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Optimized Clustering in WBSNs Using Hybrid Firefly Optimization and K-Means Algorithms

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A B S T R A C T

Recently, research on wireless body sensor networks (WBSNs) has gained significant attention and now plays a crucial role in patient monitoring. Due to power supply limitations, wireless nodes are typically organized into clusters for energy-efficient communication. To this end, clustering-based and grid-based approaches are commonly used. In the first approach, nodes are grouped into clusters in such a way that one sensor node is selected as the cluster head. In contrast, in the grid-based approach, the network is divided into limited virtual grids, usually managed by the base station. The firefly optimization algorithm (FOA), in combination with the K-Means algorithm, is used to optimally select cluster centers. Subsequently, the performance of the proposed segmentation method is evaluated and compared with existing methods. Simulation results show that the network lifetime improves by at least 7% compared to existing approaches.

Keywords: *Wireless Sensor Networks, Wireless Body Sensor Networks, Clustering, Firefly Optimization Algorithm, K-Means*

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1 Introduction

Wireless Body Sensor Networks (WBSNs) are a class of wireless sensing systems designed for monitoring physiological signals and vital signs through multiple sensor nodes deployed on or inside the human body. Sensor nodes in a WBSN are equipped with internal processors that enable them to monitor, process, and transmit physiological data within a limited body-centric environment. These nodes communicate with a central sink or coordinator node, which acts as the data collection and processing unit in the WBSN system [1-3]. The sink node may further transmit the collected data to external healthcare systems or medical servers via Internet connectivity for remote monitoring and analysis. WBSNs enable efficient data acquisition, processing, storage, and analysis for healthcare applications [4-6]. As a result, they play a crucial role in modern healthcare systems by enabling continuous and real-time patient monitoring. Despite challenges such as energy constraints, reliability, and security, WBSNs continue to evolve and offer promising solutions for medical and healthcare applications.

The architecture of a wireless body sensor network is structured into three main layers:

1. Physical Layer: This layer enables communication between body sensor nodes and the sink node using short-range wireless technologies such as radio frequency (RF), infrared, or Bluetooth, ensuring reliable body-centric connectivity.
2. Data Link Layer: This layer is responsible for establishing reliable and energy-efficient communication between sensor nodes and the sink node. Protocols such as IEEE 802.15.4 are commonly used to manage medium access control and data transmission within the network.
3. Application Layer: This layer defines how physiological data is formatted, processed, and transmitted from sensor nodes to the sink node. It supports healthcare applications such as patient monitoring, activity recognition, and medical diagnostics using appropriate communication protocols.

WBSNs are therefore a specialized extension of body-centric wireless sensing systems designed specifically for healthcare and physiological monitoring applications [7-12]. These sensor nodes continuously collect data such as heart rate, blood pressure, body temperature, and other critical health parameters, which are then transmitted for real-time analysis and medical intervention. WBSNs have emerged as a transformative technology in healthcare, enabling remote patient monitoring, chronic disease management, and enhancing the quality of life for patients. Despite their significant benefits, WBSNs face several challenges, primarily due to the severe resource constraints of sensor nodes. These constraints include limited battery capacity, restricted processing power, and short communication ranges. Since frequent battery replacement or recharging is often impractical, especially for implanted sensors, energy efficiency becomes a paramount concern. Excessive energy consumption leads to premature node failure, which can compromise the reliability and continuity of health monitoring.

Clustering is one of the most effective techniques to improve energy efficiency in WBSNs. In this approach, sensor nodes are grouped into clusters, each managed by a cluster head (CH). The cluster head is responsible for collecting data from member nodes, performing data aggregation to reduce redundancy, and forwarding the processed information to a central base station or external device. This hierarchical communication scheme reduces the number of long-distance transmissions, thereby lowering overall energy consumption across the network. Furthermore, clustering helps distribute energy consumption more evenly among nodes by periodically rotating the cluster-head role, thereby preventing the premature depletion of any individual node's battery. It also enhances scalability by simplifying network management and reducing communication overhead. Optimized clustering algorithms ensure the selection of appropriate cluster heads and cluster formation, which directly impacts network lifetime, data reliability, and latency.

This paper is organized as follows: Section 2 reviews the existing methods, covering previous techniques and algorithms. Section 3 describes the proposed approach, explaining its theoretical foundation and practical implementation. Section 4 presents the simulation results and compares the performance of the proposed method with that of existing techniques. Finally, Section 5 concludes the paper.

2 Existing Methods

Recently, research on WBSNs has gained considerable attention in medical applications and has become an essential component of modern patient monitoring systems. A secure cluster-based routing protocol named Secure

Optimal Path Routing (SOPR) has been proposed in [2]. This proposed algorithm improves communication security by detecting and avoiding attacks on one hand, and by transmitting data packets in encrypted form on the other. The main advantages of the proposed protocol include improved overall network performance, characterized by a higher packet delivery ratio, reduced detection time, lower energy consumption, and decreased communication delay. In [6], an enhanced version of the well-known MT-MAC algorithm, called DT-MAC, is proposed to ensure successful message delivery and uses virtual clusters to maintain network integrity. Simulation results show that the proposed protocol improves MT-MAC packet delivery by 13 to 17 percent and reduces response time by approximately 15 percent. Therefore, the algorithm is suitable for real-time applications where high packet delivery and low response time are required. Article [5] discusses the design challenges for cluster-based schemes, important cluster formation parameters, and the classification of hierarchical clustering protocols. Additionally, existing cluster- and network-based techniques are evaluated based on specific parameters to assist users in selecting the appropriate method. Furthermore, a detailed summary of these protocols is provided, including their advantages, disadvantages, and applications in specific cases.

In flat networks, all sensors are directly connected to each other and share the same role. According to Akaya et al. [7], data aggregation in these networks is performed through a centralized routing approach, in which the central station typically sends query messages to sensor nodes. However, frequent communication between the sensors and the central station, along with the associated computational overhead, leads to increased energy consumption at both ends. Over time, this energy depletion can significantly reduce network lifetime and may ultimately result in the failure of the entire network. Therefore, from the perspectives of scalability and energy efficiency, several cluster-based and tree-based data aggregation methods have been proposed. Wireless sensor networks consist of small, energy-limited nodes that can be mobile and deployed in large numbers in unknown environments. The paper [8] proposes improving network efficiency by combining directed diffusion with clustering and an advanced data aggregation scheme. The scheme enables nodes to process and aggregate sensor data, even in unfamiliar environments, using complete query definitions in interest messages.

To improve overall system performance, several novel features are introduced, including interest transformation, layered aggregation, and dynamic aggregation points. In the study by Du et al. [9], an energy-efficient chain construction algorithm was developed that applies fusion to minimize energy consumption across the entire chain. The main focus is on energy efficiency in sensor network broadcasting. A multi-chain scheme is proposed, dividing the entire network into regions concentrated around nodes closer to the center of the sensing area. For each region, a linear chain is created that ends at the central node.

Tan et al. proposed an energy-efficient data aggregation protocol called PEDAP [11]. The primary objective of PEDAP is to maximize network lifetime, measured by the number of operational rounds. In each round, data collected from sensor nodes are aggregated and subsequently transmitted to the sink node. PEDAP is a protocol based on the minimum spanning tree, which increases the network lifetime even when the sink is located within the field. PEDAP minimizes the total energy consumption per round by constructing a minimum spanning tree across the network, using a link cost calculated as follows. In [13], a distributed energy-aware heuristic approach, referred to as EADAT, was proposed for the construction and maintenance of a data aggregation tree in sensor networks. Simulation results showed that EADAT achieves a longer network lifetime and greater energy efficiency than routing schemes that do not incorporate data aggregation. In [14], the impact of source/destination mobility and communication network density on the energy costs associated with data aggregation was investigated. The Event Radius (ER) and Random Source (RS) models were considered for source mobility. In the ER model, all sources are assumed to lie within a fixed distance from a selected "event" location. In [15], a novel distributed clustering approach was proposed for extending the lifetime of ad hoc sensor networks. The proposed protocol periodically selects cluster heads based on a combination of each node’s residual energy and an additional parameter, such as its proximity to neighboring nodes or its node degree. Simulation results indicate that the proposed approach is effective in prolonging network lifetime and supporting scalable data aggregation.

3 Proposed Method

As the proposed clustering approach utilizes the firefly optimization algorithm (FOA) in conjunction with the K-

Means algorithm, the essential principles of these methods are first introduced.

3.1 K-Means algorithm

The K-Means algorithm is considered an unsupervised machine learning method that groups unlabeled data into distinct clusters. In this section, the functioning of the K-Means clustering algorithm is first examined. The primary objective of the K-Means algorithm is to minimize intra-cluster variance, ensuring that similar data points are grouped together, while dissimilar points are placed in separate and more distant clusters [16-19].

The steps of the K-Means clustering algorithm are as follows:

1- Initially, the number of clusters (k) is defined, and initial cluster centers are randomly assigned.
2- Each data point is then assigned to the cluster whose center is closest to it, typically using Euclidean distance as the metric.

3- Next, the centers of all clusters are updated by computing the mean of the data points within each cluster.
4- Steps 2 and 3 are repeated until a stopping criterion is met. The algorithm terminates either when the cluster assignments no longer change—meaning each point is assigned to the nearest cluster center—or when a predefined number of iterations is reached.

3.2 Firefly Optimization Algorithm

The firefly algorithm is inspired by the behavior of tropical fireflies [20-26]. The ability to emit flashing light through a bioluminescence process is the most distinctive feature of fireflies. The flashing signal serves as a primary mating signal to attract partners. Moreover, the attraction between tropical fireflies is related to the light intensity I(r), which is inversely proportional to the square of the distance r. Additionally, light intensity diminishes with increasing distance due to atmospheric absorption.

Firefly behavior is simplified in the FOA because its real interactions are too complex for standard optimization methods to model directly. In this algorithm, all fireflies are considered unisex, and the attractiveness between them is proportional to their brightness. The brightness of each firefly is determined by the value of a defined objective function. Here, D and N represent the dimensions of the candidate solutions and the population size, respectively. The attractiveness of a firefly, β, is a monotonically decreasing function with respect to the distance r.

$$\beta(r) = \beta_0 e^{-\gamma r^2} \qquad (1)$$

The distance r between two fireflies corresponds to their Euclidean distance. The terms β0 and γ represent the attractiveness at r=0 and the light absorption coefficient, respectively. The movement of a firefly xi toward another more attractive firefly xj is modeled as follows:

$$\mathbf{x}i = \mathbf{x}i + \beta^0 e^{-\gamma r^2}(\mathbf{x}j - \mathbf{x}i) + \alpha\epsilon_i \qquad (2)$$

Here, α denotes the randomization parameter, while εi is a vector of random numbers drawn from the uniform distribution U(−0.5,0.5).

The main steps of the FOA are as follows:

1. Initialization:
   - Define the objective function to be optimized.
   - Initialize a population of fireflies with random positions in the search space.
   - Set algorithm parameters: number of fireflies N, maximum iterations, light absorption coefficient γ, attractiveness β0, and randomization parameter α.
2. Evaluate Brightness:
   - Calculate the light intensity (brightness) of each firefly based on the objective function.
3. Move Fireflies:
   - For every pair of fireflies i and j, If firefly j is brighter than firefly i, move firefly i toward firefly j according to the equation (2).
4. Update Brightness:
   - Recalculate brightness for all fireflies after movement.
5. Rank and Update:
   - Rank fireflies based on brightness and update the best solution found so far.
6. Repeat:
   - Repeat steps 2 to 5 until the maximum number of iterations is reached or a stopping criterion is met.
7. Output:
   - Return the best solution found.

3.3 Clustering Using FOA and K-Means

Finally, the flowchart of the proposed method is presented in Figure 1. This flowchart illustrates the main stages of the algorithm in a step-by-step manner and provides a clear overview of the clustering process in WBSNs using the FOA. The main stages of this process are described as follows:

1. Input data acquisition: In the first step, input data from the body sensor nodes are collected and preprocessed. These data may include physiological information such as heart rate, body temperature, oxygen saturation, and other vital signs. Additionally, spatial coordinates, residual energy, and data transmission rates are considered as important features for the clustering process. After collection, the data are normalized and prepared for further processing.
2. Initial generation of cluster centers using the firefly algorithm: In this phase, the firefly optimization algorithm is employed to determine the initial positions of the cluster centers (CHs). This algorithm, inspired by the flashing behavior of fireflies and their tendency to move toward brighter individuals, explores the solution space to identify highly attractive positions. In this context, attractiveness is defined based on metrics such as minimizing the distance to sensor nodes, maximizing network lifetime, and achieving optimal coverage of the surrounding area.
3. Termination condition check: Once the cluster centers are generated, the algorithm evaluates whether the termination condition is satisfied. These conditions may include reaching a predefined number of iterations, observing no significant improvement in the fitness function over several consecutive iterations, or convergence of cluster center positions. If none of these conditions are met, the algorithm returns to step 2 to continue optimizing the cluster center locations.
4. Node clustering based on updated centers: After the cluster centers are finalized or updated, the sensor nodes are assigned to the nearest cluster center based on spatial proximity and other selected criteria such as energy level and data rate. At this stage, each node becomes a member of a specific cluster and transmits its data to the corresponding cluster head. The allocation is performed in a way that minimizes the overall energy consumption and reduces data transmission delay.
5. Final cluster formation and network structure update: In the final step, the clusters are fully formed and the network topology is updated accordingly. The selected cluster centers serve as cluster heads and manage data communication by forwarding aggregated data either through inter-cluster communication or directly to the base station. This clustering structure significantly improves energy efficiency in energy-constrained nodes and extends the overall lifetime of the WBSN.

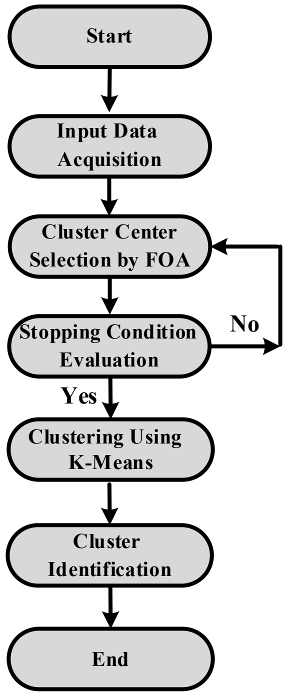


Figure 1. Clustering using FOA and K-Means

The main distinction of the proposed FOA–KMeans hybrid approach from previous hybrid clustering methods lies in the role of the FOA within the clustering process. In many existing hybrid clustering schemes, metaheuristic algorithms are primarily used for cluster-head selection after cluster formation or for routing optimization. In contrast, the proposed method employs FOA to determine near-optimal initial cluster centers before the execution of the K-Means algorithm. Specifically, the FOA explores the search space by considering node distribution, communication distance, and cluster-center placement quality. The optimized centers generated by FOA are then used as the initial centroids for K-Means. This strategy reduces the sensitivity of K-Means to random initialization, decreases the likelihood of convergence to local optima, and produces more balanced clusters. Furthermore, unlike conventional K-Means clustering, which relies solely on distance-based partitioning, the proposed hybrid framework utilizes optimization-driven centroid selection to improve cluster formation and prolong network lifetime. The optimization objective is defined as follows:

$$F = w_1\left(\frac{\sum_{i=1}^{N} d(i, CH_i)}{D_{max}}\right) + w_2\left(1 - \frac{L}{L_{max}}\right) \qquad (3)$$

Where $d(i, CH_i)$ denotes the distance between sensor node i and its corresponding cluster head CH_i, $D_{\max}$ represents the maximum possible intra-cluster distance used for normalization, L is the network lifetime achieved by a candidate clustering solution, $L_{\max}$ denotes the maximum observed (or reference) network lifetime used for normalization, and w_1 and w_2 are weighting coefficients that control the relative importance of minimizing intra-cluster communication distance and maximizing network lifetime, respectively, subject to the constraint $w_1 + w_2 = 1$.

Here is the precise pseudo-code corresponding to the flowchart described in the proposed clustering method for WBSNs using the FOA. This pseudo-code is presented step-by-step and is designed to be implementable in programming languages such as MATLAB or Python.

```
Begin

// Step 1: Input data acquisition
Load sensor node data:
  - Position of each node
  - Residual energy
  - Transmission rate
  - Sensing parameters (e.g., temperature, heart rate, etc.)

Normalize input features (if necessary)

// Step 2: Initialize parameters for Firefly Algorithm
Initialize population of fireflies Xi (i = 1 to n)
  Each Xi represents a possible set of cluster centers
Initialize light intensity Ii for each firefly
Define FA parameters:
  - Maximum number of iterations: MaxIter
  - Absorption coefficient: γ
  - Randomization factor: α
  - Attraction coefficient base value: β0

iter = 0

While (iter < MaxIter) and (not converged)

  For each firefly Xi
    For each firefly Xj (j ≠ i)
      If (Ij > Ii)
        Compute distance rij between Xi and Xj
        Move Xi towards Xj using:
          Xi = Xi + β0 * exp(-γ * rij^2) * (Xj - Xi) + α * (rand - 0.5)
      End If
    End For

    Evaluate fitness of Xi:
      - Assign each node to nearest cluster center in Xi
```

```
      - Compute intra-cluster distance
      - Compute network lifetime
      - Combine criteria into fitness function F(Xi)

     Update light intensity Ii based on fitness F(Xi)
    End For

    Check for convergence:
     - No significant improvement in best fitness?
     - Or maximum iteration reached?

    iter = iter + 1

  End While

  // Step 3: Final clustering using best firefly
  BestSolution = firefly with best fitness
  ClusterCenters = extract centers from BestSolution

  For each sensor node
    Assign to nearest cluster center in ClusterCenters
  End For

  Update network structure:
    - Define Cluster Heads (CHs)
    - Establish data transmission routes (intra- and inter-cluster or direct to sink)

End
```

Figure 2. Pseudo-code for clustering using FOA and K-Means.

4 Simulation Results

The proposed and existing method algorithms were implemented using MATLAB R2025a (MathWorks) on a system with an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz and 16 GB RAM. Table 1 provides a detailed overview of the parameters selected for the FOA. These parameters were carefully chosen to achieve an effective trade-off between computational efficiency and solution accuracy. The selection process involved preliminary experiments and references to existing literature to ensure that the algorithm maintains a reasonable convergence rate while avoiding premature convergence. By appropriately tuning these parameters, the algorithm is expected to explore the solution space adequately and exploit promising regions to obtain high-quality solutions.

Table 1. Parameters of the FOA

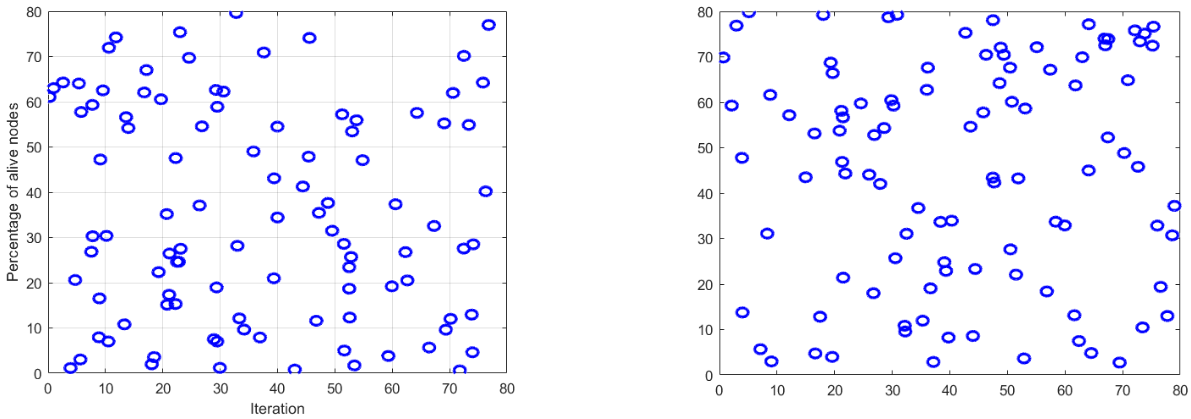
Parameters	**Values**
Maximum number of iterations	100
Population size	25
Light absorption coefficient	1
Base value of the absorption coefficient	2
Mutation coefficient	0.2
Mutation damping ratio	0.98

It is worth noting that the wireless sensor network includes several variables defined within the MATLAB environment. These variables and their corresponding values are as follows:

- Number of nodes: 100
- CH (Cluster Head) percentage: 0.03 to 0.06
- Environment dimensions (length): 80 units
- Path loss: 1×10^{-6}
- Number of iterations: 100

- Base station location: [100, 0]
- Initial battery power of nodes: 1 unit (for each of the 100 nodes)
- Number of simulation runs: 30 independent runs were performed, and results are reported as averaged values to ensure statistical reliability.
- Random seed handling: a fixed random seed was used for node deployment and FOA initialization to ensure reproducibility of results.
- Statistical analysis: the results of multiple independent simulation runs are averaged to evaluate the performance of the proposed method.
- The communication energy model is based on the standard first-order radio model, where transmission and reception energy depend on distance-based path loss. The packet size is assumed to be 4000 bits, consistent with common WBSN literature.
- Radio model parameters (including transmitter/receiver circuitry energy and amplifier energy) follow standard values used in LEACH-based clustering protocols.
- The sink node is assumed to be static and located at [100, 0], and no sink mobility is considered in this study.
- Data aggregation cost is modeled as a fixed energy consumption per cluster head per round, consistent with widely used WBSN clustering assumptions.

Several scenarios with varying percentages of CH have been considered to evaluate the network performance. The appropriate selection of CH percentage significantly affects the network's efficiency, lifetime, and energy consumption. Figure 3 illustrates a wireless sensor network composed of 100 nodes distributed randomly. The network is designed such that each node can communicate with others; however, clustering algorithms are employed to optimize energy management and overall network performance. In Figure 4, the clustering results are shown, where the CH nodes are marked as prominent points, and the member nodes are connected to their respective CHs by red lines. These connections represent the membership allocation of each node to its cluster head, clearly illustrating the cluster structure. Figure 5 presents a plot of the percentage of alive nodes versus the number of iterations of the algorithm. This curve effectively demonstrates how the network's energy depletes over time, reflecting the impact of varying CH percentages on network stability and lifetime. Finally, Figure 6 depicts the optimization process of the FOA applied to the network. The algorithm aims to find the optimal configuration and positioning of cluster heads to improve the network's performance. The convergence curve shows a gradual reduction in the cost function, indicating enhanced network efficiency and improved energy utilization over iterations.



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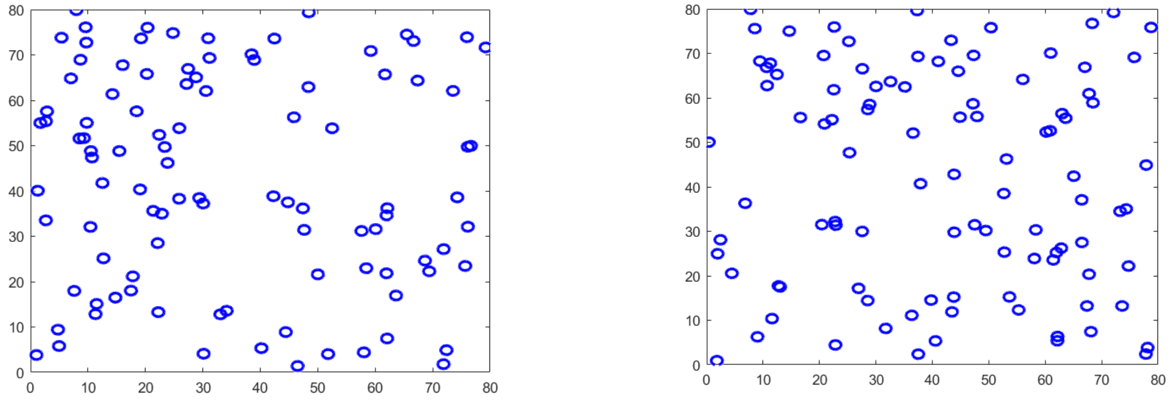
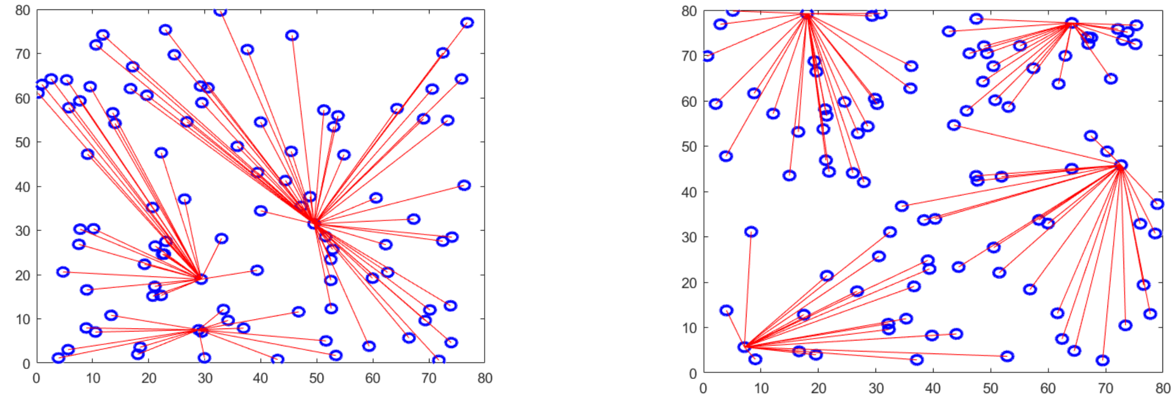


c) d)

Figure 3: Examples of WBSN composed of 100 nodes distributed randomly.



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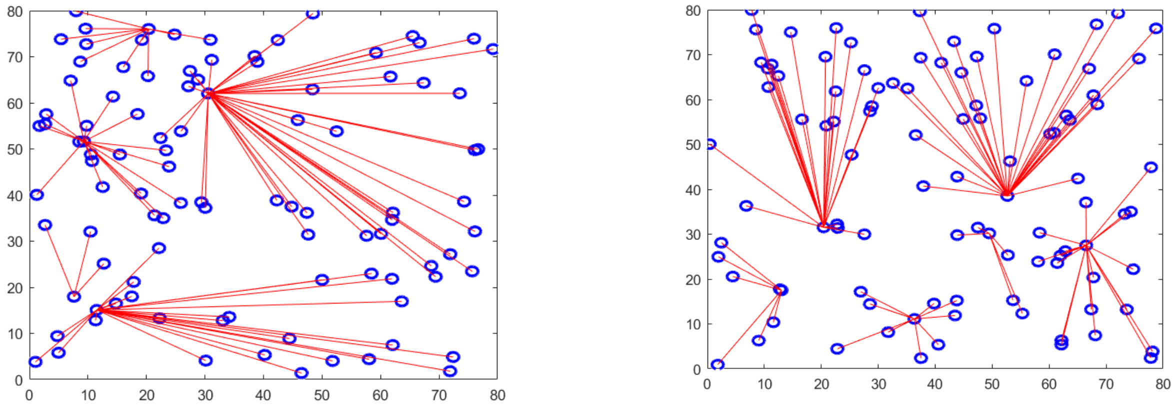
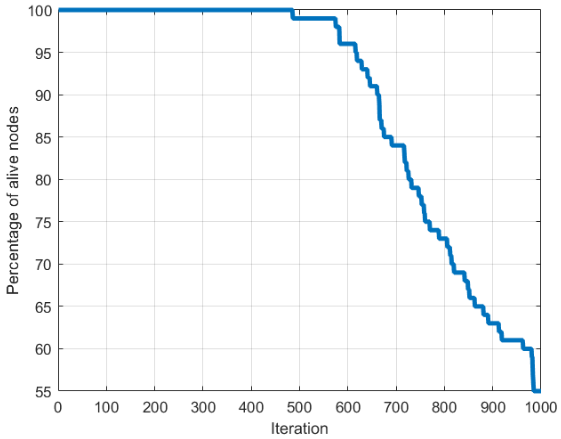


c) d)

Figure 4: Clustering results: (a) CH=0.03, (b) CH=0.04, (c) CH=0.05, (d) CH=0.06.



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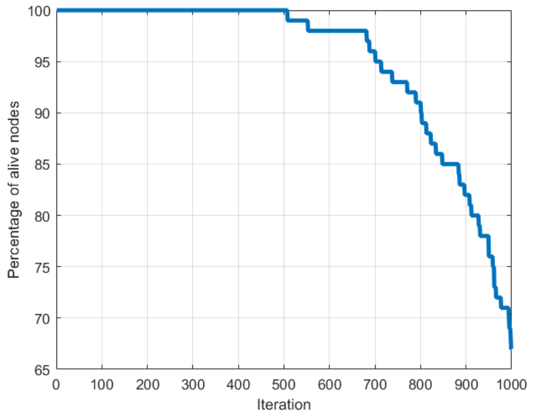

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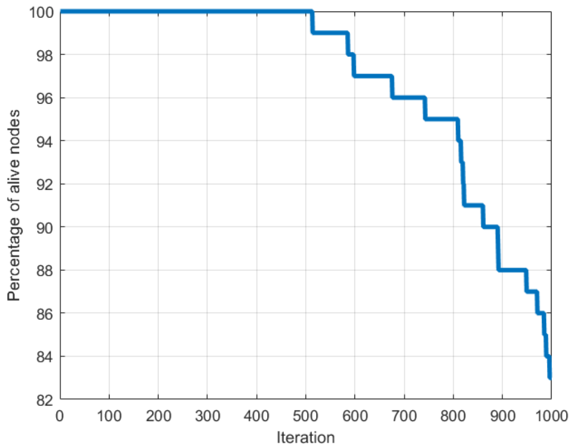

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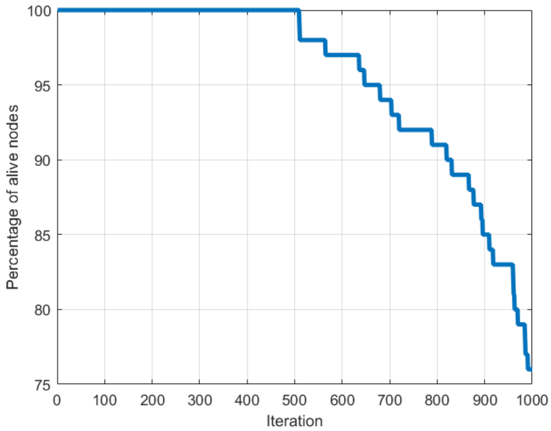
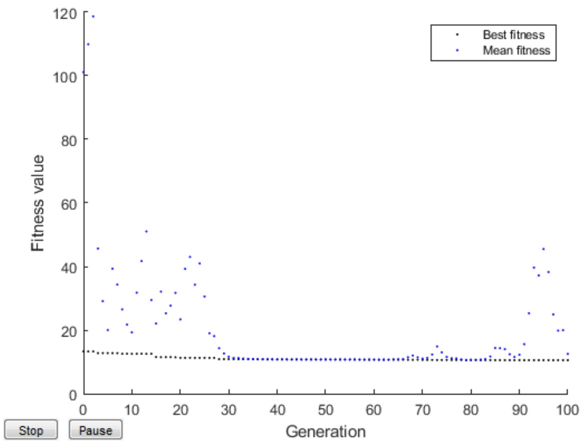


d)

Figure 5. Percentage of alive nodes versus the number of iterations**:** (a) CH=0.03, (b) CH=0.04, (c) CH=0.05, (d) CH=0.06.



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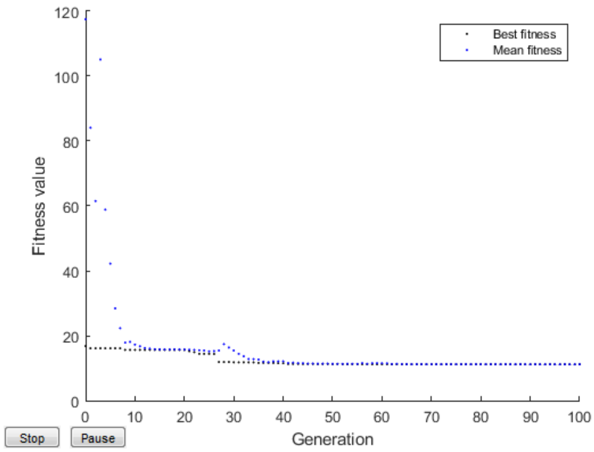

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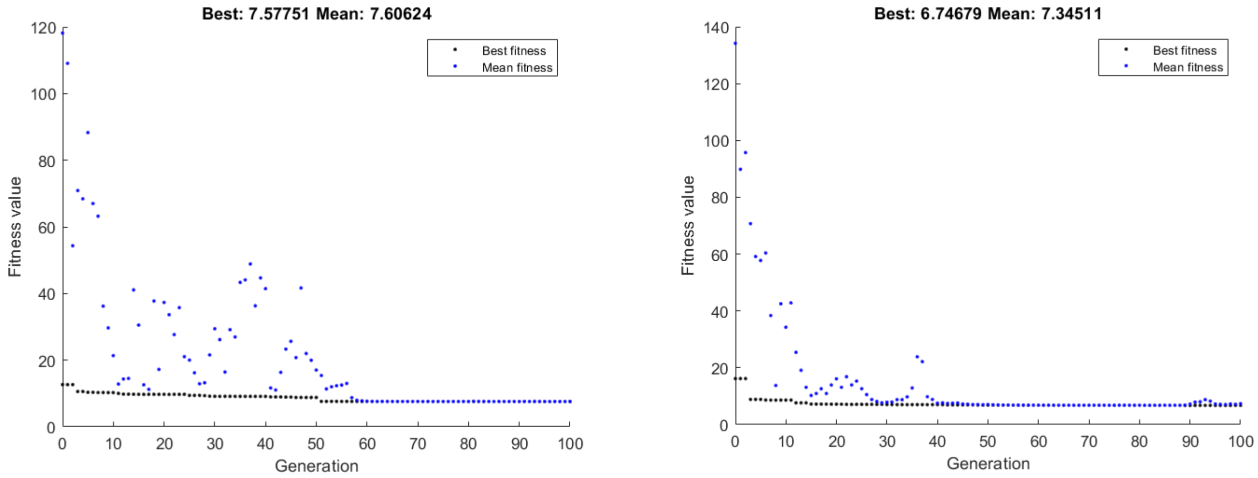

c) d)

Figure 6. Optimization process using the FOA: (a) CH=0.03, (b) CH=0.04, (c) CH=0.05, (d) CH=0.06.

The network lifetime graph, comparing the proposed method with other existing approaches, is illustrated in Figure 7. Analysis of this graph clearly demonstrates that the proposed method significantly enhances the network lifetime. This improvement is primarily attributed to the application of the FOA for the optimal selection of cluster centers within the network. Intelligent selection of cluster centers—based on criteria such as distance, residual energy, and node density—reduces the communication burden on specific nodes and delays their early depletion. As a result, a larger number of nodes remain active for a longer period, thereby substantially increasing the overall network lifetime. Thus, integrating the Firefly Optimization Algorithm into the proposed method not only contributes to extending the network's operational lifetime but also improves decision-making quality and system efficiency.

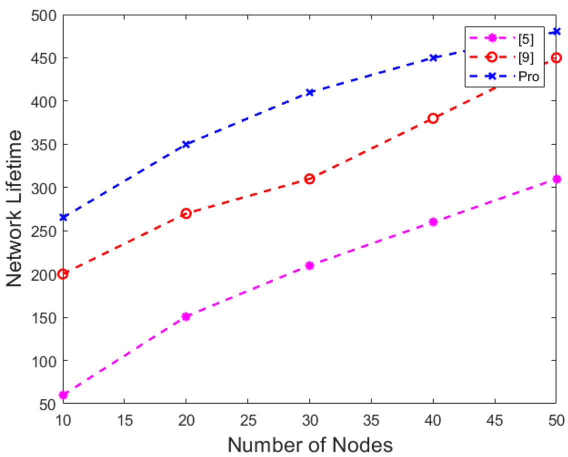

Figure 7. Performance evaluation of the proposed method and comparison with existing methods

5 Conclusions

WBSNs consist of multiple sensors that sample, process, and transmit vital signs such as heart rate, blood pressure, and blood oxygen saturation. Similarly, sensors can be employed to monitor environmental parameters such as location, temperature, humidity, and light. These sensors are often used as wearable elements or implanted devices within the body. In this study, a novel clustering method for sensor networks is proposed, which is based on a hybrid approach combining FOA and the k-means algorithm. Determining the optimal cluster centers is a challenging task, which is addressed here using the FOA. The FOA is utilized to optimize the K-means parameters to minimize intra-cluster distance and maximize network lifetime in WBSNs. The proposed method has been applied to a set of datasets, and the simulation results demonstrate the high efficiency and performance of the proposed approach. By initializing the cluster centers through FOA, the algorithm avoids the local optima problem commonly encountered in traditional k-means. Furthermore, the hybrid model achieves faster convergence and greater clustering stability in dynamic network conditions. This approach also contributes to reduced energy consumption by minimizing redundant data transmission among sensor nodes. The flexibility of the FOA-k-means algorithm allows it to adapt to both stationary and mobile WBSN scenarios. Overall, the proposed methodology offers a promising solution for intelligent and energy-aware clustering in body sensor networks.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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