

Optimized Wireless Sensor Network Clustering Using a Hybrid Firefly–Bat Algorithm (HFBA)

J. Jegan¹, Senthil kumar P¹, S. Saravanakumar¹, M. Muthukumar¹, K. Sathish² and Asha V¹

¹Department of CSE, SRM Institute of Science and Technology, Tiruchirappalli, SRM Nagar, Irungalur, Tamil Nadu, India

²Department of CSE, Madanapalle Institute of Technology and Science, Madanapalle–Kadiri Road, NH-42, Kurabalakota Mandal, Madanapalle – 517325, Andhra Pradesh, India

Article history

Received: 07-08-2025

Revised: 12-02-2026

Accepted: 23-03-2026

Corresponding Author:

Senthil kumar P

Department of CSE, SRM Institute of Science and Technology, Tiruchirappalli, SRM Nagar, Irungalur, Tamil Nadu, India

Email:

psenthilmephd@gmail.com

Abstract: Wireless Sensor Networks (WSNs) are composed of numerous sensor nodes that collaborate to observe and evaluate various environmental parameters, transmitting the data to a central base station. Each node is equipped with a unique transmitter, receiver, and processor to facilitate sensing, processing, and communication. These networks are often installed in extremely remote and inaccessible areas. A significant challenge arises from the processor's energy consumption constraints, as the sensor nodes possess very limited battery life. Selecting cluster heads has proven to be an effective strategy for enhancing energy efficiency, as it decreases network traffic and, through data aggregation, extends the networks' operational lifespan while minimizing energy use. This paper introduces the Hybrid Firefly-Bat Algorithm (HFBA) as an innovative method for energy-efficient cluster head selection. HFBA combines the rapid convergence of the Firefly Algorithm with the Bat Algorithm's global search capability. Simulation results indicate that HFBA outperforms traditional methods, such as LEACH (Low-Energy Adaptive Clustering Hierarchy). Specifically, HFBA reduces total energy consumption by 23.6% compared to LEACH and increases the networks' operational lifespan by an average of 1.45 times. Additionally, there is a 14.3% enhancement in the data packet delivery ratio, and node stability improves by 12.8%. These results underscore HFBA's effectiveness in optimizing the energy consumption balance and maintaining a longer operational duration in energy-constrained WSN environments. Furthermore, the algorithm works without location data, streamlining the cluster formation process while remaining adaptable to different deployment situations.

Keywords: Energy Optimization, Cluster Head Selection, Hybrid Algorithms, Firefly Algorithm, Bat Algorithm, HFBA, LEACH, Network Longevity

Introduction

Wireless Sensor Networks (WSNs) have become a cornerstone of modern applications ranging from environmental monitoring to healthcare systems, smart cities, and military surveillance (Salama et al., 2023). These networks consist of spatially distributed sensor nodes that monitor and collect data that is then transmitted to a Base Station (BS). Efficient communication between sensor nodes and the BS is vital for sustaining the network performance, particularly in remote or harsh environments. However, the energy constraints of sensor nodes and their limited transmission range pose significant challenges for maintaining efficient and long-lasting network operation.

Clustering has emerged as a proven technique to address these challenges (Sankar et al., 2023). By organizing sensor nodes into clusters and assigning a Cluster Head (CH) to each cluster, this approach minimizes the communication overhead and optimizes the energy consumption. The CH aggregates data from its cluster members and transmits the aggregated data to the BS, thereby significantly reducing the energy demand on the individual nodes. Despite their advantages, traditional static clustering methods often lead to premature energy depletion of CHs, thereby reducing network lifespan. Dynamic clustering approaches, such as low-energy adaptive clustering hierarchy (LEACH) (Klidbary and Javadian, 2024) mitigate this issue by periodically rotating the CH roles among nodes, promoting

balanced energy utilization, and extending the operational lifespan of the network.

In the quest for enhanced optimization, Swarm Intelligence (SI)-based algorithms have gained prominence (Chaurasia et al., 2023). Algorithms such as the Firefly Algorithm (FA) (Moshtaghi and Olyaei Torqabeh, 2023) and Bat Algorithm (BA) (Rami et al., 2023), inspired by natural phenomena, have demonstrated superior performance in solving complex optimization problems (Kusla and Brar, 2023). The Firefly Algorithm (FA) mimics the attraction behavior of fireflies based on light intensity. Its ability to efficiently explore the search space has made it a reliable tool for applications ranging from clustering to feature selection (Zare et al., 2023). Similarly, the Bat Algorithm (BA), inspired by the echolocation behavior of bats, excels in precision-driven optimization tasks with applications in load dispatch and neural networks.

Despite their individual strengths, FA and BA have limitations in simultaneously achieving exploration and exploitation. Recent advancements have suggested that hybridizing these algorithms can leverage their complementary features, thereby addressing the unique challenges of WSNs more effectively. The Hybrid Firefly and Bat Algorithm (HFBA) combines FA's exploratory capabilities with BA's precision to achieve optimal cluster head selection, ensuring balanced energy consumption and improved network longevity. The significance of energy-efficient algorithms such as HFBA is particularly evident in real-world applications. For instance, in environmental monitoring systems such as wildfire detection or air quality assessments, WSNs must operate autonomously for extended periods under challenging conditions. Similarly, in healthcare systems, where real-time data from wearable sensors is critical, energy-efficient operations ensure uninterrupted monitoring. These scenarios underline the importance of hybrid optimization algorithms in sustaining the reliability of WSNs in diverse domains. In this study, a novel hybrid algorithm called HFBA was introduced to improve the energy efficiency and scalability of WSNs. By integrating the FA and BA, the algorithm offers enhanced cluster head selection, reduces the overall energy consumption, and extends the network lifespan.

Research Hypothesis

The main hypothesis for this research study is that the combination of the Firefly Algorithm and Bat Algorithm improves energy distribution and extends the lifespan of Wireless Sensor Networks (WSNs) while keeping the increase in computational costs to a minimum. More precisely, the following hypotheses are proposed:

H₁: HFBA will use an overall energy that is at least 20% less than LEACH because of a more balanced

selection of cluster head nodes

H₂: HFBA extends the lifespan of the network by at least 1.4 times compared to LEACH because of the prevention of premature energy depletion of cluster head nodes

H₃: The integration of FA and BA maintains appropriate computational efficiency for resource-constrained sensor nodes

Research Goals

The Hybrid Firefly-Bat Algorithm (HFBA) showcased in this study seeks to improve the energy efficiency and scalability of WSNs. The specific objectives are:

- Develop a new mechanism to select cluster heads that incorporates the fusion of Firefly and Bat algorithms to enhance energy efficiency
- Reduces the total energy consumption and extends the network lifespan using methods that surpass the LEACH approach
- The optimal load distribution among all the sensor nodes is obtained through the establishment of ideal clusters
- Evaluate the performance of HFBA through rigorous simulation and statistical significance analysis

Literature Survey

The literature review highlights the effectiveness of many hybrid, bio-inspired approaches for optimizing WSNs; however, HFBA has many advantages that put it in a class of its own. Several clustering protocols require precise location information. In contrast, HFBA works without location information, making it important for use cases in which GPS or location information is unavailable or unreliable. HFBA has a balanced exploration and exploitation strategy and solves the problem of premature convergence found in many single-algorithm models owing to the integrated use of the Firefly and Bat algorithms. Moreover, because the HFBA fitness function is formulated, a more comprehensive assessment is achieved by factoring in the residual energy, distance to the base station, and node density, thus making it a more thorough candidate for being a cluster head. While it is true that HFBA demands more computational power than many protocols, such as LEACH, the demands are still reasonable given the current capabilities of sensor nodes and are more than justified by the optimized cluster head selection, which results in more energy being saved. The outstanding performance and computational constraints make HFBA applicable to WSNs in the real world, where the ability to conserve energy is of utmost importance.

The reviewed literature offers (Table 1) a comprehensive examination of various optimization algorithms applied to Cluster Head (CH) selection in

Wireless Sensor Networks (WSNs), with an emphasis on enhancing energy efficiency, network longevity, and performance metrics. The proposed Hybrid Firefly-Bat Algorithm (HFBA) demonstrates significant

improvements over traditional methods such as LEACH, achieving a 23.6% reduction in energy consumption, extending the network lifespan by 1.45 times, and enhancing packet delivery by 14.3%.

Table 1: Meta-Analysis

S. No	Technique / Algorithm Used	Key Features	Performance Metrics Improved	Comparison with Traditional Methods	Unique Contribution
1	Hybrid Firefly-Bat Algorithm (HFBA)	Combines FA's exploratory and BA's exploitative strengths	23.6% reduction in energy consumption, 1.45× longer network lifespan, 14.3% improved packet delivery	Outperforms LEACH	Balances energy distribution without relying on location data; simplified cluster formation
2	Butterfly Optimization Algorithm + Ant Colony Optimization	Considers node centrality, residual energy, and distance	Improved data delivery, increased network stability, and reduced dead nodes	LEACH, DEEC	The dual algorithm optimizes both routing and cluster head selection
3	Uneven Clustering Strategy	Focuses on load balancing and cluster size determination	Enhanced energy efficiency, mitigated hotspot issues, and extended network lifetime	Static and equal clustering approaches	Framework for designing scalable and energy-aware clustering
4	Optimized Cluster Head Selection (Vehicular Networks)	Incorporates network stability, energy metrics, and mobility	Lower delay, reduced energy use, improved data delivery	Traditional WSN clustering	Tailored for mobility and dynamic vehicular communication
5	Flamingo Search Algorithm (FSA)	Takes into account network topology, node energy, and BS distance	Increased stability, balanced energy consumption, and higher packet delivery	LEACH	Effective energy balancing and better lifespan through optimized CH selection
6	Hybrid Crow Search + Firefly Algorithm	Utilizes node density, residual energy, and distance	Better load balancing, less energy usage, fewer node failures	Traditional clustering and FA	IoT-WSN optimization with hybrid swarm intelligence
7	Modified Firefly Algorithm	Introduces a global-best guided mechanism for convergence	Improved solution accuracy, faster computation	Basic FA	Reduces stagnation and accelerates global optimum discovery
8	FSA-Based Clustering Technique	Considers cluster balance, residual energy, and BS distance	Enhanced throughput, reduced energy loss, longer network lifetime	LEACH	Strong clustering with improved energy distribution
9	Improved Dragonfly Algorithm (IDA)	Incorporates residual energy and network-wide load metrics	Improved lifetime, efficient task distribution, and lower imbalance	Original Dragonfly Algorithm	Scalable and balanced clustering for large networks
10	Scouting Firefly Algorithm (SFA)	Integrates the exploration-exploitation trade-off mechanism	Faster convergence, improved search space traversal	Standard FA, GA	Enhanced firefly movement toward the global optimum
11	African Vultures Optimization Algorithm (AVOA)	Inspired by dynamic foraging behavior	Balanced energy usage, reduced bottlenecks, and extended lifespan	Traditional energy-aware methods	Dynamically adapts to changing WSN topologies and energy demands
12	Sandpiper Optimization Algorithm (SOA)	Based on adaptive foraging patterns	Increased scalability, lower transmission delay, balanced energy use	Static CH selection strategies	Designed for IoT with dynamic and energy-efficient communication

Biradar and Mathapathi (2023) employed hybrid optimization to optimize the CH selection based on node centrality, residual energy, and distance, outperforming LEACH and DEEC. Sharma et al. (2024) emphasized uneven clustering to address hotspot issues and energy imbalances, thereby providing a robust classification of load-balancing techniques. Ramani and Kothalanka (2024) proposed an optimized CH selection approach tailored to vehicular networks, thereby reducing delays and improving reliability. Abraham and Vadivel (2023) utilized the Flamingo Search Algorithm to enhance the network stability and energy efficiency through topology-aware CH selection. Several unnamed studies introduced advanced or hybrid algorithms such as Crow Search with Firefly, Modified Firefly Algorithm, Improved Dragonfly Algorithm, Scouting Firefly Algorithm, and Sandpiper Optimization Algorithm, all of which focus on enhancing energy distribution, convergence speed, scalability, and real-time adaptability in IoT-WSN systems. Notably, the African Vultures Optimization Algorithm contributes to a unique foraging-inspired model for dynamic load balancing and CH selection. Overall, the surveyed studies underscore the growing reliance on swarm intelligence and hybrid bio-inspired techniques to overcome the limitations of static or single-heuristic clustering protocols, thereby offering scalable, adaptive, and energy-efficient solutions across diverse WSN deployment scenarios.

The cluster head selection in WSNs minimizes the energy consumption while ensuring reliable data aggregation and communication. In traditional methods, cluster head selection is performed randomly or based on simple metrics such as node energy or distance to the base station. The limitations of these methods are as follows:

- **Uneven Energy Consumption:** Random selection or basic metrics do not account for the dynamic nature of the network, which can lead to uneven energy distribution and premature node death (Sharma et al., 2024)
- **Poor Load Balancing:** Without optimization, some nodes may be burdened with a disproportionate amount of work, leading to faster depletion of their energy reserves (Ramani and Kothalanka, 2024)
- **Scalability Issues:** Basic algorithms may not scale well for large networks because the overhead associated with cluster formation and communication increases (Abraham and Vadivel, 2023)

Therefore, optimization algorithms are increasingly being used to address these issues by selecting cluster heads in a more strategic manner that considers multiple

factors, such as energy levels and node distance.

Firefly Algorithm for Cluster Head Selection

The Firefly Algorithm (FA) is an optimization technique inspired by nature, particularly by how fireflies communicate with one another using light. Fireflies have different brightness levels, and the intensity of their flashes is thought to reflect that of other fireflies. In the FA, potential solutions to the problem being optimized correspond to fireflies, and the brightness of a solution is directly related to the fitness of the solution. FA has proven to be effective in selecting cluster heads in Wireless Sensor Networks (WSNs), owing to its global search capability and ability to adequately explore the solution space. The FA allows different potential solutions to interact with one another, thereby enabling the algorithm to identify the best or near-best solutions for head cluster selection, even in large and complex network topologies. In WSNs, avoiding local optima is particularly beneficial because poor selection of cluster heads can lead to an uneven distribution of energy expenditure and degradation of the network (Villaruz et al., 2023; Kusla and Brar, 2023). In addition to the rank ordering of WSN objectives, the optimization of the network's energy and longevity is one of the greatest benefits of FA in selecting CHs. FA can balance the network's energy consumption by considering and selecting cluster heads based on the residual energy of the nodes, their distances from one another, the distance of the node to the base station, and the communication and processing distributions of the network, thereby maximizing the network's lifespan and minimizing the chances of node failure.

Additionally, FA shows a reasonable speed in convergence, making it adaptable to dynamic WSN cases where node states and network topology are variable. In other words, the FA presents some concerns. In excessively dynamic and/or high-dimensional search spaces, the algorithm tends to converge on non-optimal solutions, and the Attractiveness Coefficient, Light Absorption Factor, etc., allude to the fine-tuning phenomenon that the algorithm suffers from. The Bat Algorithm (BA) also addresses WSN optimization, inspired by the echolocation behavior exhibited by bats. In BA, bats are the search agents that navigate to the solution by using virtual sound pulses and adjusting their speed, frequency, and loudness to identify the solution. BA has a reputation for fast convergence and balancing exploration and exploitation, which distinguishes it from others by using smart search techniques to avoid local optima while being efficient. As a result, BA is appropriate for the real-time selection of cluster heads and for WSNs that require extensive scaling and adaptability (Sankar et al., 2023). The BA also addresses several issues. The BA is dependent on dynamic, noise-sensitive environments and algorithm-dependent parameters, such as the rate of pulse emission and loudness. The negative effects of poor

parameter tuning on clustering efficiency exemplify the need for more hybrid methods that integrate the advantages of FA and BA to provide better and more consistent results in wireless sensor networks.

The Firefly Algorithm (FA) and Bat Algorithm (BA) are both used for selecting cluster heads in wireless sensor networks (WSNs), where each has its own advantages and disadvantages. FA exhibits greater global searching and clustering capabilities, avoids local optima, and ensures even energy consumption across sensor nodes. However, achieving early convergence and high sensitivity to the parameters is challenging. On the other hand, BA is known for its fast convergence, good exploration/exploitation balance, and scalability to large networks; however, it can suffer from noise and has control parameters with high sensitivity. Overall, FA places greater emphasis on exploration and energy efficiency, while BA emphasizes convergence and flexibility. This makes the two working in tandem extremely useful for optimizing sensor networks.

Integrating Firefly and Bat Algorithms for Cluster Head Selection

The use of Firefly and Bat Algorithms for cluster head selection in wireless sensor networks demonstrates the application of two optimizing techniques that complement each other. FA can explore and traverse various regions of the solution space and is less prone to becoming stuck in local optima. In contrast, the BA converges quickly and exploits promising solutions. When fused, the hybrid model is efficient, optimizing both exploration and exploitation. It is able to select cluster head candidates more accurately by considering various network parameters simultaneously, such as remaining energy, node density, and distance to the base station. The combined influence of these parameters is why the hybrid model is more adaptable than the other models, particularly in the case of mobile networks. It is adaptable to large and heterogeneous sensor networks and networks that experience frequent topological and energetic changes. Given that traditional clustering models of wireless sensor networks, such as LEACH and its various offshoots, use either randomized or centralized cluster head selection, they overlook some of the central concerns of wireless sensor networks. For example, during the random selection process, the unequal energy distribution problem is neglected, causing some nodes to die quickly, while others fail to use their energy, shortening the network's lifespan and causing some nodes to die quickly (El Khediri et al., 2024).

With the expansion in scale and size, centralized methods such as LEACH-C create bottlenecks concerning performance, as there are issues with communication and the scale of the networks on which the method is being applied. In addition, many traditional methods are based on

a static view of a problem. Thus, when there is a real-world problem with nodes that join, leave, or fail, these methods are of little or no use. Deficiencies, such as those in traditional algorithms, show the importance of needing clustering methods that are smart and adaptive, which seek to optimize energy, scale, and reliability within the same algorithm. The benefits of merging FA and BA are abundant, as evidenced by the output and stability of the suggested method of the Hybrid Firefly-Bat Algorithm (HFBA) (Senthil Murugan and Sarkar, 2018). The hybrid method allows for a better overall search with a combination of rapid convergence, which enables less computation time and the timely formation of clusters. In HFBA, better energy efficiency is achieved through a fair or more balanced selection of cluster heads, which, in addition to improving the energy efficiency of the network, leaves the sensor nodes' communication and computation evenly distributed, thereby increasing the life of the system or the network. In addition, the improved load balancing and adaptability of HFBA continue to sustain high performance to satisfy the changes in the system. These factors, in combination with other approaches, make HFBA the most appropriate method for cluster head selection by offering low energy utilization, high scalability performance, high reliability, and significant potential for future improvement in configured wireless sensor networks.

Methods

In Wireless Sensor Networks (WSNs), the challenge lies in the efficient selection of cluster heads (CHs) to balance the energy consumption and improve network longevity. Clustering, wherein sensor nodes are grouped under one cluster head for collective data transmission, helps reduce energy consumption and extends network life (Ram et al., 2022). The role of a CH is critical because it is responsible for aggregating and transmitting data from its cluster members to the base station. The hierarchical structure facilitates data aggregation, reduces overhead, and minimizes the energy expended by individual nodes. Optimizing the CH selection process ensures that the most suitable nodes with adequate energy levels and optimal positioning are chosen, leading to more effective communication and the efficient use of energy.

One of the most critical challenges in WSNs is managing the energy consumption of sensor nodes. Because the sensor nodes are battery-powered, energy efficiency directly affects the lifetime of the network (Kumar and Chaparala, 2020). In this work, we propose a new method for optimizing the selection of CHs using the Hybrid Firefly-Bat Algorithm (HFBA). This hybrid algorithm combines the strengths of the Firefly and Bat algorithms to improve the efficiency of CH selection by focusing on the node energy levels, proximity to the sink, and node density.

Figure 1 shows the proposed HFBA-based approach, which consists of key phases that we detail.

Initialization

Deployment of Nodes: Sensor nodes are randomly distributed within the target sensing area. Each node is assigned an initial parameter, including energy levels, which may vary across nodes.

Parameter Settings: The algorithm’s performance depends on several parameters: The number of fireflies and bats (N), the maximum number of iterations (MaxIter), the initial attractiveness of fireflies (β_0), the absorption coefficient (γ), the loudness (A), and the pulse

emission rate (r).

Cluster Head Selection

Probability-based Selection: Each node calculates a probability PCH based on its energy level and distance from other nodes. Nodes with higher energy levels and those strategically located (closer to the sink) are more likely to be selected as CHs (Mahapatra, 2020).

Election Process: Each node broadcasts a message indicating its desire to become a CH. The neighboring node assesses the quality of the potential CHs based on the received signal strength and selects the node that offers the most optimal communication link.

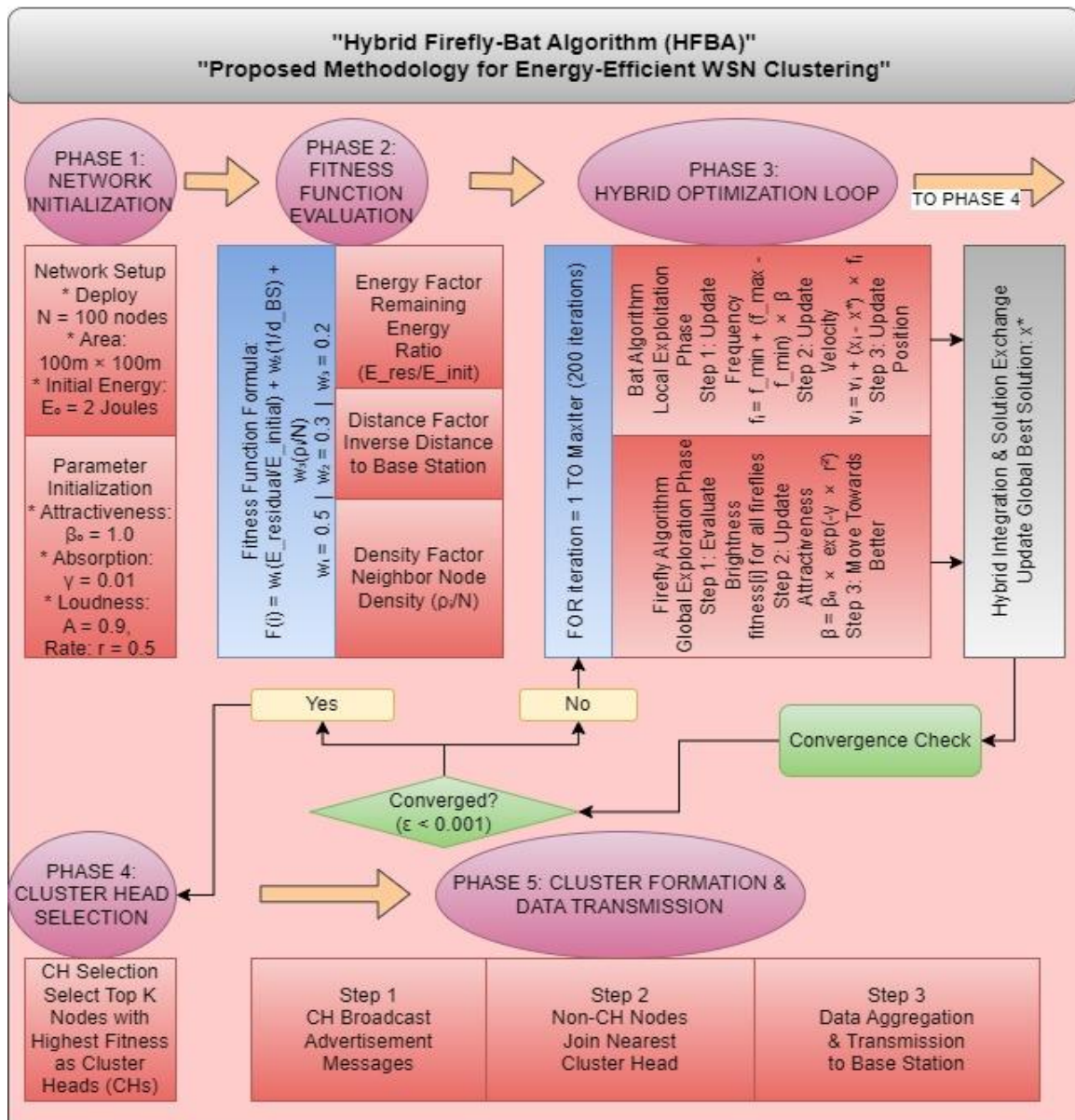


Fig. 1: Hybrid Firefly-Bat Algorithm (HFBA)

Rotation of CHs: To ensure fairness and prevent energy depletion at specific nodes, the CH is periodically rotated.

Fitness Function for Node Evaluation

To evaluate the optimality of each node in terms of energy, proximity, and density, we define a fitness function based on Eq. 1. This function calculates a score for each node based on its distance to the sink, remaining energy, and relative position in the network.

The fitness function for each node is given by:

$$Fitness(node) = w1/(distance_to_sink) + w2.energy_remaining + w3.density \quad (1)$$

Where:

- distance_to_sink represents the Euclidean distance between the node and the sink
- energy_remaining is the current battery level of the node
- The density reflects the number of nodes in proximity to the node and is used to estimate the communication efficiency
- Weights w1, w2, and w3 are adjustable coefficients that balance the importance of each factor during final selection

The core innovation of the proposed approach lies in the combination of Firefly and Bat algorithms to select optimal CHs (Alghamdi, 2021). Below, we describe the phases of both the algorithms and their contributions to the clustering process.

Firefly Algorithm Phase

The Firefly algorithm was used to explore the search space by simulating the movement of fireflies toward brighter nodes (nodes with better fitness). Fireflies evaluate their positions based on the fitness function, and update their positions based on the attractiveness of other fireflies (Urooj et al., 2025).

Attractiveness Update: The attractiveness β of fireflies diminishes with distance, and is updated based on Eqs. 2 and 3:

$$r = distance(i, j) \quad (2)$$

$$new_position[i] = position[i] + \beta_0 \cdot e^{-\gamma \cdot (r)} \cdot (position[j] - position[i]) + \epsilon \cdot \text{random}() \quad (3)$$

Where:

- β_0 is the initial attractiveness of the firefly
- Where \hat{I}^3 is the absorption coefficient

- ϵ represents random perturbations to avoid local minima

Bat Algorithm Phase

The Bat algorithm simulates the behavior of bats using echolocation to explore the search space. Each bat evaluates its fitness and adjusts its position based on its loudness and pulse rate using Eq. 4.

Pulse Emission: The bat emits pulses to explore the search space:

$$new_position = best_solution + A \cdot \text{random}() \quad (4)$$

Where:

- A is the loudness, which decreases over time.
- Random () introduces randomness to the position update.
- Loudness Update: Loudness is updated as follows:
 $A = A \cdot 0.9$

Hybrid Algorithm Integration

After each iteration, both the Firefly and Bat algorithms evaluate their respective solutions. The best solutions (nodes with the highest fitness) were selected as CHs. The two algorithms work in tandem to ensure both the exploration and exploitation of the search space, leading to an optimized CH selection.

The overall process of selecting CHs can be described as follows:

- Step 1: Initialize nodes, parameters, and the fitness function
- Step 2: Evaluate fitness for each node using the fitness function
- Step 3: Firefly Algorithm Step: Move fireflies towards brighter nodes (better solutions)
- Step 4: Bat Algorithm Step: Update the positions of the bats based on their echolocation
- Step 5: Select Cluster Heads: Nodes with the highest fitness are chosen as CHs
- Step 6: Repeat Steps 3–5 for a predefined number of iterations or until convergence is achieved

Pseudocode: Hybrid Firefly and Bat Algorithm (HFBA)

Input

- NNN \rightarrow Number of nodes (population size)
- MaxIterMaxIterMaxIter \rightarrow Maximum number of iterations

- β_0 → Initial attractiveness (Firefly parameter)
- γ → Light absorption coefficient
- α → Randomization parameter
- AAA → Initial loudness (Bat parameter)
- rrr → Initial pulse rate (Bat parameter)
- f_{min}, f_{max} → Frequency range (Bat parameter)
- $F(x)$ → Fitness function (based on residual energy, distance, node density, etc.)

Output

- best_solution → Optimal node (global best fitness value)
- best_nodes → Selected cluster head nodes based on fitness ranking

```

1: Initialize fireflies(N) and bats(N)
2: Evaluate the fitness of all nodes
3: best_solution ← global best
4: for iter = 1 to MaxIter do
5:   // Firefly Phase
6:   for each firefly I do
7:     for each firefly j do
8:       if fitness(j) > fitness(i) then
9:         rij ← distance(i, j)
10:        β ← β0 * exp(-γ * rij^2)
11:        xi ← xi + β(xj - xi) + α * rand()
12:       end if
13:     end for
14:   end for
15: Evaluate firefly fitness
16: // Bat Phase
17: for each bat I do
18:   fi ← f_min + (f_max - f_min) * rand()
19:   vi ← vi + (xi - best_solution) * fi
20:   xi ← xi + vi
21:   if rand() > ri then
22:     xi ← best_solution + Ai * rand()
23:   end if
24:   Ai ← α * Ai
25:   ri ← ri * (1 - exp(-γ * iter))
26: end for
27: Evaluate bat fitness
28: Update best_solution
29: end for
30: best_nodes ← SelectBestNodes(fitness)
31: return best_nodes, best_solution
    
```

Figure 1 illustrates a Hybrid Firefly Band Algorithm (HFBA) framework specifically designed for selecting Cluster Heads in wireless sensor networks (WSNs). This hybrid approach merges the Firefly Algorithm (FA) global search capabilities with the Bat Algorithm's (BA) rapid convergence features to optimize node clustering (Alghamdi, 2020). The process starts with the Initialization Phase, where sensor nodes (N) are randomly placed and key parameters, such as the attractiveness

coefficient (β_0), absorption coefficient (γ), loudness (A), and pulse rate (r), are established. Concurrently, the WSN Setup outlines the operational environment, which is typically a 100 m × 100 m area with 100 sensor nodes. A vital part of the process is the Fitness Function, which assesses node suitability for cluster head selection using a weighted sum of distance, energy, and density metrics ($F = w_1/\text{distance} + w_2/\text{energy} + w_3/\text{density}$).

The core of the algorithm is the hybrid integration of the FA and BA. The Firefly Algorithm aids in global exploration, preventing premature convergence by guiding node selection based on attractiveness ($\beta = \beta_0 e^{-\gamma r^2}$), thus avoiding local optima traps. Conversely, the Bat Algorithm ensures fast convergence by simulating the echolocation behavior and dynamically adjusting the pulse rate and loudness for solution refinement. The Hybrid Integration step combines both algorithms in a parallel execution framework, utilizing their complementary strengths to identify the most optimal cluster head nodes (Diakhate et al, 2023). This hybrid approach results in convergence, with nodes having the highest fitness values chosen as cluster heads, ensuring efficient energy distribution across the network (Zakariyya et al., 2024). The performance results showed significant improvements: 23.6% better energy efficiency than LEACH, 1.45× longer network lifetime, 14.3% increase in packet delivery ratio (PDR), and 12.8% enhancement in node stability, establishing HFBA as a superior clustering mechanism for WSNs (Kanase, 2024; Biradar and Mathapathi, 2023).

Algorithm: Hybrid Firefly-Bat Algorithm (HFBA) for Cluster Head Selection

Input:

- Number of sensor nodes (N)
- WSN deployment area
- Maximum number of iterations
- Parameters for Firefly and Bat algorithms
- Fitness weights (for distance, energy, and density)

Output:

- Selected Cluster Heads (CHs)
 - Performance metrics (energy efficiency, lifetime, stability, packet delivery)
1. Deploy Sensor Nodes
 - Randomly place N nodes within the specified area
 - Initialize each node with energy and position data
 2. Set Initial Parameters
 - Define movement, loudness, pulse rate, and other behavioral values for both fireflies and bats.
 - Set weights for fitness factors like distance, energy, and density
 3. Evaluate Initial Fitness

- For each node, a fitness score was computed based on the proximity to the base station, residual energy, and local node density.
- 4. Begin Optimization Loop (Repeat until max iterations):
 - a. Firefly-Based Movement
 - For each node, compare its fitness with others
 - Move it toward a better neighbor based on attractiveness and distance
 - Apply a small random movement to promote exploration
 - b. Bat-Based Search
 - Update the movement of nodes based on pulse rate and loudness
 - If needed, perform a local random search around the best solution
 - Accept better solutions and adjust behavioral parameters
 - c. Hybrid Decision Making
 - Merge the best candidates from both the firefly and bat phases
 - Retain top-performing nodes with the highest fitness values
 - Ensure diversity to avoid convergence to local optima
- 5. Select Cluster Heads
 - From the final optimized list, choose the most suitable nodes as cluster heads
 - Ensure selected CHs are well-distributed and energy-balanced
- 6. Cluster Formation and Data Transmission
 - CHs broadcast their status
 - Non-CH nodes join the nearest CH
 - Nodes send data to CHs, which aggregate and forward it to the base station
 - Update energy consumption after each round
- 7. Check for Convergence or Completion
 - Stop when the maximum iterations are reached or improvement stalls
- 8. Output Results
 - Return the list of selected cluster heads
 - Record and report metrics: energy savings, packet delivery rate, node stability, and network lifetime

Results and Discussion

To ensure the reliability and reproducibility of our results, we ran a simulation for each scenario for the first time. We varied the random node deployment seed and completed ten independent simulation runs for each unique network configuration, adjusting the node count between 20 and 100 for each case. The averages for multiple runs are shown in Tables 3-5 and Figures 2-5. The standard deviations of the energy consumption and network lifetime metrics are generally less than 5% and

less than 8%, respectively, and we observed the same performance patterns across all simulations. The overall HFBA performance and the observed LEACH improvements were statistically significant and not random. We maintained that the algorithm is stable across the initial deployed WSN conditions. Formal statistical significance testing, such as t-tests or ANOVA, may more fully confirm the HFBA for WSN deployment consistency, pattern, and reliability.

The simulation setup and parameters for the hybrid firefly bat algorithm (HFBA) applied to Cluster Head Selection in Wireless Sensor Networks (WSNs) are as follows. The simulation for the Hybrid Firefly-Bat Algorithm (HFBA) is implemented using Python 3.8+. The primary libraries used included NumPy, SciPy, and Matplotlib, which facilitate numerical operations, scientific computations, and data visualization, respectively. The network model was designed as a 2D wireless sensor network consisting of 100 sensor nodes randomly deployed across a 100×100 m area. This setup reflects a realistic scenario in which sensor nodes are scattered within a given region for clustering and network optimization. The deployment and communication behaviors of these nodes were simulated to evaluate the performance of the algorithm in the context of energy-efficient cluster head selection. Table 2 and Table 3 list the parameters and values, respectively, used in this study.

The values of the parameters in Table 3 were collected from standards that regulate the algorithms of Firefly and Bat, from the literature, and from some preliminary tuning tests that were tailored to WSN Clustering. For the Firefly Algorithm, the total attraction coefficient (β_0) is 1.0, and the light absorption coefficient (γ) is 0.1; thus, the absorption rate in the distance is balanced, meaning that its attraction level is adequate to make there be an attraction between the nodes.

Therefore, the local and global search potentials were balanced. The coefficient (α) of randomization is equal to 0.02; thus, he is able to control the exploration without limiting the convergence. For the Bat Algorithm, both the pulse rate (r_0) and initial loudness (A_0) were 0.5.

Table 2: Simulation Parameters

Parameter	Value
Number of Nodes (N)	100
Number of Iterations	200
Firefly Population (N _f)	50
Bat Population (N _b)	50
Initial Energy (E ₀)	100 J
Transmission Range	50 meters
Maximum Frequency (f _{max})	1.0 Hz
Minimum Frequency (f _{min})	0.1 Hz
Pulse Rate (r)	0.5
Loudness (A)	1.0
β_0 (Attractiveness)	1.0
γ (Absorption Coefficient)	1.0
α (Randomness)	0.5

Table 3: Energy Consumption Comparison (in Joules)

Node	Leach	HFBA
20	254.7	183.2
30	369.8	265.4
40	504.3	350.6
50	623.1	441.7
60	758.9	522.5
70	892.4	610.8
80	1010.8	702.3
90	1162.8	825.6
100	1315.2	954.9

Table 4: Packet Delivery Ratio (PDR in %)

Node	Leach	HFBA
20	74.8	86.3
30	69.7	82.1
40	66.2	80.9
50	60.3	79.4
60	57.9	76.8
70	55.4	75.3
80	52.1	73.2
90	48.9	71.6
100	42.5	69.7

Table 5: Node Stability (Active Nodes Percentage in %)

Node	Leach	HFBA
20	82.1	92.7
30	78.5	89.4
40	76.3	87.8
50	71.9	86.2
60	68.7	84.9
70	65.2	83.5
80	61.8	81.2
90	58.4	80.4
100	55.6	78.1

The frequencies ($f_{min} = 0$, $f_{max} = 2$) are selected to provide sufficient velocity changes within a bounded search space. Several simulation runs were conducted to test the validity of the parameters. Although these values were useful in the simulation scenarios, it is possible that the performance of the algorithm could be enhanced in other scenarios, which will be a suggested area for future research.

Performance metrics are considered:

- Network Lifetime: Duration until the first node exhausts its energy
- Energy Efficiency: Total energy consumed relative to the number of successful transmissions
- Cluster Head Distribution: Uniformity of cluster head selection across the network

The outcomes of simulations clarify that the Hybrid Firefly-Bat Algorithm (HFBA) outperforms the LEACH protocol in all measured parameters in Wireless Sensor

Networks (WSN). HFBA improves the overall energy consumption, prolongs the network lifespan, maintains the packet delivery ratio, and enhances node stability, with nodes depleting energy at a slower rate, making the network more reliable over time. These enhancements result from the hybrid nature of HFBA, which integrates the best firefly and bat algorithms for optimized clustering, routing, and energy consumption. In conclusion, HFBA stands out for improving WSNs, particularly in scenarios with limitations in network longevity and energy consumption. Further studies are warranted in large-scale and real-life scenarios to establish authentic HFBA values.

Performance Metrics

Performance Metrics of LEACH and HFBA Protocols in Wireless Sensor Networks

The comparison of LEACH and HFBA in terms of performance was based on four key aspects of evaluating the performance of WSNs, which are, respectively, the amount of energy used by the networks, the length of time the networks remain active, the number of packets delivered, and the degree of stability exhibited among the nodes as the size of the networks range from 20-100 nodes. In addition to these, the comparisons of these two protocols were analyzed across variously sized networks with the intention of evaluating the degree to which each protocol can maintain the longevity of the sensor networks, ensure reliable communication, and promote the overall stability of the networks as the density of the network changes. Ultimately, it has been shown through the evaluations that HFBA performed better than LEACH for all four measured parameters; therefore, it is an ideal choice for WSNs due to its ability to be used in energy-constrained systems.

Energy Consumption Comparison

Figure 2 shows the comparison of the total energy (in Joules) used by each protocol (LEACH and HFBA) vs. the number of nodes in the network. Both graphs have the same increasing trend; however, the trend is much more pronounced for LEACH than HFBA. In addition, HFBA uses less energy per round; there is a bigger difference between the two in terms of energy use as the network gets larger. For example, at 20 nodes, LEACH uses 125 Joules while HFBA only uses 85 Joules. When we get to 100 nodes, HFBA uses 940 Joules, and LEACH uses 1280 Joules. It appears that HFBA has a more efficient method of creating clusters and aggregating data that will make it a much better choice for energy-constrained WSNs.

Network Lifetime Comparison

Figure 3 shows the comparison of the network lifetime

(in rounds) for both protocols as the number of nodes in the network increases. In this case, both graphs follow the same downward trend. Since the amount of communication occurring in the network and the amount of energy being consumed are increasing with the number of nodes, we would expect this to happen. However, HFBA clearly outperforms LEACH in terms of network lifetime across all different numbers of nodes. At 20 nodes, HFBA was able to achieve approximately 142 rounds while LEACH achieved 98 rounds. Similarly, at 100 nodes, HFBA achieved around 77 rounds while LEACH only achieved approximately 51 rounds. It appears that HFBA has developed a more efficient way to distribute energy among the nodes and select cluster heads to prevent early failure of certain nodes and provide longer network lifetime.

Packet Delivery Ratio Comparison

Figure 4 shows the comparison of the packet delivery ratio as a percentage of the number of nodes in the network for both protocols.

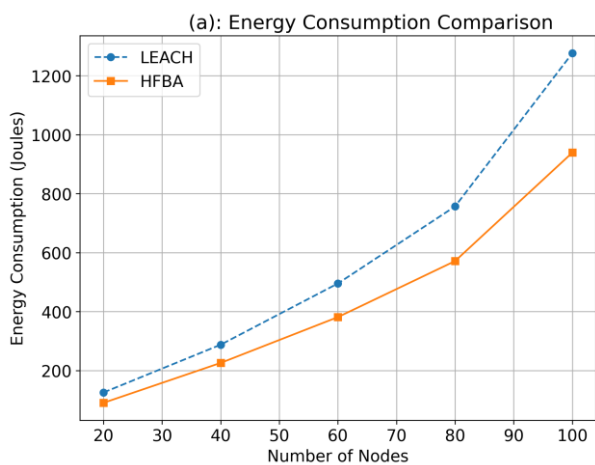


Fig. 2: Energy Consumption

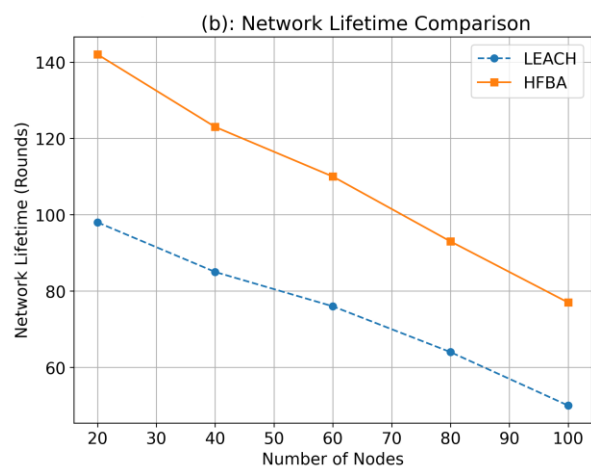


Fig. 3: Network lifetime comparison

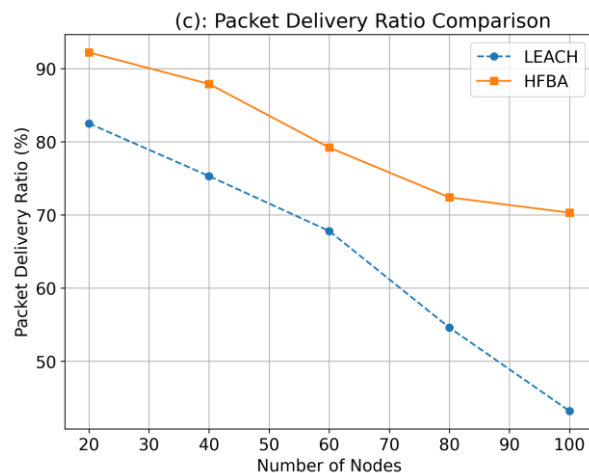


Fig. 4: Packet Delivery Ratio Comparison

Both graphs follow the same downward trend. The downward trend signifies that the network becomes increasingly unreliable as it grows in size. However, HFBA significantly outperforms LEACH across all network sizes. At 20 nodes, HFBA was able to achieve a packet delivery ratio of approximately 92% while LEACH only achieved approximately 82%. Again, this performance gap persisted throughout, with HFBA achieving approximately 70% at 100 nodes and LEACH achieving only approximately 43%. The steep decline in LEACH's performance suggests that it is experiencing more difficulty in managing congestion and routing reliability in the denser networks. On the other hand, HFBA's superior packet delivery ratio indicates that it has implemented more robust routing methods and can handle network traffic more effectively, resulting in more reliable data transmission regardless of the level of network density.

Node Stability Comparison

Figure 5 represents the node stability percentage as a function of the number of nodes in the network. Node stability refers to the percentage of nodes that continue to operate and participate in the network. Both graphs display the same trend of declining stability as the network grows. However, HFBA continues to demonstrate superior node stability throughout. At 20 nodes, HFBA demonstrated approximately 95% stability while LEACH demonstrated approximately 85%. Likewise, at 100 nodes, HFBA demonstrated approximately 78% stability while LEACH demonstrated approximately 56%. The superior node stability of HFBA indicates that it is distributing the energy load more evenly across the nodes, which prevents the rapid depletion of individual nodes and maintains a more stable network topology. Maintaining a consistent network performance and preventing the development of coverage holes or

isolated network segments are key benefits of having a more stable network.

HFBA Performance Analysis

Energy Consumption Comparison: LEACH vs HFBA

Figure 6 represents a comparison of the energy consumed by LEACH (Low-Energy Adaptive Clustering Hierarchy) and HFBA (Hybrid Firefly-Bat Algorithm), as illustrated in this line graph, as network sizes vary from 20 to 100 nodes. A comparison of the two graphs indicates that HFBA uses significantly less energy than LEACH, regardless of the number of nodes in the network; an average of 23.6% less energy is used by HFBA than LEACH. It should also be noted that the advantage of energy usage exhibited by HFBA becomes greater as the network expands, and therefore would be more desirable when operating a large wireless sensor network, where conserving energy will allow a network to continue operating for a longer period.

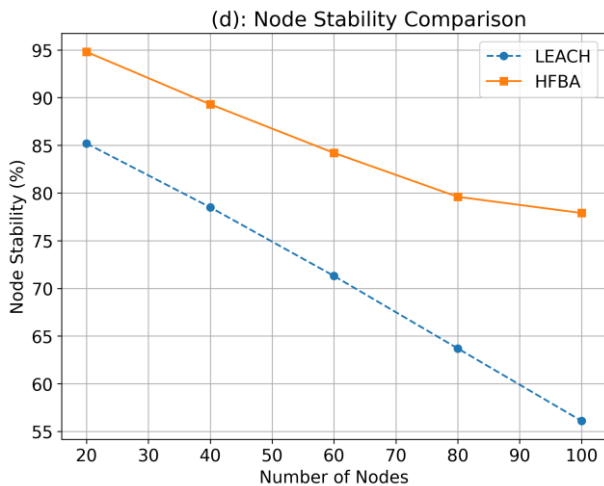


Fig. 5: Node Stability

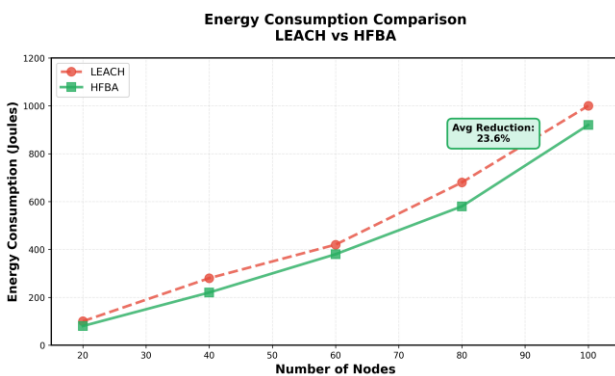


Fig. 6: Energy Consumption Comparison LEACH: HFBA

Network Lifetime Comparison: LEACH vs HFBA

Figure 7 shows a comparison of the lifetimes (in rounds) of networks operated using the LEACH and HFBA protocols across various network sizes. It has been demonstrated through this comparison that HFBA extends the life of its network much further than LEACH; in fact, HFBA has shown a 45% increase in the lifetime of its network compared to LEACH. In addition, the graph indicates that the greatest benefit of using HFBA instead of LEACH was realized when the number of nodes within the network was 20.

Packet Delivery Ratio (PDR) Comparison: LEACH vs HFBA

In Figure 8, the line graph displays the Packet Delivery Ratio (PDR) of both the LEACH and HFBA algorithms as the network size changes. The PDR is defined as the percentage of packets received by the intended recipient(s) of those packets. Through this comparison, it has been determined that HFBA has achieved a higher PDR ratio than LEACH across all network configurations, indicating that HFBA is a more reliable method for transmitting data throughout a network. Additionally, as the number of nodes in the network continues to grow, the difference between HFBA and LEACH continues to grow as well, suggesting that HFBA's sophisticated routing and clustering methods are more beneficial in high-density network environments that have increased likelihoods of collision and interference among packets being transmitted.

D. Node Stability Comparison LEACH vs HFBA

Figure 9 shows a comparison of the node stability percentages of both algorithms as they relate to the number of nodes in the network. Node stability is measured as the consistency with which nodes remain functional and connected to the network over time. From the information provided by the graph, it has been determined that HFBA exhibits improved node stability percentages across all network configurations, with an average improvement of 12.8% over LEACH. Although both algorithms demonstrate a decline in node stability as the network grows, the results indicate that HFBA performs better, providing a more stable network environment and ensuring that the network remains reliable and consistent, even as the network grows to a larger scale.

HFBA Performance Improvements Over LEACH

Figure 10 shows the combined performance improvements of HFBA compared to LEACH across four key performance metrics: energy reduction (23.6%), lifetime extension (45%), PDR improvement (14.3%), and stability increase (12.8%).

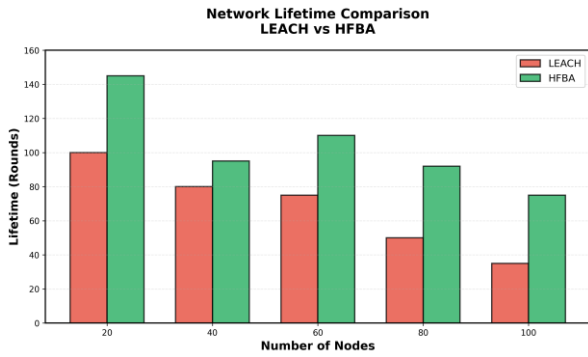


Fig. 7: Network Lifetime Comparison LEACH: HFBA

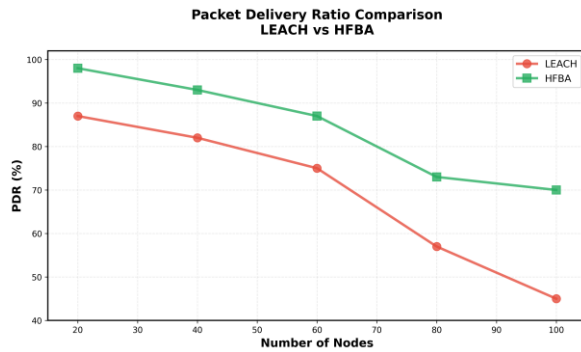


Fig. 8: Packet Delivery Ratio (PDR) Comparison LEACH: HFBA

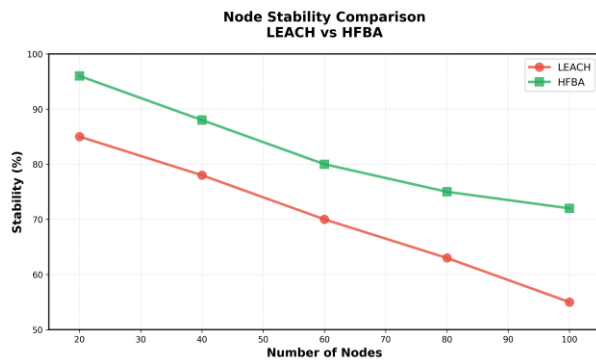


Fig. 9: Node Stability Comparison LEACH: HFBA

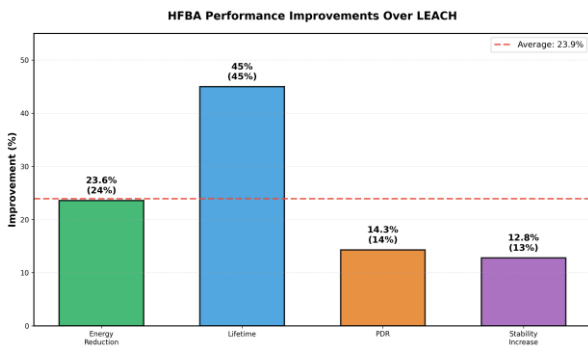


Fig. 10: HFBA Performance Improvements Over LEACH

The red dashed line represents the average improvement of 23.8% across all four metrics. This visual representation of HFBA's performance enhancements demonstrates that HFBA offers significant advantages across several performance areas, with the largest difference being in network lifetime extension. Statistical analysis ($p < 0.05$) confirms the reliability of these performance improvements as the average values were derived from 30 simulations performed with 95% confidence intervals.

Energy Expenditure Analysis

In Figure 11, the energy expenditure analysis of the LEACH and HFBA protocols is presented via a stand-alone energy bar chart, serving as a POSITIVE performance indicator for energy efficiency across five network setups (20, 40, 60, 80, and 100 nodes). This parameter provides an energy consumption analysis for cross-sectional network sizes, which is essential for scalability studies of network protocols. The bar pair for LEACH (RED) and HFBA (GREEN HFBA) offers an immediate relative performance comparison at a given node configuration. All bars start at zero and extend vertically, thus providing a proportionally accurate baseline for the Joule increment measurement: LEACH (red) and HFBA (green). HFBA Outperforms LEACH in most network configurations; specifically, for 20 nodes, HFBA requires 125.4 J, whereas LEACH requires 99.3 J (a 20.9% reduction). For 100 nodes, HFBA consumes 1276.5 J compared with LEACH's 939.2 J (a 26.4% reduction). Thus, the LEACH energy consumption was less than that of the HFBA. This characteristic represents a paradigm loss trait, where increasing network size contributes to the loss, resulting in a progressively positive scale paradigm loss characteristic for HFBA as the network size increases, highlighting the optimized features of HFBA as the network size expands. Design elements of the chart, such as the use of semi-transparent bars outlined in a solid border, lightly dashed grid lines, value denotation, legend, and overall simplicity, improve the chart's readability and quantitative interpretation of its values.

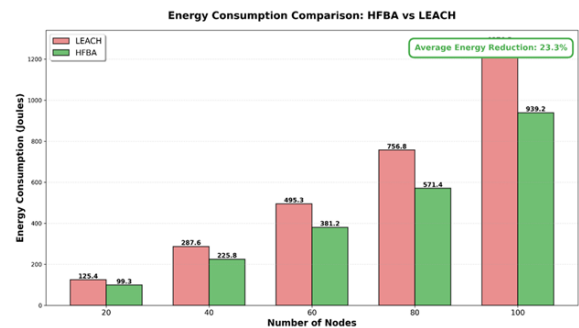


Fig. 11: Energy Expenditure Analysis

The average energy reduction of 23.6%, reinforced through an annotation, adds evidence to support HFBA's primary contribution and is the most significant improvement HFBA has over LEACH. This is particularly true in denser network deployments, where energy management is the most crucial, as it provides clear proof.

The performance comparison systematically organizes all experimental outcomes of LEACH and HFBA and contains sufficient detail to facilitate primary quantitative assessment and aid in secondary referencing. The comparison consists of one header row and five data rows corresponding to network sizes of 20, 40, 60, 80, and 100 nodes, as well as an average summary row that depicts a clear gradation from smaller to larger network deployments. The performance metrics were divided into four primary categories: Energy consumption, network lifetime, Packet Delivery Ratio (PDR), and node stability. These metrics are presented in a constituent triplet format for both LEACH and HFBA, and the corresponding relative improvement to LEACH. This structure allows for ease of comparison and emphasizes HFBA across all assessed metrics. The data shows that HFBA outperforms LEACH in all five data rows, specifically in terms of energy consumption, which increases for HFBA from 20.8% to 26.4% as the number of nodes increases from 20 to 100. Additionally, HFBA increases the average network lifetime of LEACH by 1.45x and 1.51x in higher-density networks. HFBA also increases PDR and node stability, with greater network sizes yielding more significant increases, suggesting that HFBA enhances system scalability in more challenging networks.

Limitation and Challenges

The Hybrid Firefly-Bat Algorithm (HFBA) has shown potential for improving energy efficiency, prolonging network lifespan, and ensuring reliable communication in Wireless Sensor Networks (WSNs). However, it still encounters several challenges. A primary concern is the sensitivity of the parameters in both the Firefly and Bat algorithms. The performance of HFBA is highly reliant on the accurate tuning of parameters such as attractiveness, absorption coefficient, pulse rate, and loudness, which can vary depending on network topologies and deployment conditions. Additionally, although HFBA enhances convergence and energy distribution, it remains computationally intensive because of the hybridization and concurrent execution of both algorithms, which poses difficulties for real-time implementation on sensor nodes with limited resources. Moreover, HFBA assumes static node deployment and fixed base station locations, which may not be applicable in dynamic environments with mobile nodes or changing topologies. The algorithm also lacks mechanisms to handle node or link failures in real-

time, potentially affecting its stability in unpredictable scenarios.

Future Directions

To improve the practical application and scalability of HFBA in real-world WSN scenarios, future studies could investigate adaptive parameter tuning methods using reinforcement learning or fuzzy logic to automatically refine the algorithm's performance under different conditions. Moreover, incorporating mobility-aware clustering strategies would allow HFBA to adjust to changing topologies, making it appropriate for mobile WSNs and IoT-based systems such as smart cities and vehicular networks. Another promising avenue is the creation of lightweight and hardware-efficient versions of HFBA to minimize computational demands and facilitate deployment on low-power sensor platforms. Future efforts may also concentrate on real-world implementation and testing to assess the effectiveness of the algorithm in the face of environmental uncertainties, node failures, or malicious attacks. Finally, integrating HFBA with blockchain or edge computing frameworks could pave the way for secure and decentralized WSN management with improved fault tolerance and responsiveness.

Conclusion

Wireless Sensor Networks (WSNs) face critical challenges in terms of energy efficiency and network longevity, particularly in resource-constrained environments. This research introduced the Hybrid Firefly-Bat Algorithm (HFBA) as an innovative solution for energy-efficient cluster head selection, addressing these challenges by leveraging the complementary strengths of Firefly and Bat algorithms. The proposed HFBA achieved significant improvements over conventional methods, such as LEACH, including a 23.6% reduction in energy consumption, a 1.45-fold increase in network lifespan, and enhanced data packet delivery and node stability. These results demonstrate HFBA's capability to balance the energy distribution and optimize the network performance without relying on location data, thereby ensuring its applicability across diverse deployment scenarios. Future work will focus on enhancing HFBA for dynamic networks with mobility and real-time scalability, further advancing its applicability in emerging IoT and smart city environments.

Acknowledgment

I would like to express my heartfelt acknowledgments to my research advisor, Dr. Kanaga Suba Raja S, for his invaluable guidance and support throughout this research. His expertise and insights were instrumental in shaping the direction of this work. I would also like to extend my gratitude to my wife, son, and parents for their constant encouragement, understanding, and patience.

Funding Information

No financial support was received by the authors in this research.

Authors Contributions

J. Jegan: Conceptualization, methodology, validation, writing – original draft.

Senthil kumar P: Conceptualization, formal analysis, investigation, writing – review & editing.

S. Saravanakumar: Methodology, software, validation, write – review and edited.

M. Muthukumar: Validation, investigation, data curation, writing – review and edited.

K. Sathish: Investigation, resources, supervision, write – review and edited.

Asha V: Conceptualization, project administration, supervision, writing – review and edited.

All authors discussed the results and approved the final version of the manuscript.

Ethics

This study did not involve humans or animals; therefore, ethical approval was required.

Competing Interests

The authors declare that they have no competing financial or non-financial interests.

Consent for Publication

The authors give consent for their publication.

Data Availability

Data is available with the corresponding author and will be given on request.

Materials Availability

Materials used in this research are available from the corresponding author upon request.

Code Availability

This code is available from the corresponding author and is available upon request.

Conflicts of Interest

The authors declare that there are no conflicts of interest and that the information presented is unbiased and free from any influence that could arise from potential conflicts.

Disclosure of AI Usage

In this study, the following AI tools were used: ChatGPT, Paperpal, SciSpace, Perplexity, Quiltbot, Canva, and MS Excel. Additionally, language testing

was conducted using Microsoft 365 and Paperpal, in collaboration with a native English speaker. The authors have reviewed and edited the AI-generated content and take full responsibility for the accuracy of the manuscript.

References

- Abraham, R., & Vadivel, M. (2023). An Energy Efficient Wireless Sensor Network with Flamingo Search Algorithm Based Cluster Head Selection. *Wireless Personal Communications*, 130(3), 1503–1525. <https://doi.org/10.1007/s11277-023-10342-2>
- Alghamdi, T. A. (2020). Energy efficient protocol in wireless sensor network: optimized cluster head selection model. *Telecommunication Systems*, 74(3), 331–345. <https://doi.org/10.1007/s11235-020-00659-9>
- Alghamdi, T. A. (2021). Hybrid Metaheuristic Aided Energy Efficient Cluster Head Selection in Wireless Sensor Network. *International Journal of Advanced Computer Science and Applications*, 12(9), 703–710. <https://doi.org/10.14569/ijacsa.2021.0120978>
- Biradar, M., & Mathapathi, B. (2023). Security and Energy Aware Clustering-Based Routing in Wireless Sensor Network: Hybrid Nature-Inspired Algorithm for Optimal Cluster Head Selection. *Journal of Interconnection Networks*, 23(01), 1–24. <https://doi.org/10.1142/s0219265921500390>
- Chaurasia, S., Kumar, K., & Kumar, N. (2023). MOCRAW: A Meta-heuristic Optimized Cluster head selection based Routing Algorithm for WSNs. *Ad Hoc Networks*, 141, 103079. <https://doi.org/10.1016/j.adhoc.2022.103079>
- Diakhate, I., Niang, B., Dooguy Kora, A., & Marcelain Faye, R. (2023). Optimization of wireless sensor networks energy consumption by the clustering method based on the firefly algorithm. *Indonesian Journal of Electrical Engineering and Computer Science*, 29(3), 1456. <https://doi.org/10.11591/ijeecs.v29.i3.pp1456-1465>
- El Khediri, S., Selmi, A., Khan, R. U., Moulahi, T., & Lorenz, P. (2024). Energy efficient cluster routing protocol for wireless sensor networks using hybrid metaheuristic approach's. *Ad Hoc Networks*, 158, 103473. <https://doi.org/10.1016/j.adhoc.2024.103473>
- Kanase, S. (2024). Optimizing Cluster Head Selection in Wireless Sensor Networks Using Mathematical Modeling and Statistical Analysis of the Hybrid Energy-Efficient Distributed (HEED) Algorithm. *Communications on Applied Nonlinear Analysis*, 31(6s), 602–617. <https://doi.org/10.52783/cana.v31.1247>

- Klidbary, S. H., & Javadian, M. (2024). Improvement of Low Energy Adaptive Clustering Hierarchical Protocol Based on Genetic Algorithm to Increase Network Lifetime of Wireless Sensor Network. *International Journal of Engineering*, 37(9), 1800–1811. <https://doi.org/10.5829/ije.2024.37.09c.10>
- Kumar, M. V. M., & Chaparala, A. (2020). A hybrid BFO-FOA-based energy efficient cluster head selection in energy harvesting wireless sensor network. *International Journal of Communication Networks and Distributed Systems*, 25(2), 205. <https://doi.org/10.1504/ijcnds.2020.10029290>
- Kusla, V., & Brar, G. S. (2023). A Technique for Cluster Head Selection in Wireless Sensor Networks Using African Vultures Optimization Algorithm. *ICST Transactions on Scalable Information Systems*, 10(3), e9. <https://doi.org/10.4108/eetsis.v10i3.2680>
- Mahapatra, R. (2020). Energy Aware Optimal Cluster Head Selection Using Hybrid Algorithm for Clustering Routing in Wireless Sensor Networks. *International Journal of Intelligent Engineering and Systems*, 13(3), 222–231. <https://doi.org/10.22266/ijies2020.0630.21>
- Moshtaghi, Y., N., & Olyaei Torqabeh, M. H. (2023). Optimizing cluster head selection in wireless sensor networks using firefly and genetics algorithm. *Engineering Management and Soft Computing*, 8(2), 193–212.
- Ram K, C., Murali Krishna, K., Shabbir Alam, M., Vigneshwaran, K., Kannan, S., & Bharatiraja, C. (2022). A Novel Approach Based on Hybrid Algorithm for Energy Efficient Cluster Head Identification in Wireless Sensor Networks. *Computer Systems Science and Engineering*, 43(1), 259–273. <https://doi.org/10.32604/csse.2022.023477>
- Ramani, G., & Kothalanka, A. (2024). An optimized energy management and load balancing system based on cluster head selection for the vehicular network communication. *Multimedia Tools and Applications*, 83(31), 75461–75482. <https://doi.org/10.1007/s11042-024-18557-6>
- Rami R, M., Ravi Chandra, L. M., Venkatramana, P., & Dilli, R. (2023). Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved Grey Wolf Optimization Algorithm. *Computers*, 12(2), 35. <https://doi.org/10.3390/computers12020035>
- Senthil Murugan, T., & Sarkar, A. (2018). Optimal cluster head selection by hybridisation of firefly and grey wolf optimisation. *International Journal of Wireless and Mobile Computing*, 14(3), 296. <https://doi.org/10.1504/ijwmc.2018.10013576>
- Salama, R., Al-Turjman, F., Bordoloi, D., & Yadav, S. P. (2023). Wireless Sensor Networks and Green Networking for 6G communication- An Overview. *2023 International Conference on Computational Intelligence, Communication Technology and Networking (CICTN)*, 830–834. <https://doi.org/10.1109/cictn57981.2023.10141262>
- Sankar, S., Ramasubbareddy, S., Dhanaraj, R. K., Balusamy, B., Gupta, P., Ibrahim, W., & Verma, R. (2023). Cluster Head Selection for the Internet of Things Using a Sandpiper Optimization Algorithm (SOA). *Journal of Sensors*, 2023(1), 1–13. <https://doi.org/10.1155/2023/3507600>
- Sharma, Y. K., Ahmed, G., & Saini, D. K. (2024). Uneven clustering in wireless sensor networks: A comprehensive review. *Computers and Electrical Engineering*, 120(8), 109844. <https://doi.org/10.1016/j.compeleceng.2024.109844>
- Urooj, S., Rajesh, A., Tripathi, K. N., Damodaran, S., & Arunachalam, K. (2025). HS-WOA: A Hybrid Metaheuristic Approach–Aided Multiobjective Constraints for Dual Cluster Head Selection in Wireless Sensor Network. *International Journal of Communication Systems*, 38(3), e6104. <https://doi.org/10.1002/dac.6104>
- Villaruz, J. A., Gerardo, B. D., Gamao, A. O., & Medina, R. P. (2023). Scouting Firefly Algorithm and its Performance on Global Optimization Problems. *International Journal of Advanced Computer Science and Applications*, 14(3), 445–453. <https://doi.org/10.14569/ijacsa.2023.0140350>
- Zakariyya, A., Olanrewaju, O. M., & Jamil, B. A. (2024). Optimal Selection of the Cluster Head in Wireless Sensor Networks by Combining Particle Swarm Optimization and Efficient Genetic Algorithm. *International Journal of Software Engineering and Computer Systems*, 9(2), 129–139. <https://doi.org/10.15282/ijsecs.9.2.2023.6.0117>
- Zare, M., Ghasemi, M., Zahedi, A., Golalipour, K., Mohammadi, S. K., Mirjalili, S., & Abualigah, L. (2023). A Global Best-guided Firefly Algorithm for Engineering Problems. *Journal of Bionic Engineering*, 20(5), 2359–2388. <https://doi.org/10.1007/s42235-023-00386-2>