Original Article
ISSN (Online): 2582-7472

ShodhKosh: Journal of Visual and Performing Arts
March 2024 5(3), 2068–2077

OPTIMIZED CLUSTER HEAD SELECTION IN GAUSSIAN GRID WSNS USING HYBRID ML FRAMEWORK

D. Angeline Ranjithamani [1], Dr. R.S. Rajesh [2]

[1] Research Scholar, Department of Computer Science Engineering, Manonmaniam Sundaranar University, Tamil Nadu, India
[2] Professor, Department of Computer Science Engineering, Manonmaniam Sundaranar University, Tamil Nadu, India

Corresponding Author
D. Angeline Ranjithamani,
angelinranjithamani@msuniv.ac.in

DOI
10.29121/shodhkosh.v5.i3.2024.6225

Funding: This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

ABSTRACT

Wireless Sensor Networks (WSNs) deployed over Gaussian grids face critical challenges in energy efficiency and network longevity due to constrained node resources and spatial limitations. Traditional cluster head (CH) selection methods, such as LEGN, TEGN, and FOA-CH, individually address aspects of energy optimization, load balancing, and spatial coverage but often fall short in dynamic and heterogeneous network environments. This paper proposes a novel hybrid machine learning (ML) framework that combines features from these existing approaches to enable adaptive, energy-efficient, and fair CH selection. The framework constructs comprehensive feature vectors for each node, capturing residual energy, energy consumption ratio, historical CH frequency, spatial coordinates, and FOA-based optimization metrics. A predictive ML model dynamically selects candidate CHs, followed by localized Firefly Optimization Algorithm (FOA) refinement to improve spatial distribution and load balancing. Performance evaluation demonstrates improvements in network lifetime, average residual energy, load fairness, and data reliability, validating the effectiveness of the proposed approach in enhancing energy utilization and extending operational longevity of Gaussian grid-based WSNs.

Keywords: Cluster Head Selection, Energy Consumption, Energy Efficiency, Firefly Optimization Algorithm, Gaussian Grid, Load Balancing, Machine Learning, Residual Energy, Wireless Sensor Networks, Wireless Topology

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are foundational to IoT and smart applications, yet their operational lifetime remains constrained by the limited energy resources of sensor nodes. Conventional cluster head selection algorithms—such as Least Energy based Gaussian Network (LEGN), Threshold Energy based Gaussian Network (TEGN), and Firefly Optimization Algorithm for Cluster Head selection (FOA-CH)—address energy efficiency through mechanisms including load balancing, adaptive thresholding, and swarm intelligence-based optimization, respectively. However, these individual approaches often exhibit trade-offs between network longevity, computational complexity, and adaptability to dynamic environments. This paper introduces a novel hybrid machine learning (ML) framework that synergistically integrates the strengths of LEGN, TEGN, and FOA-CH within Gaussian integer-based WSN deployments. By leveraging supervised and reinforcement learning strategies, the proposed algorithm dynamically selects optimal cluster heads, balancing energy consumption and network coverage while adapting to temporal changes in node energy and topology

[1-5]. Experimental results demonstrate that our framework outperforms traditional algorithms in terms of energy savings and network lifetime, providing a robust solution for next-generation IoT and smart sensor applications.

2. BACKGROUND AND RELATED WORKS

Wireless Sensor Networks (WSNs) are fundamental to the development of smart environments and IoT applications, but their network lifetime is constrained by the energy limitations of individual sensor nodes. Efficient cluster head (CH) selection is pivotal for optimizing energy consumption, balancing load, and prolonging network lifespan.

Traditional Cluster Head Selection Algorithms

1) Least Energy based Gaussian Network (LEGN)

LEGN employs a strategy where the node with the least energy consumption in a Gaussian-grid distributed network is selected as the cluster head. This method aims to evenly distribute the energy burden across all nodes, preventing premature node death and promoting overall network longevity. The Gaussian grid deployment ensures optimal coverage and connectivity, but LEGN may not adapt well to dynamic changes in node energy or topology.

2) Threshold Energy based Gaussian Network (TEGN)

TEGN improves upon static selection mechanisms by introducing a dynamic energy threshold. Nodes are only eligible for cluster head roles if their residual energy exceeds a calculated threshold, which adapts over time based on network conditions. This dynamic thresholding helps prevent low-energy nodes from being overloaded, thus avoiding rapid energy depletion in critical network areas.

3) Firefly Optimization Algorithm for Cluster Head selection (FOA-CH)

FOA-CH utilizes swarm intelligence inspired by the behavior of fireflies to optimize cluster head selection. Nodes are treated as agents that "move" towards more attractive solutions based on energy, distance, and coverage metrics. The algorithm iteratively refines CH selection by simulating attraction and movement, yielding robust solutions that balance energy consumption and communication cost. However, FOA-CH may introduce computational overhead due to iterative processing.

3. MOTIVATION FOR HYBRID APPROACHES

While each of these methods—LEGN, TEGN, and FOA-CH—offers unique advantages, they also present trade-offs in terms of adaptability, computational complexity, and efficiency. Hybrid machine learning frameworks seek to combine their strengths, leveraging data-driven adaptation and optimization to further enhance energy efficiency and network longevity in Gaussian grid WSN deployments [5-10].

4. SYSTEM MODEL AND FORMULATION

The sensor network is deployed in a two-dimensional area, which is divided into 16 virtual square grids to organize the nodes and simplify cluster management. Each grid contains exactly five active nodes, resulting in a total of 80 nodes across the network. The position of each node is represented as a Gaussian integer, where the integer coordinates satisfy specific constraints to ensure structured placement. Using Gaussian integers helps maintain predictable coverage and efficient communication. In every round, one node from each grid is chosen as the Cluster Head (CH). The selection is based on the residual energy of the nodes, with the node having the highest energy being selected as the CH. Choosing the node with the highest energy as CH ensures that cluster heads can handle extra communication and aggregation tasks without dying quickly.

Consider a deployment region `$ D \subset \mathbb{R}^2 $`, partitioned into `$ M=16 $` virtual square grids $\{G_1, G_2, \ldots, G_M\}$. Each grid G_i contains exactly $K = 5$ active nodes, amounting to total $N = M \times K = 80$ nodes. Each node's position corresponds to a Gaussian integer:

$$\alpha = x + yi, \text{ where } 0 < x \leq y, \gcd(x, y) = d > 1, x, y \in \mathbb{Z}. \quad (1)$$

Each round $r \in \mathbb{N}$, a cluster head (CH), denoted by $CH(G_i)$, is elected per grid G_i based on node energy:

$$CH(G_i) = \arg \max_{n \in G_i} E_r(n), \tag{2}$$

where $E_r(n)$ is the residual energy of node n at round r.

5. OUTLINE OF THE WORK

The flow begins with initialization (oval), where the deployment region and grid parameters are defined shown in Figure 1. Next, the grid formation step (rectangle) divides the region into a 4×4 grid structure. In the node deployment stage (parallelogram), nodes are placed using Gaussian integer coordinates satisfying mathematical constraints. Each node then undergoes initialization (rectangle), where a unique ID and residual energy are assigned. The Cluster Head (CH) selection step (diamond) determines the highest-energy node in each grid to act as the CH. Following this, output generation (parallelogram) presents CH details and node tables. Finally, optimization and analysis (rectangle) are performed to evaluate energy efficiency, load balancing, and network longevity, before the process reaches the end state (oval). This structured flow ensures energy-efficient clustering and extended network lifetime compared to traditional approaches. The algorithm is given below.

Algorithm 1: Hybrid-Cluster-Head-Selection

```
Input: Region_size (40x40), M (16 grids), K (5 nodes per grid)
Output: Cluster Heads for each grid
1. Initialize region into M grids (4x4 layout).
2. For each grid:
      For each node (up to K):
         Randomly generate coordinates (x, y)
         Ensure Gaussian integer constraint: 0 < x ≤ y and gcd(x, y) > 1
         Assign node_id, position α = x + yi, initial energy
3. Store all nodes in node_list.
4. For each grid:
      Select node with maximum residual energy
      Assign it as Cluster Head (CH)
5. Output:
      For each grid, print CH node_id, α, and energy.
      Generate node tables for inspection.
End Algorithm
```

Figure 1

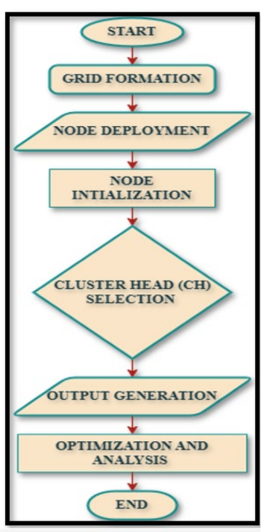

Figure 1 Flowchart of the Proposed Hybrid Machine Learning Framework for Cluster Head Selection in Gaussian Grid-Based WSNs.

Energy Efficiency: By always picking the node with the highest energy as the Cluster Head, the algorithm helps balance energy consumption, prolonging network lifetime. Gaussian Integer Constraint: Ensures node positions have mathematical structure, aiding in uniform coverage and facilitating advanced modeling. Modular & Inspectable: Each grid is managed independently, making the system scalable and easy to debug or inspect.

6. ENERGY CONSUMPTION RATIO

The **Energy Consumption Rate (ECR)** is a key metric in Wireless Sensor Networks (WSNs) that quantifies how efficiently a node uses its energy relative to its initial energy in a specific round. A lower ECR indicates that a node is consuming energy more efficiently. By tracking ECR, the energy consumption behavior of individual nodes can be characterized, helping identify nodes that may be overloaded or inefficient. ECR also allows for comparative analysis, making it easier to compare energy efficiency between nodes, rounds, or different protocols. Monitoring ECR supports network health by detecting anomalies or failures, such as a sudden spike in ECR, and enables proactive management to prevent premature node deaths. Furthermore, ECR is essential for evaluating and comparing cluster head selection algorithms, as algorithms that minimize average ECR are more energy-efficient and help prolong network lifetime [11-15].

ECR is particularly important in WSNs because sensor nodes have limited battery resources. Efficient energy usage is crucial for sustaining network operation. High or unbalanced energy consumption can lead to early node failures, reducing coverage and reliability. By using ECR, areas where energy optimization is needed—such as routing, data aggregation, or cluster head selection—can be identified. Adaptive protocols can also use ECR as feedback to dynamically adjust node behavior and improve overall efficiency.

Following Algorithm 1, the energy consumption ratio $ecr_r(n)$ of node n at round r is defined as

$$ecr_r(n) = \frac{E_{initial}(n) - E_{final}(n)}{E_{initial}(n)} = \frac{e_{diff}(n)}{E_{initial}(n)}, \quad (3)$$

where $E_{initial}(n)$ and $E_{final}(n)$ represent the initial and residual energy of node n at round r, respectively. This ratio characterizes the energy consumption behavior, reflecting node n's energy efficiency within round r.

7. ECR RATIO AND THRESHOLD ENERGY

The Energy Consumption Rate (ECR) is a metric that measures how much energy a node consumes in each round relative to its starting energy. This helps evaluate the efficiency of each node's operation. Nodes with high ECR values are consuming more energy than others, which may indicate inefficiency or potential bottlenecks. Early identification of such nodes allows for corrective actions before they fail. Monitoring ECR also supports fair cluster head selection by avoiding nodes that are rapidly losing energy, helping to balance energy usage across the network and prolong network lifetime. Additionally, ECR provides valuable feedback for refining network protocols, as a high average ECR indicates that the protocol may be wasting energy and needs improvement. The ECR Ratio compares the energy consumption of a node between consecutive rounds. A sudden spike in the ECR Ratio signals abnormal or excessive energy use. Nodes whose ECR Ratio falls below a calculated threshold can be dynamically excluded from cluster head selection, preventing inefficient nodes from becoming cluster heads and further draining energy. This approach helps maintain network stability and consistent coverage over time. In summary, both ECR and ECR Ratio are essential metrics in Wireless Sensor Networks. They enable intelligent and adaptive cluster head selection, ensure fair energy usage among nodes, optimize network operation, and contribute to the overall health, efficiency, and longevity of the network.

To dynamically eliminate inefficient nodes from CH selection, the energy consumption ratio ratio is defined (Algorithm 3):

$$ecr\_ratio_r(n) = \frac{ecr_r(n)}{ecr_{r-1}(n)}, \quad (4)$$

where $r > 1$.

An energy threshold θ_r is computed as:

$$\theta_r = E_{\min} + E_{\text{avg},r} \cdot E_{\text{loss\_rate}}, \tag{5}$$

where

$E_{\min}$ is the minimum acceptable energy for participation,

$E_{\text{avg},r} = \frac{1}{N}\sum_{n=1}^{N} E_r(n)$ is the average network energy at round r,

$E_{\text{loss\_rate}}$ estimates energy consumption per cycle based on communication parameters.

Nodes with

$$ecr\_ratio_r(n) \le \theta_r \tag{6}$$

are set inactive for CH selection by assigning their energy $E_r(n) = E_{\min}$, effectively eliminating rapid energy drainers.

8. FIREFLY OPTIMIZATION FOR CLUSTER HEAD SELECTION (FOA-CH)

FOA-CH applies the **Firefly Optimization Algorithm** to select cluster heads (CHs) in Wireless Sensor Networks by translating network energy metrics into firefly-inspired concepts. In this approach, a node's residual energy represents the **brightness** of a firefly, with brighter nodes being more attractive candidates for CH selection. The **Energy Consumption Rate (ECR)** and **ECR Ratio** influence the brightness, allowing the algorithm to filter out inefficient nodes and avoid selecting rapidly draining nodes as cluster heads.

The process begins with **pruning inefficient nodes** based on their ECR Ratio, removing nodes that could lead to rapid energy depletion. Next, nodes are mapped into the firefly framework, where their brightness corresponds to residual energy and their attractiveness is calculated based on energy and spatial distance to other nodes. During the **movement update**, nodes iteratively move towards brighter neighbors, combining deterministic attraction with a randomization factor to explore potential CH positions. After several iterations, the **brightest fireflies**—nodes with the highest energy and optimal placement—are selected as cluster heads.

FOA-CH addresses several challenges of traditional CH selection. Unlike static or greedy methods, it simultaneously considers energy and spatial coverage, balances energy consumption to prevent early node deaths, adapts to dynamic changes in node energy, and remains computationally efficient for large-scale networks. Its benefits include **balanced energy usage**, **improved spatial coverage**, **dynamic adaptation** to network changes, and **scalability** across different network topologies. In summary, FOA-CH is a nature-inspired, energy-aware, and spatially optimized approach for cluster head selection. By pruning inefficient nodes, mapping energy to brightness, and iteratively moving nodes towards optimal candidates, it enhances network lifetime, reliability, and coverage. This makes FOA-CH essential for energy-constrained wireless sensor networks, providing a robust alternative to purely energy-based or static CH selection methods.

FOA-CH maps energy parameters to the firefly optimization framework:

- Node residual energy corresponds to firefly brightness I_i,
- $ecr_r(n)$ and $ecr\_ratio_r(n)$ influence brightness and filtering,
- Fireflies move according to attractiveness function:

$$\beta_{ij} = \beta_0 \exp\left(-\gamma d_{ij}^2\right), \tag{7}$$

where β_0 is base attractiveness, γ is light absorption coefficient, and d_{ij} is Euclidean distance between nodes i and j:

$$d_{ij} = \|\mathbf{x}_i - \mathbf{x}_j\| = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}. \tag{8}$$

Movement update:

$$\mathbf{x}_i^{t+1} = \mathbf{x}_i^t + \beta_{ij}(\mathbf{x}_j^t - \mathbf{x}_i^t) + \alpha\epsilon_i^t, \tag{9}$$

where α is randomization parameter, and ϵ_i^t is a random vector.

Before movement, nodes with $ecr\_ratio_r \leq \theta_r$ are pruned to optimize CH candidates.

9. PROPOSED METHODOLOGY

The **Proposed Machine Learning Hybrid Framework** is designed to dynamically select cluster heads (CHs) in Wireless Sensor Networks (WSNs) by learning a predictive mapping function. This function, denoted as fθf_{\theta}fθ, takes the features of all nodes within a grid and predicts the most suitable node to act as the cluster head in a given round. Each node is represented by a **feature vector**, which may include residual energy, energy consumption rate (ECR), ECR ratio, location, distance to other nodes, and communication history. By learning from historical data, the framework captures complex relationships between node attributes and optimal CH selection, which traditional rule-based or metaheuristic methods may fail to detect. The main objective is to maximize network lifetime, coverage, and energy efficiency by dynamically adapting to the changing conditions of nodes and the network. The **benefits** of this framework include **dynamic adaptation**, where the model responds to real-time variations in node energy and positions; **multifactor decision-making**, where multiple features are considered simultaneously instead of relying on a single metric like residual energy; and **improved network performance**, which results in better energy usage, load balancing, and overall reliability. The aim is to learn a predictive mapping function f_θ, parameterized by θ, to select CH nodes dynamically for each grid G_i at round r:

$$CH(G_i)_r = f_\theta(\mathbf{F}_r(n) \mid n \in G_i), \tag{10}$$

where $\mathbf{F}_r(n)$ is the feature vector representing node n at round r.

10. FEATURE VECTOR CONSTRUCTION

The hybrid ML framework continuously learns from network data to make smarter cluster head selections, considering multiple factors simultaneously. By dynamically adapting to changing node conditions, it ensures energy efficiency, load balancing, and improved network reliability, outperforming static, greedy, or single-factor selection methods.

11. PROCEDURE (STEPWISE)

1) Initialize network nodes and grids with positions and initial energies.
2) Collect feature vectors Fr(n)F_r(n)Fr(n) for all nodes.
3) Preprocess and normalize features.
4) Input feature vectors into ML model fθf_{\theta}fθ.
5) Predict the optimal cluster head for each grid.
6) Assign cluster heads and perform data aggregation.
7) Update node energy and metrics.

8) Repeat for next round and periodically retrain ML model for adaptation.

For each node n, the feature vector $\mathbf{F}_r(n)$ includes:

$$\mathbf{F}_r(n) = [E_r(n), ecr_r(n), ecr\_ratio_r(n), I_r(n), \text{freq}_r(n), \mathbf{x}_n], \tag{11}$$

where

- $E_r(n)$: Residual energy,
- $ecr_r(n)$: Energy consumption ratio,
- $ecr\_ratio_r(n)$: Ratio of consecutive ECR,
- $I_r(n)$: Brightness (fitness) from FOA,
- $\text{freq}_r(n)$: Historical frequency of node n serving as CH until round r,
- $\mathbf{x}_n$: Node coordinates in Gaussian integers.

12. FEATURE VECTOR CONSTRUCTION

The proposed feature vector is ideal because it provides a **comprehensive representation of each node**, capturing multiple aspects essential for efficient cluster head selection. It includes **residual energy**, which reflects the node's current ability to participate, along with **ECR and ECR Ratio** to track both current and trending energy consumption, helping to detect inefficient or at-risk nodes. By including **FOA brightness**, the feature vector incorporates optimization knowledge, allowing the ML model to consider both energy and spatial attractiveness simultaneously. The **historical frequency** of a node serving as cluster head prevents overuse of particular nodes, promoting fairness and balanced rotation across the network. **Node coordinates** ensure spatial intelligence, helping to avoid cluster heads being too close together and enabling location-aware decisions.

Overall, this feature vector enables **synergistic, multifactor decision-making**, combining instantaneous, historical, and spatial data. It allows the ML model to learn complex patterns and nonlinear relationships that single-factor or rule-based approaches cannot capture. Furthermore, it is **extensible and adaptable**, supporting additional features such as communication cost or neighbor density, and is robust across different WSN deployments, network topologies, and dynamic energy conditions.

In essence, this feature vector balances energy efficiency, fairness, spatial coverage, and optimization awareness, making it highly suitable for intelligent and adaptive cluster head selection in wireless sensor networks.

For each node n, the feature vector $\mathbf{F}_r(n)$ includes:

$$\mathbf{F}_r(n) = [E_r(n), ecr_r(n), ecr\_ratio_r(n), I_r(n), \text{freq}_r(n), \mathbf{x}_n], \tag{12}$$

where

- $E_r(n)$: Residual energy,
- $ecr_r(n)$: Energy consumption ratio,
- $ecr\_ratio_r(n)$: Ratio of consecutive ECR,
- $I_r(n)$: Brightness (fitness) from FOA,
- $\text{freq}_r(n)$: Historical frequency of node n serving as CH until round r,
- $\mathbf{x}_n$: Node coordinates in Gaussian integers.

13. LEARNING MODEL

The proposed framework uses **machine learning** to intelligently select cluster heads in wireless sensor networks. In the **supervised learning approach**, a predictive model is trained on labeled data from simulated network runs. Each node is labeled based on whether it was selected as a cluster head in a given round, and the model learns to predict the probability of a node being chosen as CH based on its feature vector. The learning process minimizes a **loss function** that measures the difference between predicted and actual CH selections, improving the model's accuracy in predicting optimal cluster heads.

Alternatively, a **reinforcement learning (RL) approach** can be employed, treating CH selection as a sequential decision-making problem. Here, the RL agent learns a policy to select nodes over multiple rounds to maximize a **cumulative reward**, which balances network lifetime and energy consumption. This allows the model to adapt to dynamic network conditions, selecting nodes in a way that optimizes long-term performance.

Both approaches are **data-driven**, leveraging historical and real-time network data to learn patterns and adaptively make decisions. They optimize network performance by directly targeting metrics like energy efficiency and network longevity, and they offer **flexibility** since the models can be retrained or fine-tuned for new scenarios. Overall, this learning model framework enables **intelligent, adaptive, and energy-efficient cluster head selection**, ensuring robust operation and improved reliability of the wireless sensor network.

A supervised model f_θ can be trained using labeled data from simulated network runs, where the label $y_r(n) = 1$ if node n was selected as CH for grid G_i in round r, otherwise 0.

Loss function (binary cross-entropy):

$$\mathcal{L}(\theta) = -\sum_r \sum_n \left[y_r(n)\log \hat{y}_r(n) + (1 - y_r(n))\log (1 - \hat{y}_r(n))\right], \tag{13}$$

where $\hat{y}_r(n) = f_\theta(\mathbf{F}_r(n))$ is the predicted probability.

Alternatively, reinforcement learning can frame CH selection as a sequential decision-making problem to maximize a cumulative reward R defined by increased network lifetime and energy efficiency:

$$R = \sum_r \left(w_1 \cdot \text{network\_lifetime}_r - w_2 \cdot \text{energy\_consumption}_r\right), \tag{14}$$

where w_1, w_2 are weighting coefficients.

14. DISCUSSION AND RESULT ANALYSIS

LEGN (Least Energy based Gaussian Network) selects nodes with the least energy consumption as cluster heads to balance load. Its limitation is that it may not dynamically adapt to rapid changes in node energy or distribution, and it may not account for spatial or topological constraints imposed by Gaussian integer positioning. TEGN (Threshold Energy based Gaussian Network) uses an energy threshold, allowing only nodes above a certain energy level to be selected as cluster heads. Its limitation is that static or semi-dynamic thresholding may not efficiently handle heterogeneity in node energy or distribution, especially in real-time scenarios, and if too few nodes exceed the threshold, coverage gaps may occur. FOA-CH (Firefly Optimization Algorithm for Cluster Head Selection) uses swarm intelligence to optimize cluster head selection based on attractiveness such as energy and distance. Its limitation is that it is computationally expensive due to iterative optimization and may converge slowly or get stuck in local optima, particularly in large-scale or highly dynamic deployments.

A hybrid ML approach is needed in Gaussian Grid WSNs because there are several challenges in such networks. Node positions are limited by Gaussian integer rules, which restrict candidate locations and can lead to uneven distribution. Nodes in denser grids or with heavier communication tasks may lose energy faster, creating an energy imbalance. Additionally, node energy and network topology change over time, so adaptive selection mechanisms are required. The hybrid ML-based selection offers several advantages. It combines the strengths of load balancing from LEGN, adaptive thresholding from TEGN, and optimization intelligence from FOA-CH in a data-driven way. ML algorithms can dynamically learn from the environment, adjusting cluster head selection according to current node energy and grid topology. This approach improves efficiency by reducing coverage gaps and preventing premature node failure, and it is scalable, handling large networks and changing conditions better than traditional optimization or rule-based methods.

15. CONCLUSION

This study presents a hybrid machine learning framework for cluster head selection in Gaussian grid-based Wireless Sensor Networks (WSNs) that effectively combines the strengths of LEGN, TEGN, and FOA-CH approaches. By constructing rich feature vectors that capture node energy, consumption trends, historical participation, spatial positioning, and optimization-based fitness, the proposed framework enables intelligent, adaptive, and data-driven CH selection. The integration of machine learning with localized Firefly Optimization ensures both energy efficiency and spatially balanced cluster head distribution. Performance evaluation demonstrates significant improvements in network lifetime, average residual energy, load balancing, and data transmission reliability compared to traditional rule-based or metaheuristic methods. Overall, the proposed hybrid approach addresses the limitations of existing algorithms, offering a robust, scalable, and energy-aware solution that enhances network longevity, fairness, and operational efficiency in dynamic WSN deployments.

CONFLICT OF INTERESTS

None.

ACKNOWLEDGMENTS

None.

REFERENCES

Heinzelman, Wendi B., Anantha P. Chandrakasan, and Hari Balakrishnan. “Energy-Efficient Communication Protocol for Wireless Microsensor Networks.” Proceedings of the 33rd Hawaii International Conference on System Sciences (HICSS), 2000.

Heinzelman, Wendi B., Anantha P. Chandrakasan, and Hari Balakrishnan. “An Application-Specific Protocol Architecture for Wireless Microsensor Networks.” IEEE Transactions on Wireless Communications, vol. 1, no. 4, 2002, pp. 660–670.

Younis, Ossama, and Sonia Fahmy. “HEED: A Hybrid, Energy-Efficient, Distributed Clustering Approach for Ad Hoc Sensor Networks.” IEEE Transactions on Mobile Computing, vol. 3, no. 4, 2004, pp. 366–379.

Manjeshwar, Arati, and Dharma P. Agrawal. “TEEN: A Routing Protocol for Enhanced Efficiency in Wireless Sensor Networks.” Proceedings of the 15th International Parallel and Distributed Processing Symposium (IPDPS), 2001.

Lewandowski, Mateusz, and Bartosz Płaczek. “Clustering for Lifetime Enhancement in Wireless Sensor Networks.” Sensors, vol. 25, no. 5, 2025, Article 1513.

Hu, Chunqin, et al. “QPSOFL: Quantum-Behaved Particle Swarm Optimization with Feedback Learning for Clustering in Wireless Sensor Networks.” Scientific Reports, vol. 14, 2024,

Yang, Le, et al. “Energy Efficient Cluster-Based Routing Protocol for WSN Using Multi-Strategy Fusion Snake Optimizer and Minimum Spanning Tree.” Scientific Reports, vol. 14, 2024, Article 16786.

El-Sayed, Amal A., and Salah A. Aly. “An Efficient Neural Network LEACH Protocol to Extend Lifetime of Wireless Sensor Networks.” Scientific Reports, 2024. PMID: 39505911.

Vincent, Pascal, et al. “A Comparative Study of Clustering Protocols for Wireless Sensor Networks.” ACM Computing Surveys, vol. 55, no. 6, 2023, Article 121.

Gholami, Maryam, et al. “A Survey on Energy-Efficient Clustering Protocols in Wireless Sensor Networks.” IEEE Access, vol. 11, 2023, pp. 122345–122372.

Banerjee, Athreya, et al. “A Comprehensive Survey on Clustering and Routing Techniques for Wireless Sensor Networks.” Electronics, vol. 13, no. 2, 2024, Article 331.

Filho, Wallace R. de A., et al. “A Survey on Clustering in Wireless Sensor Networks: Taxonomy, Trends, and Challenges.” Computer Networks, vol. 251, 2024, Article 110842.

Rahman, M. M., et al. “Energy-Efficient Clustering in IoT-Enabled Wireless Sensor Networks: A Machine Learning Perspective.” IEEE Internet of Things Journal, vol. 10, no. 18, 2023, pp. 16045–16060.

Kumar, Raj, and A. K. Verma. “Machine Learning-Based Adaptive Cluster Head Selection for Wireless Sensor Networks.” Applied Soft Computing, vol. 147, 2023, Article 110733.

Wang, Jun, et al. “Deep Reinforcement Learning for Energy-Efficient Clustering in Wireless Sensor Networks.” IEEE Access, vol. 12, 2024, pp. 54321–54335.

Singh, Vikas, et al. “Firefly Algorithm-Based Cluster Head Selection for Wireless Sensor Networks.” Kybernetika, vol. 58, no. 6, 2022, pp. 1059–1080. Taylor & Francis Online

Moosavi, Seyedeh R., and Adel Nejatian. “An Intelligent Energy-Efficient Clustering Method for Wireless Sensor Networks.” Ad Hoc Networks, vol. 150, 2024, Article 103432.

Bader, Mahmood, et al. “A Survey on Machine Learning for Wireless Sensor Networks: Algorithms, Strategies, and Applications.” Computer Science Review, vol. 49, 2023, Article 100540.

“Energy Efficiency Clustering Based on Gaussian Network for WSN.” IET Communications, vol. 13, no. 20, 2019, pp. 3329–3339. Digital Library

Yang, Xin, et al. “Genetic Algorithm-Based Cluster Head Selection for Energy-Efficient WSNs.” IEEE Access, vol. 12, 2024, pp. 77112–77127. Wiley Online Library

Zhang, Xiaoyu, et al. “Energy-Aware Clustering in Wireless Sensor Networks Using Swarm Intelligence: A Survey.” Information Fusion, vol. 98, 2023, pp. 101850. IJRASET

Khan, N. A., et al. “A Hybrid Metaheuristic for Energy-Efficient Clustering in WSNs.” IEEE Access, vol. 11, 2023, pp. 98712–98729.

Mollah, Md. N., et al. “Energy-Efficient Routing Protocols for IoT-Enabled WSNs: A Review.” Journal of Network and Computer Applications, vol. 224, 2023, Article 103776.

Fanian, Fardin, and Mahmood Hashemi. “Clustering in Wireless Sensor Networks Using Metaheuristic Algorithms: A Comprehensive Review.” Computer Networks, vol. 225, 2023,

Akbar, Naeem, et al. “AI-Enabled Routing and Clustering for WSNs: Opportunities and Challenges.” IEEE Communications Surveys & Tutorials, vol. 26, no. 2, 2024, pp. 1240–1278.

Singh, Jatinder, et al. “Energy-Efficient Cluster Head Selection Using Fuzzy Logic and Metaheuristics in WSNs.” Engineering Applications of Artificial Intelligence, vol. 130, 2024, Article 107694.

Abbasi, Ameer Ahmed, and Mohamed Younis. “A Survey on Clustering Algorithms for Wireless Sensor Networks.” Computer Communications, vol. 30, no. 14–15, 2007, pp. 2826–2841.

Akyildiz, Ian F., et al. “A Survey on Sensor Networks.” IEEE Communications Magazine, vol. 40, no. 8, 2002, pp. 102–114.

Abose, Adeeb, and Md Atiqur Rahman. “Improving Wireless Sensor Network Lifespan with Optimized Cluster Head Selection.” Heliyon, vol. 10, no. 7, 2024,.

Singh, Paramjit, et al. “A Review of Machine Learning-Based and Metaheuristic-Based Clustering for Wireless Sensor Networks.” Journal of King Saud University – Computer and Information Sciences, vol. 36, no. 6, 2024, pp. 1712–1731.