# Comparative Analysis of PSO vs. GWO-Enhanced LEACH in Energy-Efficient Wireless Sensor Networks

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***Abstract***

*Wireless Sensor Networks (WSNs) are extensively used in applications such as environmental monitoring, surveillance, and smart security, but their performance is limited by the restricted energy capacity of sensor nodes, particularly in remote deployments. Efficient cluster head (CH) selection is therefore essential to extend network lifetime and maintain reliable data transmission. This paper presents a comparative study of the conventional Low Energy Adaptive Clustering Hierarchy (LEACH) protocol and its bio-inspired variants based on Particle Swarm Optimization (PSO) and Grey Wolf Optimization (GWO). The proposed approach integrates energy-aware fitness functions into the LEACH setup phase while preserving the standard data transmission process. Simulation results show that PSO-LEACH improves network stability by approximately 25% and increases throughput by nearly 18% compared to standard LEACH. GWO-LEACH achieves superior performance, extending overall network lifetime by about 40% and maintaining a higher number of active nodes throughout the simulation. The core finding indicates GWO-based CH selection significantly enhances energy efficiency and network longevity over conventional LEACH.*

***Keywords:*** *LEACH, WSN, PSO, GWO, Energy Optimization*

## 1. Introduction

Over the next 10 years, life will differ due to accelerated technological advancements, notably in WSN, IoT, and AI/ML. However, these advancements pose several societal challenges, like high implementation costs, device heterogeneity, diverse standards and protocols, mobility issues, dynamic architectures, and concerns about security and privacy. One widely used technology is Wireless Sensor Networks (WSNs). WSN is a collection of devices capable of sensing information from the surrounding environment. It collects information from all connected sensors and passes it to the data center where information is further processed to extract useful information. Data centers exist nearby or remotely to WSN. The Base Station (BS), also known as the sink node, plays an intermediate role in information exchange among data centers and WSN nodes. During the routing and data collection process, information is directly sent from all nodes to the BS or to an intermediate node where data are aggregated and then forwarded to the BS (classical routing). That intermediate node is called the Cluster Head (CH). One of the nodes will act as the Cluster Head; data are collected from the CH and then transformed to a particular Base station, as shown in Figure 1. The CH selection is concentrated among the nodes with maximum energy [1]. For the selection of CH, many algorithms are defined.

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Among all of them, the most widely used is Low Energy Adaptive Clustering Hierarchy (LEACH), which works on a dynamic clustering strategy for WSNs. It was first proposed by Heinzelman in 2000 [2]. Along with this, many nature-inspired algorithms have been defined by many researchers, which are more efficient than the LEACH algorithm. In this paper, a comparison is made between LEACH and two BIO-Inspired algorithms, namely PSO and GWO. The algorithms are analysed on the same platform with the same parameters. The results are compared using alive nodes count, and number of packets transmitted from the Cluster Head to its Base Station, i.e., throughput. It is analysed that BIO-Inspired algorithms show better results than the LEACH algorithm.

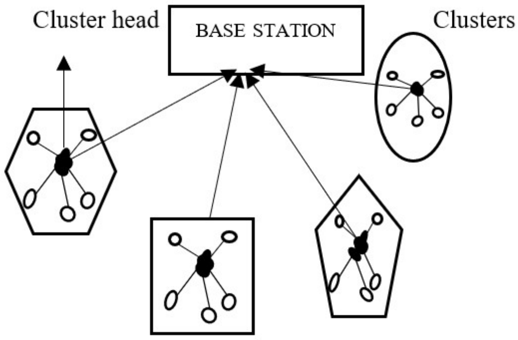


Figure 1. A Typical cluster formation in WSN

The LEACH algorithm works to expand the network's lifespan by equally distributing energy utilized by all nodes. This is achieved through a pseudo-random process that selects cluster heads in each round. The CH is selected based on the node that has the maximum energy. LEACH's algorithm consists of two main phases- the set-up phase and the steady-state phase, each containing several overlapping sub-stages. During the CH-selection sub-stage, CHs are chosen from the candidate nodes using equation (1).

$$T(n) = \frac{p}{1 - p*(r \bmod 1/p)} \quad \text{if } n \in G \tag{1}$$

$T(n) = 0$ otherwise

where,
P is the probability of a node becoming a cluster head,
r is the current round index,
G consists of those nodes that have not been the cluster head in the last 1/P rounds, and n is the number of nodes.

Each node n, picks a random RN(n) within the range of 0 and 1, and compares it with a threshold T(n). If RN(n) is less than T(n), it is selected as CH; otherwise, the next node is considered. WSN nodes use this distributed method to decide CH selection based on their remaining energy. After 1/P rounds, the process restarts for a new selection cycle. CHs act as intermediaries between sensor nodes and the BSN, helping to minimize energy utilization during data transmission, using a clustering approach. This method effectively impacts the network's lifespan and survivability. Following CH selection, cluster formation begins with nodes within radio range joining as cluster members. CHs broadcast their IDs using the Carrier Sense Multiple Access (CSMA), the MAC protocol to nearby nodes, which determines the best CH to join the cluster based on the Received Signal Strength Indicator (RSSI). Nodes within range that are not CHs receive this broadcast and join the cluster by sending request message to the nearest CH. To minimize energy consumption and avoid congestion, the CH creates TDMA schedule for its cluster members, allowing nodes to turn off when they have no data to send.

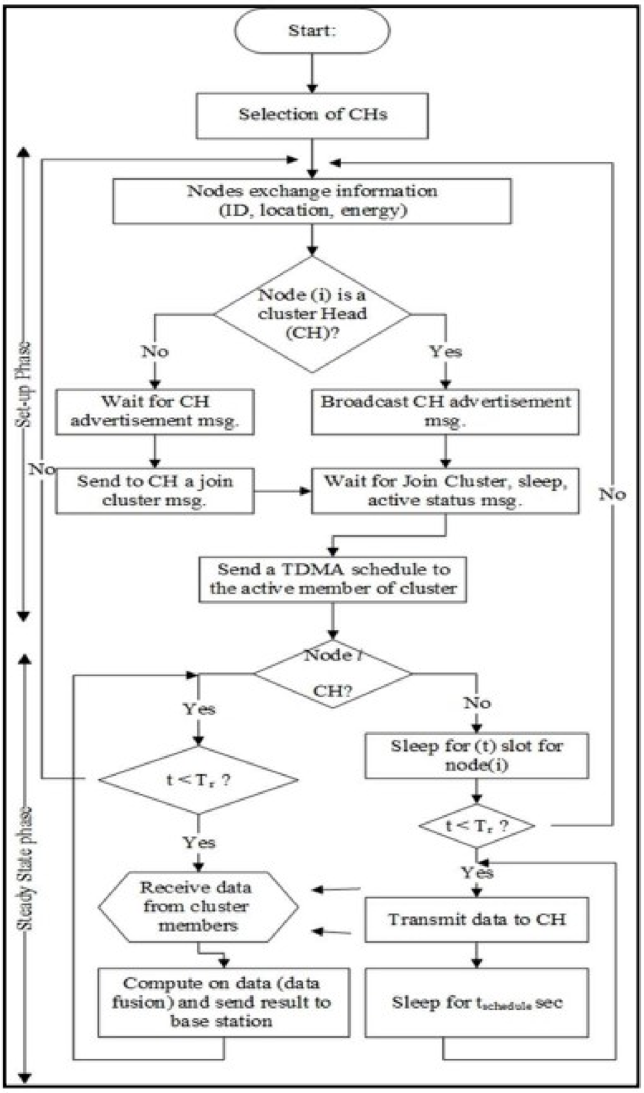


Figure 2. Working of the LEACH algorithm.

Once the clusters are created, the steady-state phase starts, where information is gathered from sensors and sent to their CH based on a predetermined time by TDMA. The CH aggregates data from all cluster nodes, processes it by compressing it into a single packet, and then transforms it to the Base Station. It is the CH node that keeps track of its receiver and gathers all information from all sensor nodes. This aggregation process minimizes energy consumption by minimizing bandwidth usage and unwanted communication from nodes sensing similar data. After collecting data from every sensor node, the CH aggregates it into a convenient form and finally transmits it to the BSN [3]. Figure 2 represents the working of the LEACH algorithm.

To overcome these limitations, many bio-inspired and meta-heuristic algorithms have been introduced for improving the performance of LEACH. However, in current research, many studies are conducted on individual algorithms or combined algorithms without comparing their efficiency in the same environment. In particular, the effectiveness of two individual algorithms: Particle Swarm

Optimization Algorithm (PSO) and Grey Wolf Optimization Algorithm (GWO) for energy-efficient CH selection has been demonstrated individually in previous research, but a comparative study of both algorithms combined in LEACH has not been explored.

The selection of Cluster Head (CH) is a major concern in Wireless Sensor Networks, as CHs are responsible for data aggregation as well as for transmitting data from a longer distance to the base station. Hence, there is substantial consumption of energy in this case. Sometimes, if the selection process of the CHs is not done in a proper manner, it may lead to early exhaustion of energy, as well as an imbalanced load and failure of the whole network. Although the LEACH protocol takes care of the issue related to the consumption of higher amounts of energy, it does not give importance to either the energy level or the distance of communication.

To address such limitations, bioinspired optimization algorithms have been introduced, but current research is primarily limited to standalone and hybrid schemes without an impartial comparative evaluation in a common setting. More specifically, PSO and GWO are two fundamentally different swarm-intelligence models characterized by different exploration/exploitation properties. Therefore, it is necessary to comparatively evaluate the PSO-LEACH and the GWO-LEACH schemes to fully grasp the relative efficacy of both approaches in CH selection based on energy considerations. This work aims to address such research gaps by impartially evaluating both schemes within the same context to enable an impartial and fair comparative study.

Although this is an area of great concern and various studies have been performed in this field, this paper tries to bridge the gap in existing research on LEACH and its optimized versions, PSO-optimized LEACH and GWO-optimized LEACH, through a comparative analysis using an equal simulation setup. Here, PSO and GWO are implemented in the CH selection process of LEACH with an unchanged data transmission system. Results show enhancement in energy consumption through bio-Inspired optimization techniques, and GWO-optimized LEACH outperformed both LEACH and PSO-optimized LEACH techniques.

## 2. Related Work

All WSNs are capable of real-time data detection, storage, and transmission, all of which must be executed efficiently to save the limited sensor's battery life. Given that most sensors are deployed in hard-to-access locations, extending sensor lifespan through external or additional energy provision is not feasible. Notable efforts are being implemented for prolonging the life span of sensor nodes. Besides energy constraints, Wireless Sensor Networks (WSNs) encounter several challenges, including accurate sensing and non-redundant information [4]. Three significant issues within WSNs include efficient energy use, security, and Quality of Service (QoS). These problems and challenges involve trade-offs, such as sacrificing the network's lifetime for improved QoS, which applies similarly to security parameters. Addressing these issues individually has required significant time and effort, yet doing so often reveals various flaws. Accordingly, to enhance WSNs effectively, a simultaneous approach to tackling these problems is necessary.

Clustering algorithms play a very important role in ensuring efficient transmission and maintaining the powered path in WSNs. LEACH, an adaptive clustering algorithm, is most widely used in WSNs. Nature-inspired algorithms, such as PSO (Particle Swarm Optimization) and GWO (Grey Wolf Optimizer), are employed for clustering tasks, specifically for selecting Cluster Heads (CHs) among nodes during cluster formation. Routing and clustering are two primary issues in WSNs that reduce data transmission rates, and this is addressed through separate fitness functions based on PSO. For uninterrupted data transmission to the BS, it is essential to consider that some CHs may deplete their energy rapidly and die during communication [5]. Thus, energy conservation and balancing among CHs during the routing process are necessary for prolonging the operational lifetime of the WSN. In IOT devices, load-balanced cluster head selection is another criterion that can be focused on. To mention one Multi-Attribute Decision Making [6] method is used for CH selection. BIO algorithms are used in Data Aggregation for WSN [7]. Here, it is observed that, by keeping LEACH as the base algorithm, they tried for improving the efficiency using bio algorithms.

By segmenting the network into grids, the authors of [8] have suggested energy-apprehensive clustering and efficient CH selection. The selection of this cluster head was based only on leftover energy, proximity to the Base Station, and proximity to nearby locations. In order to improve network continuity and lower packet loss in mobile detector networks, the authors of [9] suggested a low-energy clustering scale. The authors of [10] suggested a novel routing style that maximizes network continuance and efficient consumption through cluster head selection. However, the selection of Cluster Heads is based solely on the remaining energy and the distance from the base station to the CH. Fuzzy- grounded clustering techniques are represented in [11-12], where two types of detectors are employed for communication: videlicet and free detectors.

The author of [13] suggested a new APRO algorithm that considers 21 attributes to choose cluster leaders in a way that is both cargo-balanced and increases network durability. During the process of gathering data, each attribute was considered into account and accompanied by others. Among the detector nodes, the designated cluster heads (CHs) have a balanced payload with the most suitable strength intake for the facts transmission to the base station. The outcomes confirm the development of this algorithm, which supports the use of the most energy-efficient transmission methods. The examined 21 qualities have a remarkable impact on increased network continuity and efficient energy consumption, according to the results.

The author of the paper [14] suggested using a mongrel bio-inspired optimization algorithm as an artificial WSN localization method. To achieve low calculation time and great delicacy, the suggested solution combines the PSO algorithm and the Dragonfly solution (DA). Previous workshops have demonstrated the inherent benefits of bio-inspired algorithms in facilitating precise and efficient localization. Here, they demonstrate the collaborative localization script, in which neighbouring anchor nodes and previously positioned unknown nodes will be asked for support by unknown nodes. This technique is contrasted with PSO and DA in a mesh detector network. The results show that, while considering all localization errors and computation time, the suggested set of criteria performs better than the various approaches.

Furthermore, the hybrid bio-inspired algorithms have demonstrated better results. The Firefly Algorithm with Particle Swarm Optimization (HFAPSO) was presented by the author in the publication [15] as an improvement over the LEACH-C method for the best cluster head selection. This hybrid approach uses PSO to optimize cluster head positioning while utilizing firefly's global search activity. Metrics including total performance, energy availability, and the number of active nodes are used to assess how effective the proposed methodology is. In order to increase network longevity, the author [16] proposed the Hybrid GWO based Sunflower Optimization (HGWSFO) technique for good Cluster Head Selection (CHS) under particular restrictions like energy consumption and separation distance. The network's critical performance is enhanced across measures like throughput, node remaining energy, active nodes, inactive nodes, network surviving index, and convergence rate by striking a balance between exploration and exploitation.

Recent advancements in bio-inspired optimization algorithms strive to remove the constraints of the classical method of optimization, presenting implicit results for diving into complex optimization challenges. Then, we spotlight several prominent algorithms named after colourful nature-inspired methodologies. Given their strengths and applicability to tone association, these algorithms are important in the admixture of algorithms within WSNs exploration. However, this research contributes to these previous efforts by incorporating simplicity in its methodology. This research chooses not to design another hybrid approach; rather, it presents an equal comparison between two popular bio-inspired approaches, namely PSO and GWO, when they are combined with the LEACH protocol. This allows an equal environment to be tested with the same simulation parameters and fitness functions, in order to exclude any effects of complexity and to reveal insights into the true optimisation capability of GWO and PSO. Such simplicity is not only an advantageous factor in this research, but it also makes this contribution an extension to previous approaches, while being able to provide a straightforward comparison in real-world sensor networks.

## 3. Bio-Inspired Algorithms

Bio-inspired algorithms have emerged as more popular for solving application-related problems in decision-making, information handling, and optimization across diverse fields in science and engineering. It is expected that these Intelligent Optimization algorithms will become increasingly effective in addressing issues such as anomaly and failure detection in the coming years [17].

### 3.1. Particle Swarm Optimization (PSO)

The PSO algorithm, inspired by the behaviours of bird flocking, was initially simulated by Craig Reynolds [18] and later analysed by Frank Heppner [19]. This algorithm works for optimal solutions by emulating the movement patterns of birds. In a large dimensional search area, each particle represents a potential solution, moving with a velocity influenced by both its past performance and the performance of its neighbours [20].

In PSO, particles adjust their positions based on their local best positions and the global best position found by the swarm. This kind of sharing information allows particles to converge toward optimal solutions effectively. The key advantage of PSO is its ability to leverage both individual and collective experiences to navigate the search space [21]. Each swarm updates its velocity and position by considering its previous best position and the best positions of its neighbours. The global best value is continuously updated with the best result found by any particle. Through iterative adjustments, particles refine their search, moving near the optimal solution. The working of PSO is briefed as follows:

Randomly initialize the population of the swarm
While (Size of the Population)

```
{
Calculate fitness value,
If fitness values are better from best fitness value(pbest) in past, then update pbest values with the new pbest.
Select the one swarm which has the best fitness value from all particles as gbest.
While the (maximum iteration or minimum error) criteria are not gained,
{
  For all particles, calculate velocity by equation (1)
Change the position of particles according to equation (2)
}
```

Particle Swarm Optimization (PSO) relies on two key equations to update the position and velocity of each particle after identifying the two best values. The equations are:

Velocity update:

$$v_{ik} = w * v_{ik} + c1 * r1 * (pbest_{ik} - x_{ik}) + c2 * r2 * (gbes_k - x_{ik}) \qquad eq\ (1)$$

Position update:

$$x_{ik}+1 = x_{ik}+v_{ik}+1 \qquad eq\ (2)$$

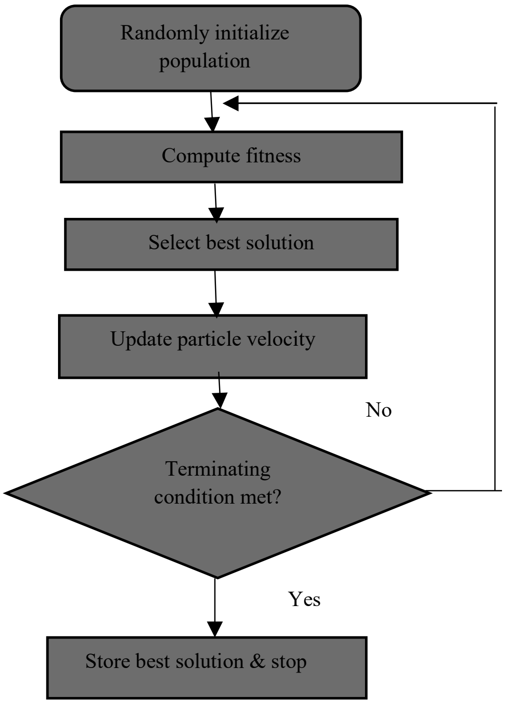


Figure 3. Working of PSO

PSO is widely used across various domains, from agriculture to industry. In geotechnical engineering, it is applied in slope stability analysis, foundation engineering, rock and soil mechanics, and tunnelling [22]. PSO is also significant in planning problems, especially for substation locating and sizing [23-25]. In the heating supply sector, PSO is mainly used for heating load forecasting, though it is less common in heat system planning. PSO is effective for optimizing energy storage and simulating particle movement for visual effects in movies.

### 3.2. Grey Wolf Optimization (GWO)

Grey Wolf Optimization (GWO) is a meta-heuristic swarm-based technique introduced by Simon Fong [26]. This algorithm is motivated by the hunting behavior of wolves. During the hunt, wolves do not communicate physically; instead, each wolf independently identifies and attacks silently by itself. Their food search was followed by the Levy flight model. When wolves discover a new location that is more advantageous than their current one, they relocate and merge with another pack of wolves. A random wolf is chosen from the pack to hunt for prey, identifying potential positions to catch the prey based on its current line of sight. Its algorithm and flowchart are shown below.

Mathematical model and algorithm [10]: Social hierarchy:

- The first fittest solution is an Alpha wolf ($\alpha$)
- Second-best solution as a Beta wolf ($\beta$)
- Third-best solution as a Delta wolf ($\delta$)
- Rest of the candidate solutions as Omega wolves ($\omega$)

$$A = 2 * a * r1 - a \quad C = 2 * r2 \qquad \textit{eq (3)}$$

where:

$a = 2 * (1 - t / T)$
$r1, r2$ □ $[0, 1]$

Distance from prey
$D = | C * Xp - X |$ *eq (4)*

where:

$Xp$ = position of prey (best solution)
$X$ = current wolf position

$X(t+1) = Xp - A * D$ *eq (5)*
$D_\alpha = | C1 * X_\alpha - X |$
$D_\beta = | C2 * X_\beta - X |$
$D_\delta = | C3 * X_\delta - X |$

$X1 = X_\alpha - A1 * D_\alpha$
$X2 = X_\beta - A2 * D_\beta$
$X3 = X_\delta - A3 * D_\delta$

$X(t+1) = (X1 + X2 + X3) / 3$ *eq (6)*

Pseudocode of the GWO algorithm:

Step1: Randomly initialize the population of grey wolves Xi (i=1,2,…,n)
Step2: Initialize values of a=2, A and C ( using eq.3)
Step3: Calculate the fitness of each member of the population
Xα=member with the best fitness value
Xβ=second best member (in terms of fitness value)
Xδ=third best member (in terms of fitness value)
Step4: FOR t = 1 to Max_number_of_iterations:
Update the position of all the omega wolves by eq. 4, 5 and 6
Update a, A, C (using eq. 3)
a = 2(1-t/T)
Calculate the Fitness of all search agents
Update Xα, Xβ, Xδ.
END FOR
Step5: return Xα

Grey wolves are considered powerful predators and are at the top of the food chain. Grey wolves prefer to live in groups called packs; each group contains 5-12 individuals on average. All the individuals in that group have a very strict social dominance hierarchy.

In grey wolf optimization, the social hierarchy within the pack is modelled to design the algorithm. The hierarchy includes:

- Alpha (α) wolf: The dominant wolf in the pack whose orders are followed by other members.

- Beta (β) wolves: Subordinate wolves that assist the alpha in decision-making and are considered the best candidates to become the next alpha.
- Delta (δ) wolves: These wolves submit to the alpha and beta but dominate the omega wolves. Delta wolves include different categories such as Scouts, Sentinels, Elders, Hunters, and Caretakers.
- Omega(ω) wolves: The least important individuals in the pack, acting as scapegoats, and only allowed to eat at the end.

The primary phases of grey wolf hunting, which are mathematically modelled in GWO, include:
- Tracking, chasing, and approaching the prey.
- Pursuing, encircling, and harassing the prey until it is immobilized.
- Attacking the prey.

This hierarchy and behavior of wolves are utilized to design and implement the Grey-Wolf Optimization algorithm.

GWO have been used in various domains, to name a few, for Fault system estimation and prediction, Hydro-power optimal operation station, Optimization in multi-layer perception, Optimal allocation in electronics for system power loss reduction and Fault detection and contingency management in power systems.

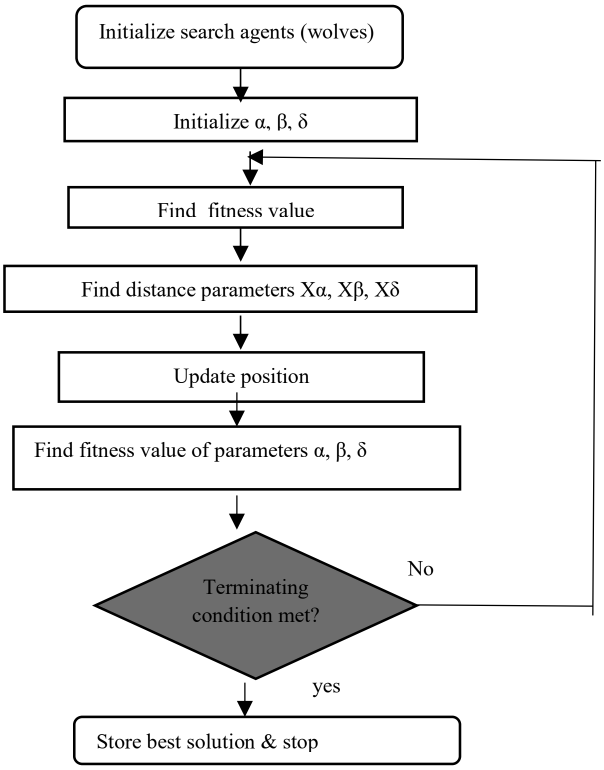


Figure 4. Working of GWO

### 3.3. Particle Swarm Optimization for CH Selection in WSNs

Particle Swarm Optimization (PSO), inspired by bird flocking behaviour and initially simulated by Craig Reynolds [18] and analysed by Frank Heppner [19], is used to determine optimal cluster head (CH) nodes in Wireless Sensor Networks. In PSO, each particle represents a candidate solution, i.e., a set of potential CHs. The particles update their positions in the search space based on individual experience (pbest) and global best performance (gbest) [20].

Unlike generic optimization scenarios, PSO in WSNs evaluates each candidate CH using a fitness function that incorporates residual energy of nodes, intra-cluster distance, and distance from CHs to the base station. A typical fitness function used is:

$$Fitness = w1 \times Eres\,1 + w2 \times DCH - BS + w3 \times Dintra$$

where:

- (E_{res}) = average residual energy of selected CH nodes
- (D_{CH-BS}) = average distance from CHs to base station
- (D_{intra}) = average intra-cluster communication distance
- (w_1, w_2, w_3) = weighting coefficients

Lower fitness values indicate more energy-efficient CH selection.

Integration with LEACH

PSO replaces the random CH selection phase of LEACH. Instead of probabilistic threshold-based selection, PSO optimizes CHs before cluster formation. The LEACH protocol phases modified are:

- Set-Up Phase: PSO determines CHs rather than random selection.
- Steady-State Phase: Data transmission remains unchanged.

Thus, PSO enhances LEACH by balancing energy consumption and increasing network lifetime.

PSO algorithm then proceeds:

1. Initialise the swarm with random CH candidate sets
2. Evaluate fitness using WSN metrics
3. Update pbest and gbest
4. Update velocity and position via eq (1) & (2)
5. Iterate until maximum iterations or threshold
6. Deploy the best CH set in the LEACH setup phase

Thus, PSO effectively refines CH selection, improving network stability, coverage, and energy efficiency [21].

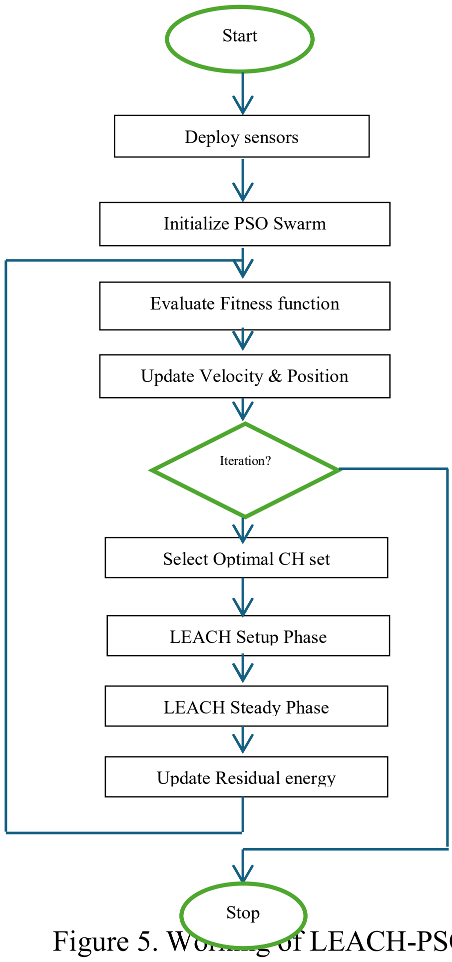


Figure 5. Working of LEACH-PSO

### 3.4. Grey Wolf Optimization for CH Selection in WSNs

Grey Wolf Optimization (GWO), a swarm-based metaheuristic introduced by Simon Fong [26], mimics the hierarchical leadership and cooperative hunting behaviour of wolf packs. In WSNs, each wolf represents a candidate CH set, and hunting corresponds to exploring optimal CH placement in the network.

The fitness function in GWO for WSN CH selection evaluates candidate CH nodes using energy and communication metrics:

$$Fitness = \alpha \times Eres1 + \beta \times DCH - BS + \gamma \times Dintra + \delta \times NodeDensity$$

Where:

- (NodeDensity) ensures balanced cluster formation
- coefficients adjust metric priority
- Lower values indicate optimal CH configurations.

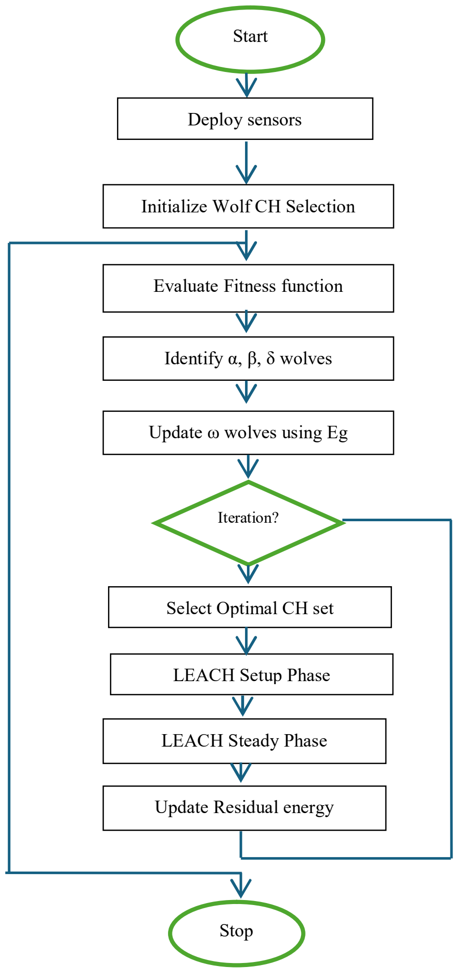


Figure 6. Working of LEACH-GWO

**Integration with LEACH**

Similar to PSO, GWO replaces LEACH's random CH selection by applying its hierarchical search model:

- $\alpha$ solution = best CH set
- $\beta$ and Delta $\gamma$ refine search
- $\delta$ explore alternates

The modified LEACH process:
- Setup Phase: GWO selects CHs using social hierarchy-driven optimization
- Steady-State Phase: data transmission remains LEACH standard

The result is a more balanced energy distribution and an extended network lifetime.

**GWO process in the WSN context**:

1. Initialise the wolf population with candidate CH sets
2. Evaluate fitness using WSN metrics
3. Identify alpha, beta, and delta wolves
4. Update the position of omega wolves
5. Refine CH selection iteratively
6. Finalise the α-wolf candidate for CH deployment in LEACH

GWO's exploitation-exploration balance provides efficient CH selection and improved packet delivery while reducing control overhead.

**Key Benefits for CH Selection**

- Reduced energy consumption
- Balanced load distribution
- Minimized communication distance
- Improved network lifespan
- Enhanced stability period (FND, HND metrics)

## 4. A Simulation Setup and Methodology

A performance analysis of the Particle Swarm Optimization algorithm and the Grey Wolf Optimization algorithm was conducted using the Python 3.10 environment and utilizing standard scientific libraries such as NumPy and Matplotlib. This was carried out with the standard implementation of the same algorithm. This is owing to the requirement for the same optimization algorithm. The fitness function used was expressed as follows:

$$Fitness = \sum_{i=1}^{n}(ypredicted(i) - yactual(i))^2$$

This algorithm aims at optimizing the mean squared error function, which is the difference between the predicted output values and actual output values of a system. In the case of PSO, the number of particles was taken as 30, and the initial value of the inertia weight (*w*) was 0.9, decreasing linearly over iterations to 0.4. Learning from personal experiences as well as global information was handled by the constants *c1 = 2.0* and *c2 = 2.0*. The equations (1) & (2) were employed.

For the GWO model, the population size was also fixed at 30. The convergence parameter (a) started with 2 and decreased to 0 through iteration based on equation (3), while coefficients A and C changed through iteration. The transition between the exploration and exploitation phases was guaranteed.

Each algorithm was run with a maximum of 1000 iterations, and a total of 25 runs was carried out to reduce the effect of stochastic variability. For all runs, the best fitness, mean squared error, running time, and rate of convergence of the algorithms were measured. After the runs, the results were averaged, and statistical measures of central tendency and variability, including mean and variance, were calculated. The graphs of convergence of the algorithms were drawn using Matplotlib plots. This approach also enables an effective and accurate comparative assessment and analysis among PSO and GWO algorithms in Python code.

## 5. Simulation Results

All the above-mentioned algorithms are implemented using the Anaconda Python environment. Network design used parameters are represented in Table 1. The PSO algorithm and GWO are compared with LEACH. Performance is measured in terms of the number of alive nodes, energy dissipation, and throughput. Figure 6 shows the performance of algorithms, which is measured in terms of alive nodes for different rounds. The LEACH algorithm results show that the number of alive nodes was almost the same during the initial 500 rounds, but the performance suddenly drops in rounds 600-1200. The PSO and GWO algorithms, even though the initial results are not good, maintain consistency up to around 1500, which shows that the results are comparatively acceptable compared to LEACH.

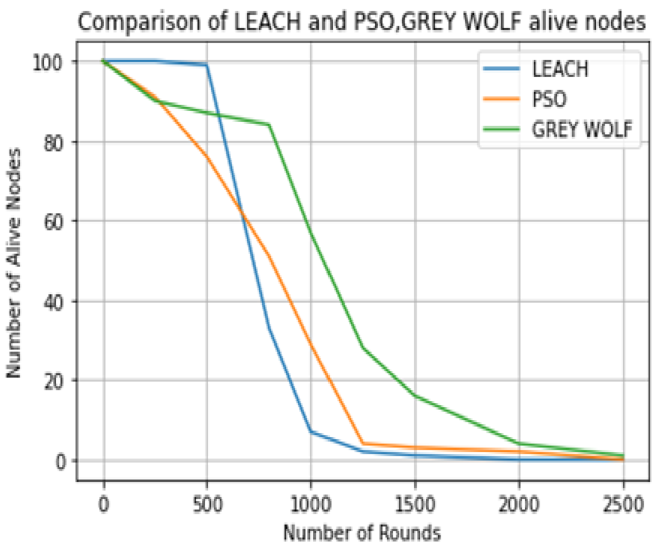


Figure 6. Number of alive nodes.

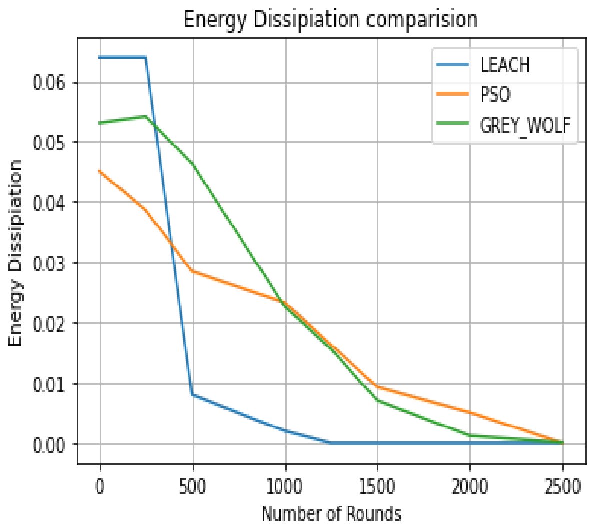


Figure 7. Energy dissipation appraisals in different rounds

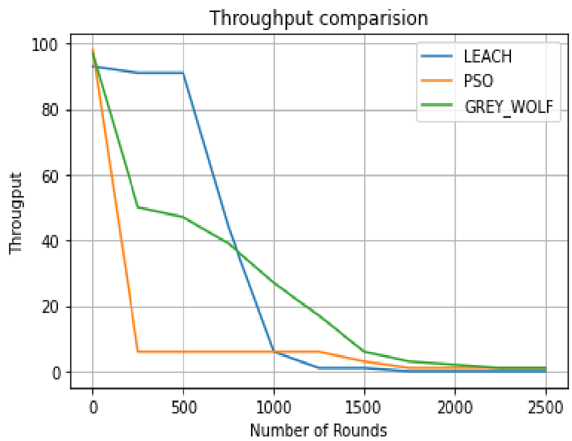


Figure 8. Throughput appraisals in different rounds

Table 1. Parameters used for simulation.

| **Parameters** | **Description** | **Values** |
|---|---|---|
| A | Network dimension (area) | 100 x 100 |
| N | Total nodes | 100 |
| x,y | Position of Base Station | 50 x 50 |
| Initial_energy | Starting energy of the node | 0.5 J |
| E_fs | Amplifier energy consumption for small distance | 103 pJ/bit/m2 |
| E_mp | Amplifier energy consumption for larger distance | 1.3x103 pJ/bit/m4 |
| E_elec | Circuit energy consumption to forward/receive signal | 50 Pj/bit |
| message_size | Length of packet | 4000 bits |
| p | Cluster head probability | 5% |
| r | Fusion rate | 0.9 |
| c_len | Control message size | 32 bits |
| adv_ratio | Advanced node ratio | 0.1 |
| alpha | Energy factors of advanced nodes | 0.5-1.0 |
| rounds | Number of rounds | 2500 |

Figure 7 depicts the energy dissipation, which means the fall of energy, as the number of alive nodes falls, the energy level will also fall, in the LEACH algorithm after 500 rounds, whereas PSO & GWO maintain the consistency till 1500 rounds, and hence justifying the improved performance of bio-inspired algorithm over LEACH. Figure 8 shows the throughput, in terms of the number of packets transformed from the Cluster Head to the Base Station.

## 6. Conclusion

This work focused on the enhancement of the LEACH routing protocol through the use of bio-inspired optimization techniques in selecting cluster heads for Wireless Sensor Networks in an energy-efficient manner. Particle Swarm Optimization and Grey Wolf Optimization were applied to the setup phase in LEACH using a multi-objective fitness function developed based on residual energy, communication distance, and node density. From the simulation results, it can be noticed that PSO-LEACH enhances the stability period by roughly 25% and reduces energy consumption by about 20% over conventional LEACH. GWO-LEACH performed better, improving the lifetime of the entire network by a factor of about 40%, and the death of the first node was delayed substantially. All these improvements confirmed the evidence of optimized CH selection, which can efficiently balance energy usage and enhance network sustainability. The work concludes that GWO-based CH selection is robust and scalable for prolonging the lifetime of WSN, thus being quite appropriate for large-scale sensor network applications with energy-constrained sensors.

In the future, the work will be concentrated on an adaptive weighting of fitness functions concerning network conditions, hybrid models of PSO and GWO for better convergence, and validation in mobility and heterogeneous node scenarios. The extension of the developed approach to IoT-enabled large-scale networks and real-time testbed implementation is also a promising direction for research.

## Conflict of Interest

We declare no conflict regarding the publication of the study.

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