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Enhancing Wireless Sensor Networks Performance by Integrating Particle Swarm Optimization with Intelligent Clustering Techniques

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Abstract: Wireless sensor networks play a crucial role in various applications, including industrial automation, healthcare, and environmental monitoring. Energy consumption remains a major challenge due to the limited energy of sensor nodes. This study utiliz-es FCM, Heuristic, K-Means, DBSCAN, and PSO to enhance network performance and longevity. K-Means balances clusters, DBSCAN detects dense regions, FCM assigns flexible memberships, and heuristic clustering adjusts clusters based on energy and base station proximity. The proposed method dynamically selects cluster heads based on energy levels and base station prox-imity. PSO optimizes selection by evaluating intra-cluster distances and residual energy, enabling dynamic reselection for improved efficiency, lower transmission costs, and extended network lifespan. Simulations show high energy savings in FCM (1.7213J for 50 nodes, 5 clusters), while K-Means depletes energy the fastest (1.5394J for 150 nodes) and DBSCAN consumes the most energy (1.0258J), rendering it unsuitable for longevity-focused applications. FCM ensures the longest network lifespan (904 iterations), compared to K-Means (483 iterations) and Heuristic (443 iterations). In terms of latency, K-Means experiences the highest delays (1.5s), while FCM and heuristic clustering maintain lower delays around 1.0s or less. The hybrid FCM-PSO approach reduces energy consumption by 12–15% and extends network lifespan by 20%.

Keywords: Energy efficiency, Cluster head selection, Particle swarm optimization (PSO), Heuristic clustering

Introduction

Wireless sensor networks have been used in a variety of fields including industrial automation, healthcare, and military surveillance has grown significantly in importance (Majid et al., 2022). As sensor nodes typically operate on batteries and have a restricted amount of electricity available, WSNs require energy (Riaz et al., 2021). Poor energy management leads to node failure, which causes the network to collapse more quickly (Miglani etal., 2020). Therefore, clustering techniques are used to help distribute and connect the network efficiently, as well as to select Cluster Heads more effectively, improving network performance and extending its lifespan (Lata et al., 2020). Traditional techniques are ineffective in large networks with a high number of nodes, leading to network failure due to poor connectivity and improper Cluster Head selection (Zaiter et al., 2025). Selecting Cluster Heads optimally enhances network efficiency and extends its lifespan (Sucasas et al., 2016). Traditional clustering algorithms like K-Means, DBSCAN, and Fuzzy C-Means (FCM) are commonly used for CH selection but have limitations. K-Means requires prior knowledge of cluster numbers and ignores energy constraints, leading to uneven energy distribution (Abdulaal et al., 2024). DBSCAN struggles in dynamic environments and non-uniform node densities, while FCM incurs high computational costs and energy inefficiencies due to overlapping cluster memberships (Albasri et al., 2022). This study explores an integrated clustering mechanism with PSO to optimize CH selection, balance energy consumption, and improve WSN adaptability. Although it distributes nodes into clusters efficiently but ignores energy levels, causing high-energy nodes that have been assigned by cluster heads to quickly drop (Jan et al., 2017). DBSCAN method is identified by density-based clustering. FCM offers a more adaptable clustering technique by enabling nodes to be a part of several clusters with different levels of membership (Shafi et al., 2024). It is computationally de-manding more tuning is required for energy efficiency. Heuristic clustering methods enhance node organization by employing rule-based clustering techniques (Sert & Yazici, 2021). Despite their superior energy efficiency, it is unable to dynamically adjust to node energy depletion. PSO is unable to control clustering requires integration with clustering algorithms to improve performance (Alam et al., 2014). The work combines K-Means, DBSCAN, FCM, heuristic algorithms, and PSO to provide an energy-efficient clustering solution for WSNs in order to overcome over the disadvantages of traditional clustering strategies (Kaddi et al, 2024). The proposed method optimizes cluster head selection based on node density in order to increase network durability residual energy levels, and base station distance. The method dynamically adjusts to network changes by routinely updating cluster heads and reassessing node energy levels, ensuring balanced energy usage and extended network operations (Raj & Duraipandian, 2023).

Related Work and Theoretical Background

Related Work

Zagrouba & Kardi (2021) proposed to improve energy efficiency, reduce delays, and increase scalability. The study investigates methods that enhance clustering in WSNs. It categorizes clustering methods into meta-heuristic, fuzzy logic, and hybrid approaches, and compares protocols based on cluster size, CH selection, and energy consumption. Jubair et al. (2021) presented several WSN routing protocols are presented and categorized into nine groups, including network topology-based and latency-aware approaches. It analyzes energy usage and network longevity by evaluating protocols such as LEACH, Mod-LEACH, iLEACH, E-DEEC, multichain-PEGASIS, and M-GEAR using NS3 simulations. The study emphasizes how crucial intelligent routing is to maximizing WSN performance and guaranteeing network sustainability. Kavya & Ravi (2021) presented energy-efficient routing strategies for WSNs, with a particular emphasis on clustering-based approaches such as LEACH and its variations. It examined packet delivery, scalability, and energy consumption while contrasting threshold-based, bio-inspired, and hierarchical CH selection techniques. Adaptive and hybrid clustering enhances efficiency according to the results, bio-inspired techniques maximize CH selection. But there are still prob-lems with synchronization and control. Behera, et al. (2022) improved the efficiency of Wireless Sensor Networks (WSNs) by utilizing machine learning techniques and leveraging swarm intelligence methods to enhance network performance. Rizky et. al. (2024) proposed an improved Multi-Channel Clustering Hierarchy method for WSNs. They used four-channel clustering with odd-even activation to cut congestion and save energy. The method optimized energy and minimized congestion; it lowers throughput as nodes are not always active. Throughput values were 1.88, 1.68, 1.62, and 2.22 for Channels 1 to 4, with Channel 4 having the highest packet loss (0.616) and Channel 2 the highest delay (0.0039). In this paper covers energy-efficient cluster head selection, literature review, theoretical background, meth-odology, simulation results, and comparative analysis, concluding that hybrid clustering with PSO improves energy efficiency, extends network lifespan, and optimizes data transmission. Latiff et. al. (2007) used PSO for dynamic CH selection and demonstrated its ability to balance load and reduce energy consumption.

Theoretical Background

Wireless Sensor Networks (WSNs) are vital for applications like environmental monitoring and industrial automation, but their sensor nodes limited energy resources make achieving energy efficiency crucial for ensuring long net-work lifetimes (Rashid & Rehmani, 2016).

Wireless Sensor Networks (WSNs)

Wireless Sensor Networks are essential in environmental monitoring, healthcare, military applications, and industrial automation. It consists of multiple sensor nodes distributed across a predefined area. These nodes collect data and transmit it to the Base Station (BS) as see in Figure1. Since sensor nodes possess limited energy resources, achieving energy efficiency remains a crucial challenge for ensuring long network lifetimes (Kalaimani et al., 2021). Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol optimize energy consumption. LEACH dynamically rotates Cluster Head (CH) roles among nodes, operating in setup and steady-state phases. CH selection occurs probabilistically using a threshold function, ensuring balanced energy usage and extended network lifespan. Each node generates a random value between 0 and 1, if this value falls below a predetermined threshold, the node becomes a CH for the current round (Khudhair, 2025). The threshold function is expressed in equation 1 bellow.

$$\boldsymbol{T(n)} = \frac{\boldsymbol{P}}{\boldsymbol{1-P\times\left(r mod \frac{1}{P}\right)}} \text{ .if n∈G} \qquad \text{Eq.(1)}$$

The LEACH protocol provides each node a probability (P) of becoming a Cluster Head (CH) during each round. The set (G) consists of nodes that were not CHs in the previous (1/P) rounds. A node within (G) produces a random number, when it is under a computed threshold, the node turns into a CH. During the setup phase, selected CHs transmit advertisements while non-CH nodes connect to the CH that has the strongest received signal (Al-Baz & El-Sayed, 2018). The steady-state phase follows, where data transmission takes place. Each CH creates a Time Division Multiple Access (TDMA) schedule for its cluster members, assigning them specific time slots for data transmission to avoid collisions. Node's sense environmental parameters and transmit data to their CHs, which aggregate the data and forward it to the BS in a single transmission. In each cycle, the Iteration of the Cluster Head is updated, and the process is repeated to ensure balanced energy consumption in the network (Tambawal et al., 2019).

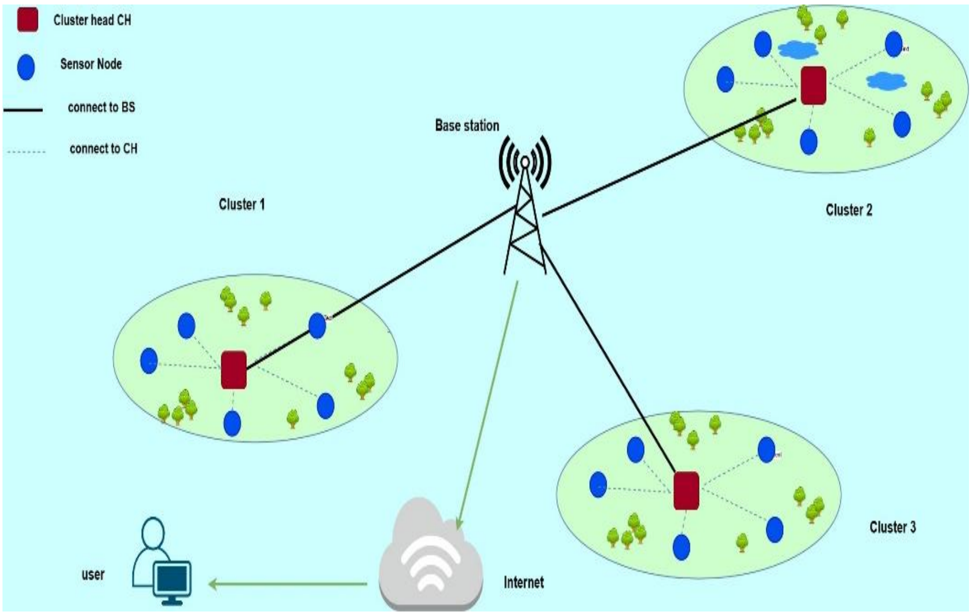

Figure. 1. Cluster-based wireless sensor network (WSN) architecture with data transmission to the base station

Clustering Techniques in Wireless Sensor Networks (WSNs)

Common clustering techniques include K-Means, DBSCAN, and Fuzzy C-Means (FCM), where the selection of a technique depends on network limitations, application requirements, and available energy (Miraftabzadeh et al., 2023; Omran et al., 2025). K-Means Clustering: It is a centroid-based algorithm that organizes sensor nodes into clusters based on spatial proximity. After determining number of cluster (k) centroids then assigns each node to the nearest centroid using the Euclidean distance formula as shown in equation (2) (Peter et al., 2019):

$$d(i.j) = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad \text{Eq.(2)}$$

where d(i,j) represents the distance between node, and (x, y) are the coordinates of the respective nodes. the centroids are recalculated by determining the average of all node positions within each cluster (Kamil, 2017).

$$C_j = \frac{1}{N_j}\sum_{i=1}^{N_j} X_i \qquad \text{Eq.(3)}$$

where Cj denotes the updated centroid of cluster j, Nj indicates the count of nodes in cluster j, and Xi represents the position of nodes inside of the cluster. The continuing process continues on until the centroids transform into stable. K-Means is computationally efficient and provides clear cluster separation. It performs not assume energy levels into account when selecting CHs (Tambawal et al., 2019). DBSCAN (Density-Based Spatial

Clustering of Applications with Noise): DBSCAN is a density-based clustering algorithm that identifies dense regions of sensor nodes and groups them into clusters based on a predefined radius (ε) and a minimum number of points (MinPts). The algorithm initiates by selecting a node that has not been visited and calculates the number of neighboring nodes within distance ε using as shown in equation (4) (Kamil, 2017):

$$d(i.j) \leq \varepsilon \qquad \text{Eq.(4)}$$

where d(i,j) represents the Euclidean distance between nodes i and j. DBSCAN effectively detects clusters of arbitrary shapes and identifies outliers but struggles in networks with sparse deployments or varying node densities, making it less adaptable to dynamic WSN environments (Kamil, 2017). Fuzzy C-Means Clustering: it is contrast to rigid clustering techniques by permits nodes to belong to multiple clusters with variance degrees of membership. The algorithm assigns membership values to each node based on its proximity to different cluster centers, calculated using (Jamel & Akay, 2019):

$$uij = \frac{1}{\sum_{k=1}^{C}\left(\frac{d_{ij}}{d_{ik}}\right)^{\frac{2}{m-1}}} \text{ Eq.(5)}$$

where uij represents the membership of node i in cluster j, dij is represent Euclidean distance between node and cluster center, and m is represent the fuzziness parameter the cluster are updated iteratively by using (Jamel & Akay, 2019):

$$C_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} Xi}{\sum_{i=1}^{N} u_{ij}^{m}} \qquad \text{Eq.(6)}$$

Whe re Cj is the updated cluster center, and N is the number of nodes in the network. The process repeats until membership values stabilize. heuristic-based approaches create clusters dynamically according to specific criteria such as node density, spatial distribution, energy levels, and application-specific constraints.

Particle Swarm Optimization (PSO) in Wireless Sensor Networks (WSNs)

PSO is an evolutionary optimization algorithm utilized in Wireless Sensor Networks (WSNs) for cluster head selection optimization by improving energy efficiency and network longevity. It evaluated candidate nodes according to residual energy and location to the base station. Each sensor node is considered a particle in an investigation space, with its position updated iteratively according to its best-position (Pbest) and the best global solution (Gbest), The velocity update is governed by the equation (Loganathan & Arumugam, 2021):

$$V_i^{t+1} = w \cdot V_i^t + c_1 \cdot r_1 \cdot (P_{best.i} - X_i^t) + c_2 \cdot r_2 \cdot (G_{best} - X_i^t) \text{ Eq.(7)}$$

where w is the inertia weight controlling the influence of previous velocities, c1and c2 are acceleration coefficients, and r1, r2 are random numbers and theee position of each particle is updated according to the equation bellow (Yadav et al., 2022; Sahoo et al., 2022):

$$X_i^{t+1}=X_i^t+V_i^t+1, \text{ Eq.(8)}$$

To ensure the progress of searching for the best Cluster Head in WSN, the selection process applies a fitness function based on factors such as residual energy, distance to the Base Station (BS), and node density, as shown in the equation below where α,β,γ are weight factors (Zhao et al., 2022):

$$Fitness = \alpha \cdot \frac{1}{Eresidual} + \beta \cdot \frac{d_{BS}}{d_{max}} + \gamma \cdot \frac{N_{density}}{N_{max}} \text{ Eq, (9)}$$

Methodology

Clustering techniques including K-Means, DBSCAN, and FCM, are used to organize sensor nodes efficiently, with each method offering different trade-offs in terms of energy efficiency, adaptability, and computational complexity. Figure.2 shows the flow chart for Cluster Head selection in WSN using hybrid clustering and PSO.

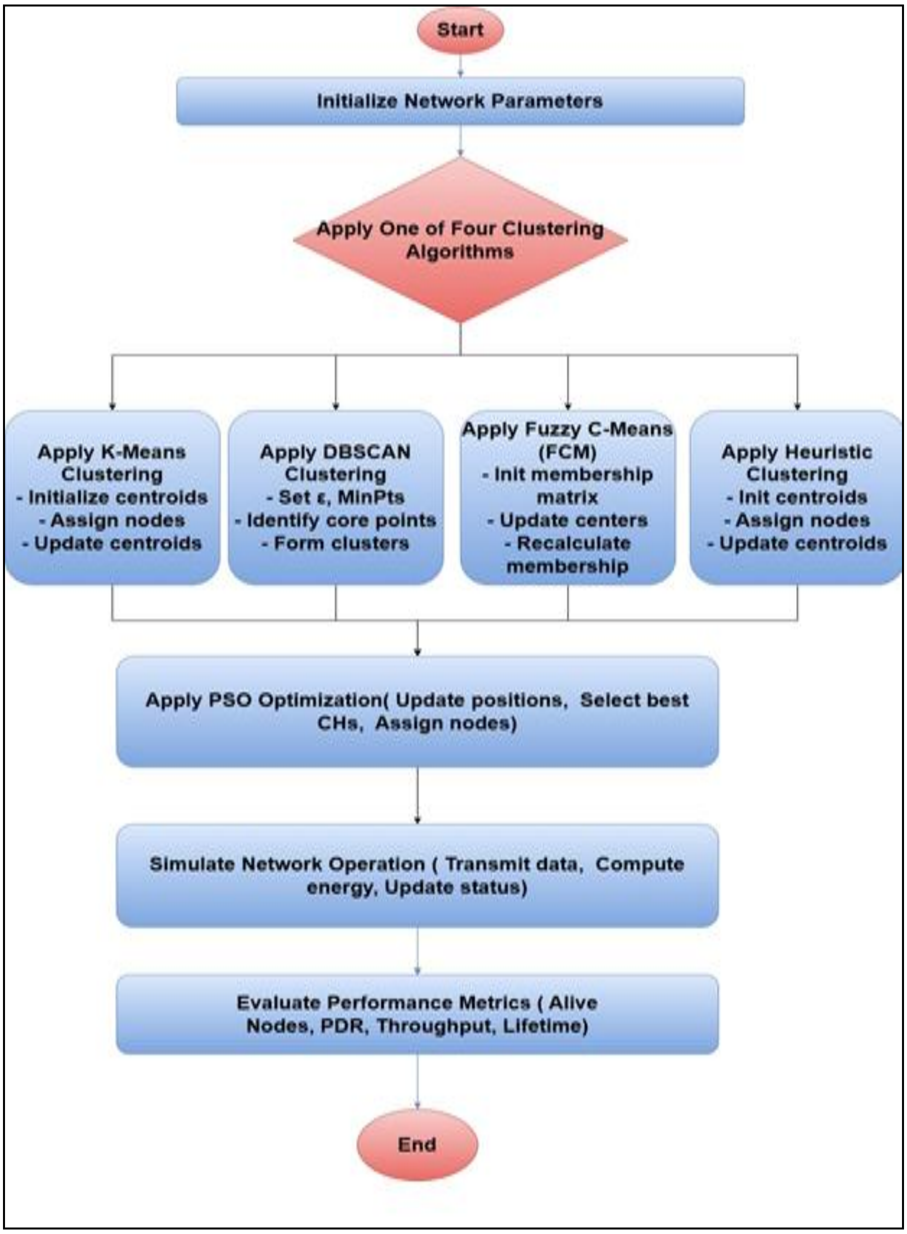

Figure 2. Flow chart for cluster head selection in WSN using hybrid clustering and PSO

In this work apply hybrid clustering algorithms with the Particle Swarm Optimization (PSO) algorithm to improve the selection of Cluster Heads (CHs) in Wireless Sensor Networks (WSNs). In the first step defining network parameters such as deployment area, number of nodes, and initial energy per node, then randomly distribute the nodes on the map. In this work apply the LEACH protocol to enhance energy efficiency through the dynamic distribution of nodes. Next, utilize clustering algorithms such as K-Means, FCM, DBSCAN, and heuristic clustering to form clusters. Then the PSO algorithm to select Cluster Heads based on residual energy, distance to the Base Station (BS), and node location. Cluster Heads are periodically updated to adapt to energy consumption and node mobility, ensuring balanced energy distribution and prolonging network lifetime.

Algorithm: Energy-Efficient Cluster Head Selection in Dynamic Wireless Sensor Networks Using K-Means, DBSCAN, Fuzzy C-Means, Heuristic Algorithms, and Particle Swarm Optimization

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Input: Network dimensions (X, Y), Number of sensor nodes (N), Desired cluster heads (C), Initial node energy (E_init), Transmission parameters (E_elec, E_fs, E_amp), Base station location, Clustering algorithm parameters, PSO parameters.

Output: Optimized cluster head assignments, Cluster formations, Energy consumption metrics, Network performance metrics.

1. Initialize Network Parameters
    - o Define the network area A=X×Y, where X and Y represent the width and height of the region.

- Set the number of cluster heads C.
- Define the initial energy of each node $E_{init,}$ typically set to 2J.
- Define transmission parameters: E_{elec}=50nJ/bit, E_{fs}=10pJ/bit/m^2, E_{amp}=0.0013pJ/bit/m^4.

2. Deploy Sensor Nodes
   - Each sensor node is randomly placed in the area: $Pi=(x_i,y_i),x_i\sim U(0,X),y_i\sim U(0,Y)$
   - The base station (BS) is located at $P_{BS}=(X/2,Y/2)$.
3. Apply one of these algorithms each time to select the best cluster head from initialize population
   - Apply K-Means Clustering
     1. Initialization: select k initial cluster centroids
     2. Compute the Euclidean distance between each node ii and each cluster center j: d(i,j)= $\sqrt{(xi-xj)2+(yi-yj)2}$
     3. Assign each node to the nearest cluster center j: C(i)=arg $min_j\ d(i.CH_j)$
     4. Update cluster centers iteratively using: $x_j=\frac{1}{c_j}\sum_{i\in cj}x_i.y_j=\frac{1}{c_j}\sum_{i\in cj}y_i$
   - Apply DBscan Clustering
     1. Parameter Setting: Define two parameters:
        - ✓ ϵ: The maximum radius of the neighborhood to be considered.
        - ✓ MinPts: The minimum number of points required to form a dense region.
     2. Core Point Identification: For each node iii, identify its ϵ\epsilonϵ-neighborhood: $N_\epsilon(i)=\{j|d(i,j)\leq\epsilon$

        Where d(i,j) is the Euclidean distance between nodes i and j.

        If $|N_\epsilon(i)|\geq$MinPts, then node i is a core point.
     3. Cluster Formation: Starting from an unvisited core point, recursively visit all points in its ϵ-neighborhood. If those points are also core points, continue to their neighbors. This process forms a cluster of density-connected points.
     4. Noise Identification: After processing all points, those that are not part of any cluster are labeled as noise
   - Apply Fuzzy C-Means (FCM) clustering
     - ➢ Initialize Membership Matrix: Create a membership matrix U=[uij] with random values between 0 and 1, ensuring that for each data point ii, the sum of its memberships across all clusters : $\sum_{j=1}^{c}u_{ij}\,\forall i$
     - ➢ Compute Cluster Centers: Calculate the center vj of each cluster j using the current membership values: $v_j=\frac{\sum_{i=1}^{n}u_{ij}^{n}x_i}{\sum_{i=1}^{n}u_{ij}^{n}}$
     - ➢ Update Membership Values: For each data point ii and cluster jj, update the membership value uij based on the inverse distance between the data point and the cluster centers: $u_{ij}=\frac{1}{\sum_{k=1}^{c}(\frac{\|x_i-v_j\|}{\|x_i-v_k\|})^{2m-1}}$
     - ➢ Iterate: Repeat steps 2 and 3 until the membership matrix U stabilizes, i.e., the changes between iterations fall below a predefined threshold.
   - Apply Heuristic clustering algorithms
     - ➢ Initialization: select k initial cluster centroids from the dataset.
     - ➢ Assignment: For each data point xi, compute the Euclidean distance to each centroid v_j: $d(x_i,v_j)=(x_i-v_j)^2$
     - ➢ Assign x_i to the cluster with the nearest centroid: $C(i)=\arg\min_j d(x_i,v_j)$
     - ➢ Update: Recalculate each centroid v_j as the mean of all data points assigned to cluster j: $vj=\frac{1}{|C_j|}\sum_{x_i\in C_j}x_i$
     - ➢ Iteration: Repeat steps 2 and 3 until the centroids converge (i.e., their positions no longer change significantly
4. Apply the PSO optimization:
   - Update particle velocity and position using:

$$v_i^{t+1}=wv_i^t+c1r1(pbest-x_i^t)+c2r2(gbest-x_i^t)$$

$$X_i^{t+1}=X_i^t+V_i^t+1$$

   - Assign the best nodes as cluster heads by Apply one of algorithms in step 3
   - Evaluate the fitness of each particle in PSO based on residual energy E(i) and distance to BS: $f(i)=\frac{E(i)}{d(i.BS)}$
   - Update the global best (gbest) by selecting the best position among all particles. Each node joins the nearest cluster head CH_j: CH_j =arg $min_j\ d(i.CH_j)$

- Nodes send data to cluster heads, and cluster heads forward it to BS.
- Compute transmission energy based on distance:
  - ✓ $E_{Tx}(i) = kE_{elec} + kE_{fs}d^2, if\ d < d0$
  - ✓ $E_{Tx}(i) = kE_{elec} + kE_{amp}d^4, if\ d \geq d0$
- Compute reception energy: $E_{Rx}(i) = kE_{elec}$
- Energy Consumption Calculation: Update the energy level of each node: $E(i) = E(i) - E_{Tx}(i) - E_{Rx}(i)$
- Mark a node as dead if E(i)≤0 .
- Continue iterations until all nodes have depleted energy.
- Early Stopping Condition : If the improvement in global best fitness remains below a threshold ε (0.001) for 10 consecutive iterations, the optimization stops. This avoids unnecessary computation once the solution stabilizes. The condition is given by: $\Delta fgbest(t)=|fgbest(t)-fgbest(t-1)|<\varepsilon$ for 10 iterations

5. Evaluate Performance Metrics
   - Compute the number of alive nodes at each iteration: $N_{alive}(t)=\{i|E(i)>0\}|$
   - Compute packet delivery ratio (PDR): PDR=$\frac{Preceived}{Psent}$
   - Compute throughput: $T = \frac{Preceived \times k}{Ttotal}$
   - Compute network lifetime as the iteration where all nodes die: $T_{lifetime} = max_t\ N_{alive}(t) = 0$

Simulation and Results

The work implements an energy-efficient Cluster Head selection algorithm for dynamic Wireless Sensor Networks (WSNs) by integrating K-Means, DBSCAN, Fuzzy C-Means (FCM), heuristic algorithms, and Particle Swarm Optimization (PSO) by using Matlab R2023b. The proposed work defines a 100m × 100m network with 50, 100, and 150 sensor nodes, each with 2J initial energy, using transmission parameters Eelec (50 nJ/bit), Efs (10 pJ/bit/m²), and E_amp (0.0013 pJ/bit/m⁴),the BS is at (50m, 50m), clustering parameters are k=3,5,10 (K-Means), ε=15m & MinPts=5 (DBSCAN), and m=2 (FCM), PSO parameters include a population size of 30, inertia weight w=0.5, and cognitive/social coefficients c1=c2=1.5, ensuring balanced energy distribution and valid WSN simulation results. The parameters of wireless sensor networks are shown in Table 1.

Table 1. The parameter of wireless sensor networks

Parameter	Value
Network Area (A)	100m × 100m
Number of Sensor Nodes (N)	50,100,150
Initial Energy per Node (E_init)	2 Joules
Transmission Energy (E_elec)	50 nJ/bit
Free Space Model (E_fs)	10 pJ/bit/m²
Multipath Model (E_amp)	0.0013 pJ/bit/m⁴
Iteration (time)	5000
Base Station Location	(50m, 50m)
K-Means: Number of Clusters (k)	3, 5, 10
DBSCAN: ε, MinPts	15m, 5
FCM: Fuzziness Parameter (m)	2
PSO: Population Size	[10, 20, 30, 40, 50] the optimal 30
PSO: Inertia Weight (w)	[0.1, 0.3, 0.5, 0.7, 0.9] the optimal 0.5
PSO: Cognitive Coefficient (c1)	[1.0, 1.5, 2.0, 2.5] the optimal 1.5
PSO: Social Coefficient (c2)	[1.0, 1.5, 2.0, 2.5] the optimal 1.5

Figure 3 illustrates Sensor nodes (blue circles) connect to their nearest cluster head (red squares), while the base station (green star) manages data transmission. K-Means clusters nodes by Euclidean distance, DBSCAN detects dense regions, FCM assigns nodes flexibly, and Heuristic algorithms optimize cluster head selection. Figure 3 shows the initial clustering of 50 nodes in a 100 × 100 m² WSN. DBSCAN creates dense, irregular clusters; FCM assigns fuzzy memberships; Heuristic selects cluster heads based on energy and proximity; and K-Means forms uniform clusters

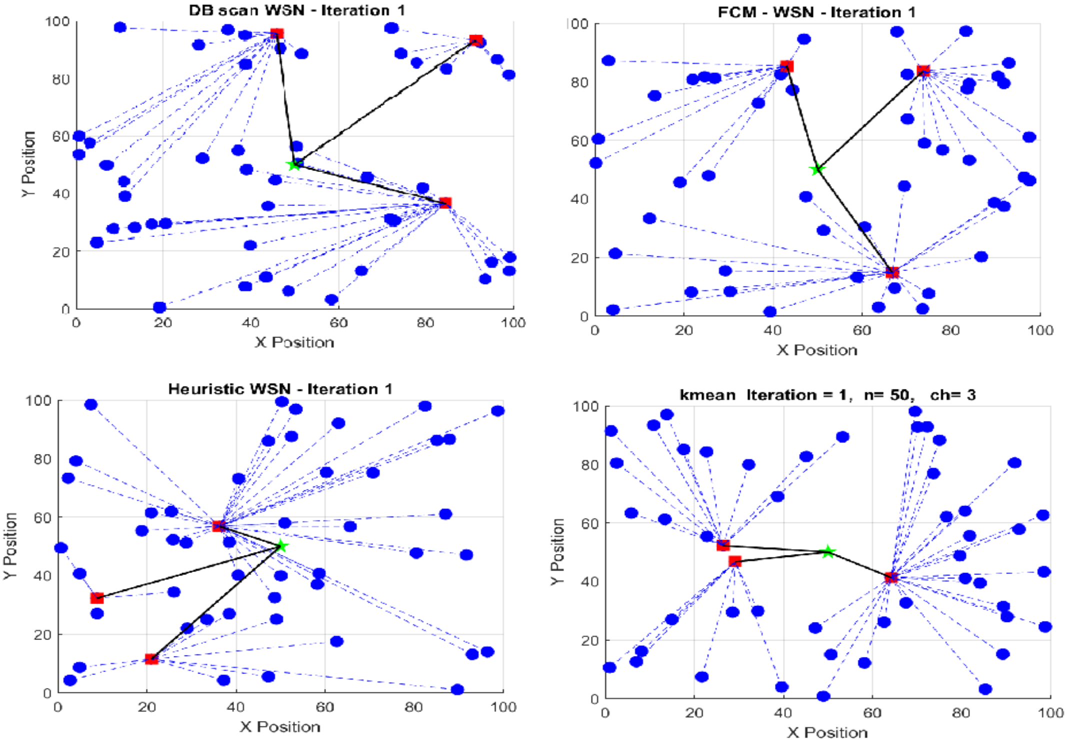

Figure. 3. Comparison of WSN clustering techniques using K-Means, DBSCAN, FCM, and heuristic algorithms with 50 sensor nodes and 3 cluster heads in a 100m × 100m area

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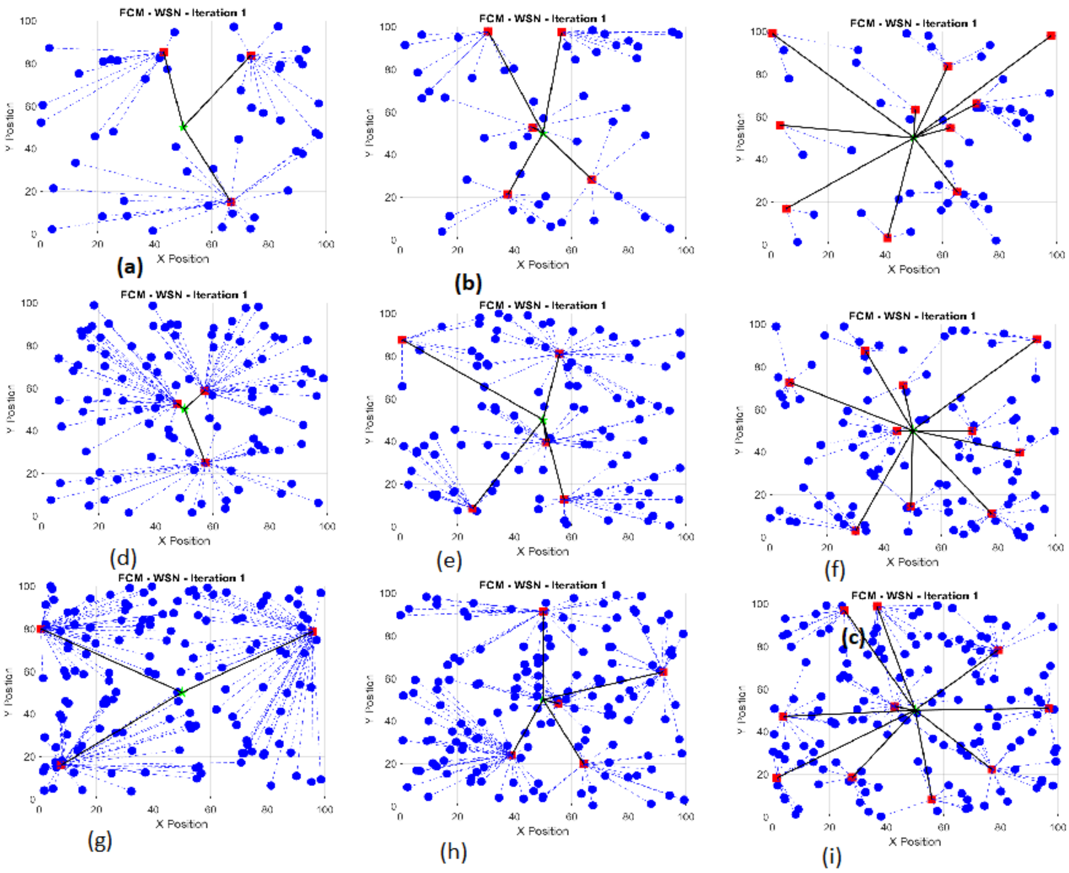

Figure. 4. Evaluation of fuzzy C-means (FCM) clustering in wireless sensor networks with varying cluster heads and node densities

Data flows from nodes to cluster heads and then to the base station, highlighting differences in spatial distribution and routing efficiency. In this work illustrates the impact of varying Cluster Heads (CHs) and Sensor Nodes (SNs) on network performance using Fuzzy C-Means (FCM) clustering, mean, Dbsccan, and Heuristic algorithm in a Wireless Sensor Network (WSN). Figures 4 (a, b, c) represent 3 CHs with 50, 100, and 150 SNs, respectively, showing that fewer CHs lead to longer transmission distances, increasing energy consumption per CH. Figures 4 (d, e, f) with 5 CHs distribute the load more effectively, reducing communication costs and balancing energy consumption. In Figure 4 (g, h, i) with 10 CHs, network density is higher, minimizing individual node transmission distances but introducing additional overhead in cluster management. The results confirm that 5 CHs (d, e, f) provide the best balance between energy efficiency, load distribution, and network longevity, while 3 CHs (a, b, c) suffer from high energy depletion and 10 CHs (g, h, i) introduce unnecessary cluster overhead. This work evaluates key metrics including node count, clusters, energy used, alive and dead nodes, latency, packet delivery ratio (PDR), throughput, coverage, fault tolerance, scalability, and reliability. Additionally, it examines network lifecycle through first, half, and full node depletion iterations to optimize efficiency and longevity.

Figure 5 compares the number of alive nodes in a WSN across different clustering algorithms (K-Means, DBSCAN, Heuristic, FCM) with 3, 5, and 10 cluster heads (CHs) and varying sensor nodes (50, 100, 150) . For 3 CHs, K-Means has the lowest alive nodes (≈30 for 50 nodes, ≈80 for 100 nodes, ≈120 for 150 nodes), while FCM and Heuristic maintain higher survivability (≈40, ≈100, and ≈140 respectively). In 5 CHs, K-Means still results in the lowest node survival (≈35, ≈90, and ≈130), while DBSCAN and Heuristic perform better (≈45, ≈110, and ≈145). For 10 CHs, survivability improves across all methods, with K-Means showing ≈50, ≈120, and ≈145, whereas DBSCAN and FCM keep the highest alive nodes at ≈60, ≈130, and ≈150. These results indicate K-Means depletes energy faster, while FCM, DBSCAN, and Heuristic clustering provide better energy efficiency and network longevity, especially as CHs increase.

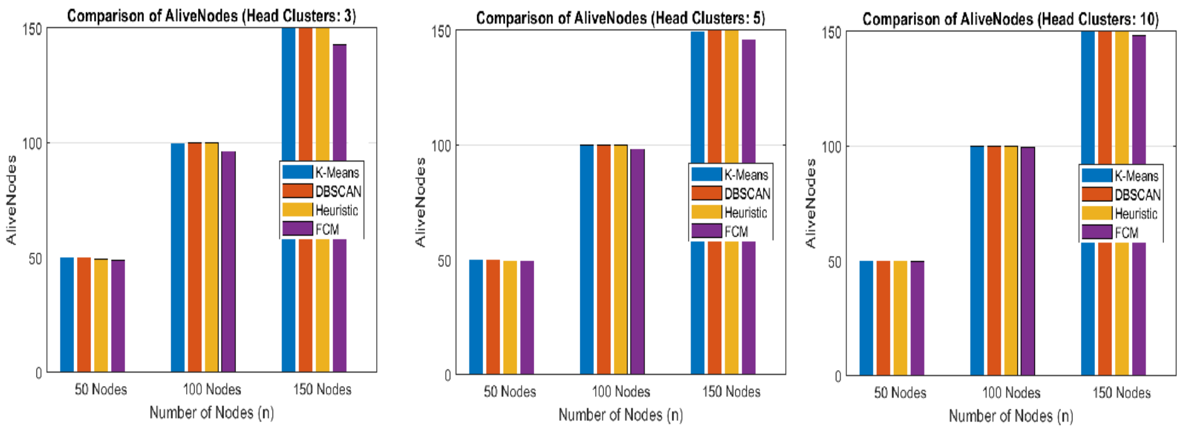

Figure 5. Comparison of alive nodes in WSN using different clustering algorithms with varying cluster heads and node densities

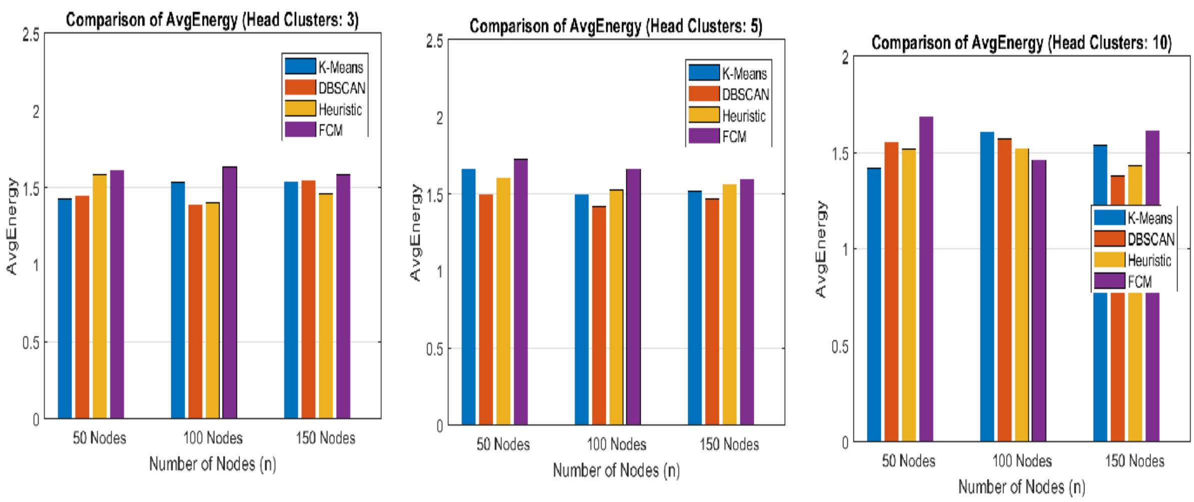

Figure 6. Comparison of average energy consumption in WSN using different clustering algorithms with varying cluster heads and node densities

Figure 6 presents a comparison of average energy consumption in a Sensor WSN for different clustering algorithms (K-Means, DBSCAN, Heuristic, and FCM) with 3, 5, and 10 cluster heads (CHs) and varying sensor node counts (50, 100, and 150 nodes). In the 3 CH scenario, FCM, K-Means exhibits higher energy consumption, while Heuristic and DBSCAN maintain more balanced energy usage. With 5 CHs, energy efficiency improves across all algorithms, particularly for FCM and K_Means clustering, which distribute energy consumption more evenly. In the 10 CH scenario, FCM and Heuristic continue to demonstrate better energy management, whereas K-Means still shows higher energy depletion. The results indicate that increasing the number of CHs enhances energy distribution, reducing the load on individual nodes. FCM and K_Means clustering consistently achieve better energy efficiency, making them more suitable for extending WSN lifetime.The algorithms considered include K-Means, DBSCAN, Heuristic, and Fuzzy C-Means (FCM), with different numbers of cluster heads (CHs) and sensor nodes (50, 100, 150) as shown in Table 2.

Table 2. Performance metrics for clustering algorithms in WSN

Algorithm	Node Count	Num Clusters	Avg Energy	Alive Nodes	Dead Nodes	Latency	Coverage	Fault Tole	Scalability
K_Means	50	3	1.4259	50	0	0.5	1	1	1
K_Means	100	3	1.5324	99	1	0.9968	0.99676	0.9967	0.99676
K_Means	150	3	1.5394	150	0	1.5	1	1	1
DBSCAN	50	4	1.4496	50	0	0.5	0.98823	0.9882	0.98823
DBSCAN	100	1	1.38940	100	0	1	1	1	1
DBSCAN	150	1	1.54773	150	0	1.5	1	1	1
Heuristic	50	3	1.5852	49	1	0.4924	0.98485	0.9848	0.9848
Heuristic	100	3	1.4015	100	0	1	1	1	1
Heuristic	150	3	1.4564	150	0	1.5	1	1	1
FCM	50	3	1.6154	48	2	0.4874	0.97492	0.9749	0.9749
FCM	100	3	1.6319	95	4	0.9633	0.96334	0.9633	0.9633
FCM	150	3	1.5835	143	8	1.4271	0.9514566	0.9514	0.9514
K_Means	50	5	1.6602	50	0	0.5	1	1	1
K_Means	100	5	1.4937	100	0	1	1	1	1
K_Means	150	5	1.5210	149	1	1.4962	0.9975	0.9974	0.9974
DBSCAN	50	1	1.4970	50	0	0.5	1	1	1
DBSCAN	100	3	1.4177	100	0	1	1	1	1
DBSCAN	150	1	1.4667	150	0	1.5	1	1	1
Heuristic	50	5	1.51644	49	1	0.4941	0.98823	0.9882	0.9882
Heuristic	100	5	1.52089	100	0	1	1	1	1
Heuristic	150	5	1.43032	150	0	1.5	1	1	1
FCM	50	5	1.72129	49	1	0.4952	0.99058	0.9905	0.9905
FCM	100	5	1.66062	98	2	0.9825	0.98255	0.9825	0.9825
FCM	150	5	1.59638	145	5	1.4594	0.97297	0.9729	0.9729
K_Means	50	10	1.42018	50	0	0.5	1	1	1
K_Means	100	10	1.60749	100	0	1	1	1	1
K_Means	150	10	1.53621	150	0	1.5	1	1	1
DBSCAN	50	2	1.55623	50	0	0.5	1	1	1
DBSCAN	100	3	1.56910	100	0	1	1	1	1
DBSCAN	150	1	1.379255	150	0	1.5	1	1	1
Heuristic	50	10	1.516441	50	0	0.5	1	1	1
Heuristic	100	10	1.520898	100	0	1	1	1	1
Heuristic	150	10	1.430322	150	0	1.5	1	1	1
FCM	50	10	1.687899	49	1	0.4986	0.9971	0.9971	0.9971
FCM	100	10	1.46203	99	1	0.9941	0.99409	0.9940	0.9940
FCM	150	10	1.616078	148	2	1.481	0.98736	0.9873	0.9873

As shown in Figure 7, increasing population size improves exploration ability but leads to higher computational overhead. The best energy-lifespan balance is achieved at 30 particles. Similarly, an inertia weight of 0.5 shows better convergence stability. Higher cognitive and social coefficients ($c1 = c2 = 1.5$) yield optimal clustering with minimal transmission delay. Among all configurations, the optimal PSO parameters are: Population Size = 30, Inertia Weight = 0.5, $c1 = 1.5$, $c2 = 1.5$. These settings resulted in 12–15% energy savings and a 20% increase in network lifespan compared to traditional approaches.

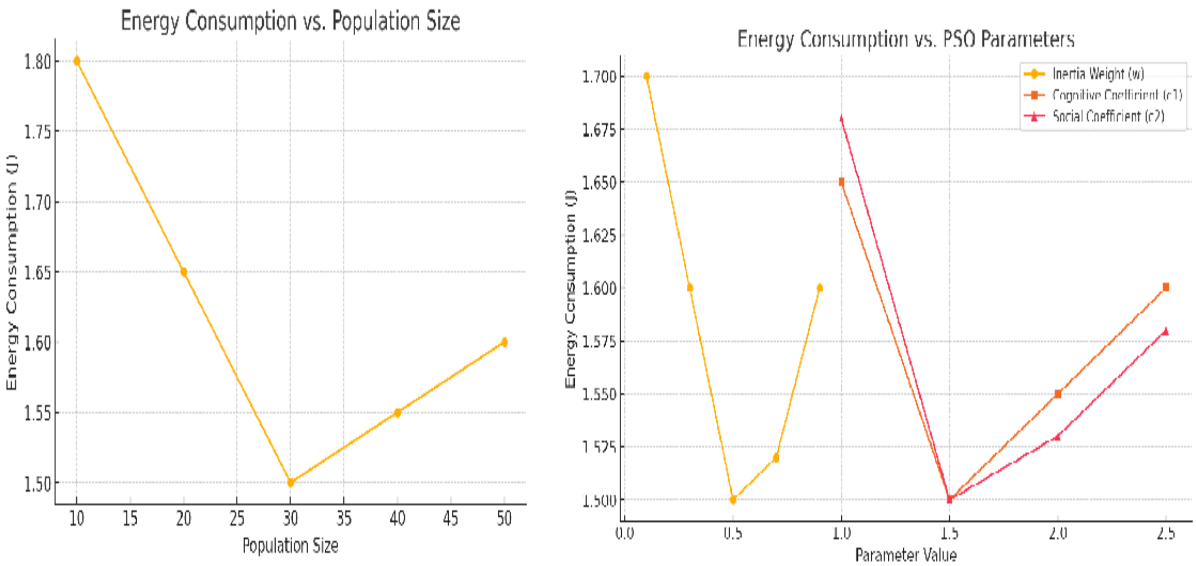

Figure 7. Effect of PSO parameters on energy consumption in wireless sensor networks

The results show that DBSCAN maintains 100% alive nodes across all cases, while Heuristic, K-Means and FCM exhibit slight node loss, such as FCM with 150 nodes and 5 clusters having 145. alive nodes (97) and 5 dead nodes. The average energy consumption ranges from 1.3894 (DBSCAN, 100 nodes, 1 cluster) to 1.7213 (FCM, 50 nodes, 5 clusters), with FCM generally consuming more energy. Latency varies from 0.487 (FCM, 50 nodes, 3 clusters) to 1.5 (multiple cases across algorithms), while PDR remains consistently at 1. Throughput remains at 3,200,000 across all cases, while coverage and reliability are mostly at 1, except for minor drops in FCM (e.g., 0.9515 for 150 nodes, 3 clusters). These results indicate that DBSCAN and Heuristic provide stable energy efficiency and network longevity, while FCM may have higher energy consumption but maintains reasonable network performance. FCM offers significant energy savings and improved network lifetime, but this comes at the cost of higher computational overhead due to its iterative nature and fuzzy membership calculations.

The results show that FCM achieves the highest energy efficiency with the lowest consumption (0.8996J), followed by K-Means (0.9275J), while Heuristic (0.9626J) and DBSCAN (1.0258J) consume more. K-Means ensures the longest network lifespan with the first node dead at 483 rounds, followed by FCM (904) and Heuristic (443), whereas DBSCAN fails immediately. All algorithms maintain high reliability (PDR = 1), but DBSCAN and Heuristic experience higher latency (1.5s at 150 nodes). FCM and Heuristic are the best choices for long-term WSN applications. In terms of network lifetime, FCM shows superior performance with the first node dying at 904 iterations, compared to K-Means (483) and Heuristic (443), while DBSCAN fails immediately.

To validate the observed differences in energy consumption across clustering algorithms, a one-way Analysis of Variance (ANOVA) test was conducted. The test compared the average energy consumption among four algorithms: K-Means, DBSCAN, Heuristic, and FCM. The results revealed a statistically significant difference with a p-value of 0.00052, which is well below the conventional threshold of 0.05. This indicates that the choice of clustering algorithm has a significant impact on energy efficiency within the wireless sensor network. The accompanying boxplot visually confirms these differences, particularly highlighting the higher energy variability in FCM and the more consistent performance of K-Means.

Table 3. Node lifetime and average energy consumption analysis

Parameter	K-Means	DBSCAN	Heuristic	FCM
First Node Dead	483 iterations	-1	443 iterations	904 iterations
Half Node Dead	-1	-1	-1	-1
All Node Dead	-1	-1	-1	-1
Average Energy Consumption	0.92753	1.02580	0.96261	0.89963

While Comparative previous studies explored clustering (Zagrouba & Kardi, 2021), routing protocols (Jubair et al., 2021), and bio-inspired methods (Kavya & Ravi, 2021; Behera et al., 2022), they lacked integrated optimization. Our work combines intelligent clustering (K-Means, DBSCAN, Heuristic, FCM) with PSO for adaptive cluster head selection based on energy and proximity. Unlike Rizky et al. (2024), who reduced congestion but faced packet loss, our approach optimizes both energy and network lifetime. As shown in Table 3, FCM-PSO achieves the lowest energy consumption (0.8996 J) and longest lifetime (904 iterations), demonstrating superior performance over existing methods.

Conclusion

The work implements an energy-efficient Cluster Head selection algorithm for dynamic WSNs using clustering methods and PSO, with results showing that FCM and K_Means algorithms enhance network longevity, energy effi-ciency, and data reliability. FCM achieves the lowest energy consumption (0.8996J), then K_Means(0.9275J), then Heuristic (0.9626J), while DBSCAN consumes the most (1.0258J). The average throughput remains stable at 3.2 Mbps across all clustering methods, ensuring consistent data transmission performance. In latency, K-Means exhibits the highest delay (1.5s), while FCM and heuristic clustering maintain lower delays (around 1.0s), making them more efficient for real-time applications. Increasing the number of Cluster Heads helps balance energy consumption, reduc-es transmission waste, and further extend network lifespan. For instance, with 150 nodes and 5 clusters, FCM retains 145 alive nodes, ensuring better survivability compared to K-Means and DBSCAN. Compared to traditional clustering methods, the proposed FCM-based approach reduces total energy consumption by 12–15% and extends the network's operational lifetime by approximately 20%. FCM most effective clustering algorithm for WSNs, offering optimal energy efficiency, extended lifespan, and strong fault tolerance. Future work can focus on enhancing the PSO tech-nique using adaptive or hybrid approaches to improve performance in dynamic WSN environments.

Scientific Ethics Declaration

* The authors declares that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

Conflict of Interest

* The authors declare that they have no conflicts of interest

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