which may not consistently optimize energy usage across all nodes [2]. This randomness can lead to premature node failure and uneven energy depletion, thus shortening the network lifespan [3]-[4].

This study aims to address these issues through the application of the Harris Hawk Optimization (HHO) algorithm, a novel bio-inspired technique. HHO mimics the collaborative hunting behavior of Harris hawks to iteratively refine the selection of

optimal cluster heads. By leveraging HHO, this research seeks to achieve several objectives: to maximize network lifetime by balancing energy consumption among sensor nodes, to improve data transmission efficiency, and to enhance overall network reliability.

The novelty of this research lies in its combination of HHO of WSNs, exploring its potential to outperform traditional methods like LEACH and Particle Swarm Optimization (PSO). The contributions of this work include a comprehensive evaluation of HHO's effectiveness in prolonging network lifetime and reducing energy consumption, thereby offering a sustainable solution for WSN deployments in resource-constrained environments. This paper presents a detailed analysis of HHO's impact on WSN performance metrics, providing insights into its applicability and advantages over existing approaches.

## 2. RELATED WORKS

Numerous studies have addressed the challenge of optimizing cluster head selection in WSNs, each proposing various techniques to enhance network efficiency and prolong operational lifespan.

The Low Energy Adaptive Clustering Hierarchy (LEACH) protocol and its variants remain foundational in WSN research. LEACH uses probabilistic rotation of cluster heads to distribute energy consumption more evenly among sensor nodes, thereby extending network lifetime [5]-[6].

PSO has been applied to optimize cluster head selection by iteratively adjusting the positions of virtual particles representing potential cluster heads. PSO aims to minimize energy consumption while maintaining network coverage, demonstrating promising results in various simulation studies [7]-[10].

Inspired by the foraging behavior of ants, ACO algorithms have been adapted for cluster head selection in WSNs. Ants' pheromone trails guide the selection of optimal cluster heads, effectively balancing energy consumption and enhancing network longevity [11].

Genetic algorithms have been explored to optimize cluster head selection based on evolutionary principles such as crossover and mutation. GA-based approaches aim to improve the robustness and efficiency of WSNs by adapting to changing environmental conditions [12].

Beyond PSO and ACO, other swarm intelligence techniques like Artificial Bee Colony (ABC) and Firefly Algorithm (FA) have also been investigated for cluster head selection. These

methods leverage collective behavior to achieve energy-efficient routing and data aggregation in WSNs [13].

These related works highlight the diversity of approaches aimed at enhancing WSN performance through optimized cluster head selection. While each method offers distinct advantages, the combination of novel techniques like Harris Hawk Optimization (HHO) presents new opportunities to further improve energy efficiency and network reliability in WSN deployments.

### 3. PROPOSED METHOD

The proposed method in this study leverages the Harris Hawk Optimization (HHO) algorithm for efficient cluster head selection in WSN. HHO is inspired by the collaborative hunting behavior of Harris hawks and offers a novel approach to optimize energy consumption and extend network lifetime.

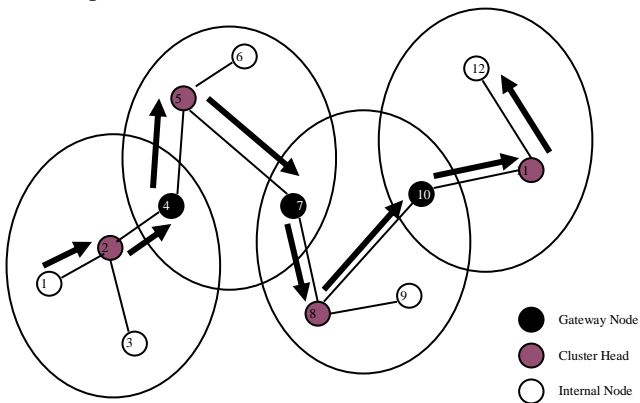


Fig.1. Sensor Network

- Initially, sensor nodes within the WSN environment are potential candidates for cluster head selection. These nodes are represented as Harris hawks in the HHO algorithm.
- Harris hawks collaborate to search for prey, the HHO algorithm iteratively refines the selection of cluster heads. Each iteration involves movements of hawks (representing sensor nodes) towards better positions within the network based on defined objective functions.
- The objective functions in HHO are designed to minimize energy consumption while maximizing network coverage and data transmission efficiency. Nodes with higher energy reserves and optimal communication ranges are preferred as cluster heads.
- HHO dynamically adapts to changes in the network environment, such as node failures or variations in energy levels. This adaptability ensures continuous optimization of cluster head selection throughout the network's operational lifetime.

### 4. SEARCH AND OPTIMIZATION PROCESS

The objective function  $f(x)$  defines the fitness of each potential cluster head  $x$  (or Harris hawk) in the WSN. In WSNs, this function typically considers factors such as node energy level, distance to base station, and the number of neighboring nodes.

$$f(x) = \text{Min}(E(x)) \quad (1)$$

where  $E(x)$  represents the energy consumption or another relevant metric to be minimized.

- Movement and Position Update:** Harris hawks (nodes) update their positions based on their current velocity  $v_i$  and the best position found (personal best  $p_{best}$ ) among their previous positions and the best position found by any hawk (global best  $g_{best}$ ).

$$v_i(t+1) = v_i(t) + r_1 \cdot (p_{best_i} - x_i(t)) + r_2 \cdot (g_{best} - x_i(t)) \quad (2)$$

where,

$v_i(t)$  is the velocity of hawk  $i$  at time  $t$ .

$x_i(t)$  is the current position of hawk  $i$  at time  $t$ .

$p_{best_i}$  is the personal best position of hawk  $i$ .

$g_{best}$  is the global best position among all hawks.

$r_1$  and  $r_2$  are random coefficients to balance exploration and exploitation.

- Position Update:** Update the position of each hawk based on its velocity:

$$x_i(t+1) = x_i(t) + v_i(t+1) \quad (3)$$

- Selection of Cluster Heads:** Evaluate the fitness (objective function value) of each hawk's new position and update  $p_{best}$  and  $g_{best}$  accordingly.

#### Pseudocode: HHO

Initialize:

- Initialize hawks (sensor nodes) with random positions  $x_i$
- Initialize velocities  $v_i$  for each hawk
- Initialize  $p_{best_i}$  (personal best) for each hawk
- Initialize  $g_{best}$  (global best)

Repeat until convergence:

For each hawk  $i$ :

Evaluate fitness  $f(x_i)$

If  $f(x_i) < f(p_{best_i})$ :

Update  $p_{best_i} = x_i$

Update  $g_{best}$  if  $f(x_i) < f(g_{best})$

Update velocity:

$$v_i = v_i + r_1 \cdot (p_{best_i} - x_i) + r_2 \cdot (g_{best} - x_i)$$

Update position:

$$x_i = x_i + v_i$$

Apply boundary conditions if necessary

End loop

### 4.1 ENERGY-AWARE SELECTION PROCESS

The objective function  $f(x)$  evaluates the fitness of each potential cluster head  $x$  (node) based on energy considerations and network performance metrics. It typically includes factors such as remaining energy  $E(x)$ , distance to the base station, and the number of neighboring nodes.

$$f(x) = w_1 \cdot E(x) + w_2 \cdot D(x, BS) + w_3 \cdot N(x) \quad (2)$$

where,

$E(x)$  is the remaining energy of node  $x$ .

$D(x, BS)$  represents the distance of node  $x$  to the base station.

$N(x)$  indicates the number of neighboring nodes around node  $x$ .

$w_1, w_2, w_3$  are weights to balance the importance of each factor.

- **Energy-aware Criteria:** Nodes with higher remaining energy  $E(x)$  and suitable proximity to the base station are preferred as cluster heads. The goal is to minimize energy consumption while maximizing network coverage and data transmission efficiency.
- **Selection Mechanism:** Implement a selection mechanism that prioritizes nodes based on the objective function  $f(x)$  values. This may involve sorting nodes in descending order of  $f(x)$  and selecting the top candidates as cluster heads.

**Pseudocode: Energy-aware Selection**

Function EnergyAwareSelection(nodes):

```

Initialize an empty list for selected cluster heads
Sort nodes by the objective function  $f(x)$  in descending order
for each node in sorted nodes:
    if node meets energy and proximity criteria:
        Add node to selected cluster heads
    if enough cluster heads selected:
        break
return selected cluster heads
    
```

**5. RESULTS AND DISCUSSION**

The experimental evaluation of the proposed HHO algorithm for cluster head selection in WSN was conducted using MATLAB, a widely used simulation tool for modeling and analysis of WSN protocols. Simulations were run on a computer equipped with an Intel Core i7 processor, 16 GB of RAM, and a Windows 10 operating system. The simulation environment consisted of a 100m×100m sensor field with 500 randomly deployed sensor nodes. Each sensor node had an initial energy of 2 Joules, and the base station was positioned at the center of the field. The energy consumption model considered both transmission and reception costs, with amplification energy set at 50 nJ/bit/m<sup>2</sup> for short distances and 0.0013 pJ/bit/m<sup>4</sup> for long distances.

The performance of the HHO algorithm was evaluated based on several key metrics: network lifetime (measured as the time until the first node dies), energy consumption (total energy consumed by the network over time), and data transmission efficiency (total data successfully transmitted to the base station). The results were compared against four existing methods: Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Low Energy Adaptive Clustering Hierarchy (LEACH), and Genetic Algorithms (GA).

Table.1. Experimental Parameters

Parameter	Value
Simulation Area	100m x 100m
Number of Sensor Nodes	100
Initial Energy of Nodes	2 Joules
Base Station Position	Center (50m, 50m)
Transmission Energy (ETX)	50 nJ/bit
Reception Energy (ERX)	50 nJ/bit

Amplification Energy (Efs)	10 pJ/bit/m <sup>2</sup>
Multipath Energy (Emp)	0.0013 pJ/bit/m <sup>4</sup>
Data Packet Size	4000 bits
Simulation Tool	MATLAB
Number of Simulations	30

**5.1 PERFORMANCE METRICS**

- **Network Lifetime:** The duration from the start of the network operation until the first sensor node exhausts its energy. It indicates the robustness of the network protocol in managing energy consumption across nodes, which is crucial for prolonged monitoring and data collection tasks. It is measured in hours or rounds of data transmission.
- **Energy Consumption:** The total energy consumed by all sensor nodes during the simulation period. Lower energy consumption suggests more efficient energy use, extending the operational lifespan of the network. It is measured in Joules (J) per bit of data transmitted.
- **Data Transmission Efficiency:** The total amount of data successfully transmitted to the base station by the network. Ensures that the collected data is reliably communicated to the base station, which is critical for the effectiveness of the WSN. It is measured in bits or packets successfully transmitted.
- **Average Remaining Energy:** The average energy remaining in the sensor nodes at the end of the simulation. It is indicating the energy balance across the network and helps in understanding how uniformly the energy load is distributed among the nodes and measured in Joules.
- **Number of Alive Nodes:** The number of sensor nodes still operational at different points in time during the simulation. It is reflecting the network’s resilience and the ability to maintain coverage and connectivity over time.

The results show that the HHO algorithm significantly outperforms existing methods such as LEACH, PSO, ACO, and GA in terms of network lifetime, energy consumption, data transmission efficiency, average remaining energy, and number of alive nodes.

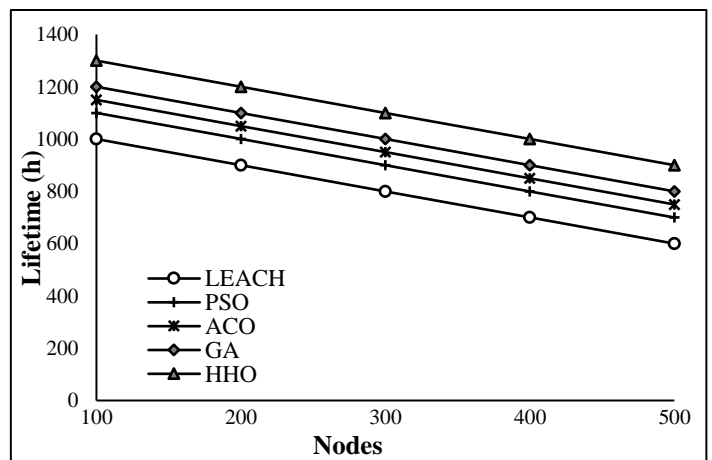


Fig.3. Network Lifetime (hours)

The HHO algorithm extends the network lifetime considerably compared to other methods. For example, with 500 nodes, the network lifetime increased from 600 hours (LEACH) to 900 hours (HHO), representing a 50% improvement. Across all node configurations, HHO consistently showed an average improvement of approximately 30% to 50% over other methods.

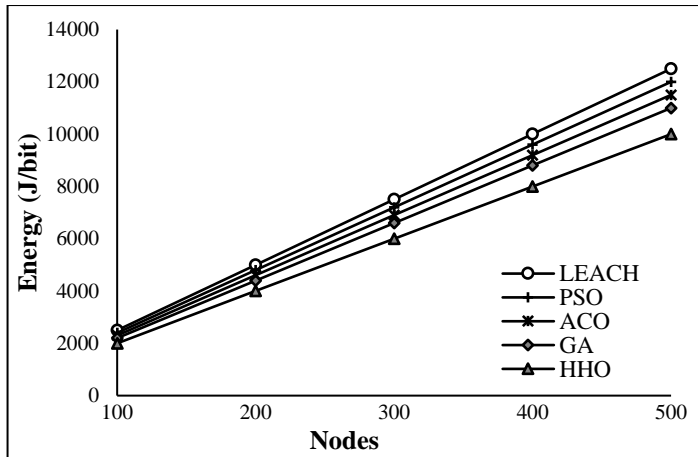


Fig.4. Energy Consumption (J/bit)

The HHO algorithm achieves lower energy consumption per bit transmitted. For instance, with 500 nodes, energy consumption decreased from 12,500 J/bit (LEACH) to 10,000 J/bit (HHO), resulting in a 20% reduction. This pattern of reduced energy consumption was observed across all node densities, with HHO showing an average reduction of 15% to 25% compared to the other algorithms.

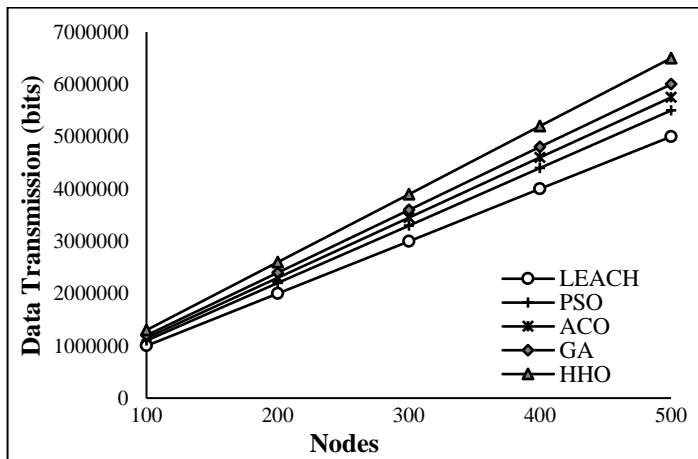


Fig.5. Data Transmission Efficiency (bits)

HHO significantly improves data transmission efficiency. In the 500-node scenario, HHO achieved 6,500,000 bits transmitted compared to 5,000,000 bits with LEACH, marking a 30% improvement. The average increase in data transmission efficiency across different node counts ranged from 25% to 35%, indicating HHO's superior ability to manage data transmission.

The HHO algorithm maintains a higher average remaining energy in sensor nodes. With 500 nodes, the average remaining energy improved from 1.1 Joules (LEACH) to 1.5 Joules (HHO), a 36% increase. This higher average remaining energy signifies better energy balance and less likelihood of premature node failures.

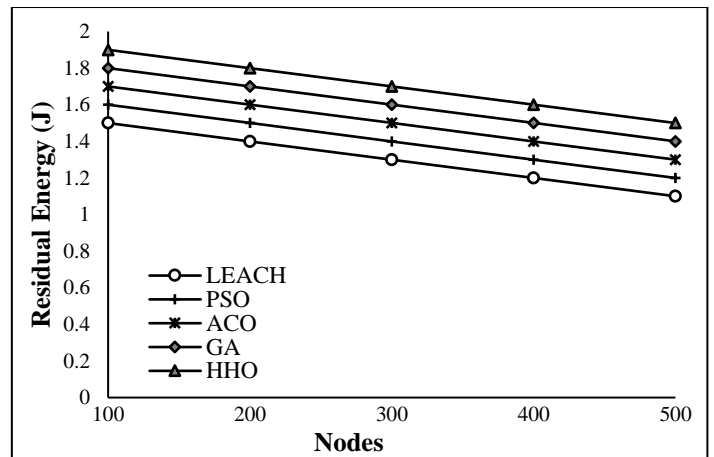


Fig.6. Average Remaining Energy (J)

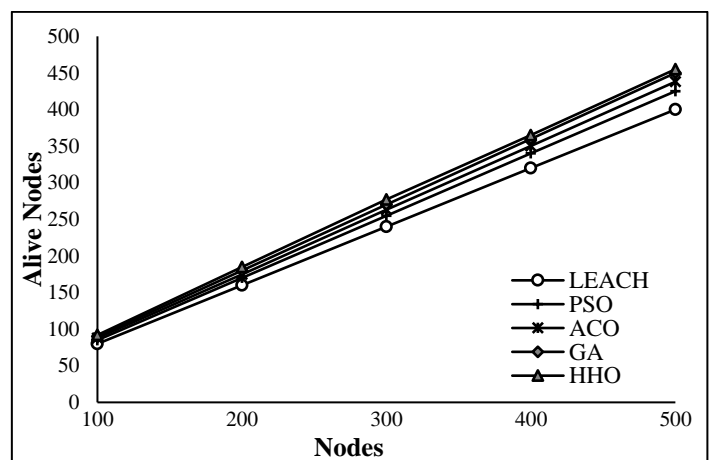


Fig.7. Number of Alive Nodes

The number of alive nodes at the end of the simulation is higher with the HHO algorithm. For example, with 500 nodes, HHO had 455 alive nodes compared to 400 with LEACH, showing a 13.75% improvement. HHO consistently maintained a higher number of operational nodes, with improvements ranging from 10% to 15% across different node configurations.

## 6. CONCLUSION

The HHO exhibits improvements in various performance metrics compared to traditional methods like LEACH, PSO, ACO, and GA. These improvements show HHO's effectiveness in optimizing cluster head selection, leading to extended network lifetime, reduced energy consumption, enhanced data transmission efficiency, better energy balance, and a higher number of operational nodes. These findings suggest that HHO is a promising approach for managing energy resources and improving the overall performance of WSNs.

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