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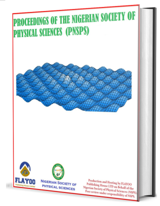

A grid-based sectoring for energy-efficient wireless sensor networks

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ABSTRACT

Extending the network lifetime of Wireless Sensor Networks (WSNs) while meeting user needs is crucial, given the limited energy capacity and rapid depletion of nodes. Clustering is an effective strategy for prolonging network lifetime by reducing energy overhead in data transmission. The Sector-Low Energy Adaptive Clustering Hierarchy (S-LEACH) method mitigates energy depletion by grouping nodes into sectors and selecting Cluster Heads (CHs) based on either the highest residual energy or a random number. However, its CH selection process remains suboptimal, leading to energy imbalance and inefficiencies due to fixed sector boundaries. This research improves CH selection by organizing sensor nodes into square grid clusters and employing a routing algorithm for randomized CH selection. Game theory (GT) and Ad hoc on Demand Vectors (AODV) were used to choose the optimal routing path, while Grey Wolf Optimization (GWO) was used to determine the optimal CHs. MATLAB 2023a was utilized for network design and algorithm implementation. After 1,000 transmission rounds, the proposed method extended the network lifetime to 582 seconds, compared to 565 seconds in S-LEACH, representing a 3% improvement. Results indicate that the proposed approach enhances network longevity and balances energy consumption across clusters, ultimately improving overall performance.

Keywords: Wireless sensor networks, Cluster head, Game theory, Energy-efficient routing.

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1. INTRODUCTION

Wireless Sensor Networks (WSNs) have become fundamental in applications such as environmental monitoring, industrial automation, and healthcare due to their low cost, small size, and self-organizing capabilities [1]. These networks enable real-time data collection, seamless integration with other information processing platforms, and enhanced monitoring efficiency. Their increasing role in pervasive computing and the Internet of Things (IoT) has led to widespread adoption across various sectors [2].

Despite their advantages, WSNs face critical challenges, primarily related to energy efficiency and network longevity. Sensor nodes operate on limited energy resources, and the energy-intensive nature of data transmission and routing accelerates depletion [3]. This problem is exacerbated in large-scale networks with unbalanced data loads and non-uniform node distribution, leading to inefficient Cluster Head (CH) selection, uneven energy consumption, and network instability [4–6]. Addressing these inefficiencies is essential for ensuring the sustainability and reliability of WSNs.

Clustering techniques have been developed to mitigate these issues by reducing radio transmissions and optimizing energy

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distribution [7]. However, conventional clustering and routing methods often struggle in large networks due to suboptimal CH selection, energy imbalance, and inefficient routing, which can create "energy holes" and reduce resilience [8]. To overcome these limitations, grid-based sectoring has emerged as a promising solution. By systematically organizing WSNs into structured grid clusters, this method minimizes long-distance transmissions, enhances localized communication, and improves energy distribution [9]. Additionally, dynamic CH selection based on residual energy and spatial proximity further enhances network longevity [10, 11].

While grid-based clustering improves energy efficiency, it still faces limitations in adapting to fluctuating network conditions such as node failures and varying energy levels [12]. Many existing methodologies lack adaptability and scalability, making them less effective in dynamic environments. Research has suggested that integrating machine learning (ML) and evolutionary algorithms into clustering techniques can significantly enhance energy efficiency and robustness [13, 14].

This research extends the Sector-Low Energy Adaptive Clustering Hierarchy (S-LEACH) by incorporating grid-based sectoring to enhance scalability and energy efficiency [15]. Unlike traditional methods with fixed sector boundaries, dynamic clustering balances energy consumption and prevents premature node depletion [16]. Additionally, the integration of Game Theory (GT) and Modified Grey Wolf Optimization (MGWO) refines CH selection and optimizes routing. GT models sensor nodes as strategic players, enabling optimized energy usage [17], while MGWO enhances CH selection by minimizing energy consumption and balancing network load [18]. This combined approach significantly extends network lifetime, improves energy efficiency, and enhances WSN reliability in dynamic environments [19].

2. LITERATURE REVIEW

The deployment and clustering of sensor nodes significantly influence the energy efficiency of WSNs. Optimal node placement and clustering techniques are essential for minimizing energy consumption, extending network longevity, and ensuring reliable communication. Numerous approaches, including grid-based, hierarchical, and adaptive clustering, as well as deployment techniques tailored for specific applications, have been explored in recent studies. However, existing methods often face challenges related to adaptability, scalability, and energy balance, which this research aims to address.

2.1. GRID-ORIENTED DEPLOYMENT AND CLUSTERING

Several studies highlight the advantages of grid-based clustering strategies. Ref. [20] introduced an Energy-Aware Grid-Based Clustering Power Efficient Data Aggregation Protocol that arranges nodes into geographic clusters to reduce long-distance transmissions. The approach dynamically selects CHs based on residual energy and proximity, improving energy efficiency. Similarly, Ref. [21] developed a Grid-Based Clustering Method for Data Acquisition, which enhances data collection efficiency and reduces transmission overhead by leveraging localized data aggregation. Their method also employs dynamic CH selection to distribute energy consumption more equitably.

Ref. [22] proposed a Neighborhood Grid Clustering Algorithm (NGCA) integrated with a Genetic Algorithm (GA) to improve localization precision. This hybrid approach reduces computational complexity and energy consumption compared to conventional techniques such as Multidimensional Scaling (MDS). While these grid-based methodologies enhance energy efficiency, their static sector boundaries and limited adaptability to network dynamics remain challenges. Our research extends these methods by incorporating a more flexible grid-based clustering approach that dynamically adjusts CH selection using Game Theory (GT) and Modified Grey Wolf Optimization (MGWO) to optimize energy use and scalability.

2.2. HIERARCHICAL AND ADAPTIVE CLUSTERING METHODS

Hierarchical clustering is another widely explored approach for improving energy efficiency. Ref. [23] introduced a Multi-Level Hierarchical Clustering Algorithm, where higher-level CHs aggregate data from lower levels to reduce inter-cluster communication costs. This method proves beneficial for large-scale networks with heterogeneous node distributions. Similarly, Ref. [24] proposed an Adaptive Energy-Efficient Clustering Algorithm that selects CHs based on energy thresholds and node mobility patterns, improving adaptability to changing network conditions.

While hierarchical and adaptive clustering methods improve energy balance and network longevity, they often involve high computational overhead and do not fully address the issue of fixed cluster boundaries. In contrast, our proposed approach integrates adaptive CH selection within a grid-based clustering framework, leveraging GT for optimal routing decisions and MGWO for efficient CH selection, ensuring energy-efficient operations under dynamic network conditions.

2.3. RANDOM AND DETERMINISTIC DEPLOYMENT STRATEGIES

Deployment strategies significantly impact clustering efficiency and energy consumption. Ref. [25] examined Random Deployment Models, highlighting their susceptibility to coverage gaps and energy imbalances. Conversely, Ref. [26] introduced a Hexagonal Grid Deployment Scheme that ensures uniform node distribution, leading to more balanced energy consumption and improved coverage.

Although deterministic deployment guarantees better energy distribution, it lacks the adaptability required for dynamic environments. Our approach bridges this gap by combining deterministic grid-based clustering with adaptive CH selection, ensuring balanced energy usage while maintaining flexibility in response to network changes.

2.4. OPTIMIZATION TECHNIQUES IN CLUSTERING

Optimization algorithms are increasingly being integrated into clustering strategies to enhance energy efficiency. Ref. [27] applied Particle Swarm Optimization (PSO) for dynamic CH selection in a Hybrid Clustering Algorithm, demonstrating improved energy efficiency and reduced packet loss. Similarly, Ref. [28] introduced a GA-Optimized Clustering Protocol that strategically selects CHs to prolong network longevity.

Despite their advantages, optimization-based methods often require significant computational resources, limiting their practicality in real-time WSN applications. Our research addresses this by employing MGWO, a lightweight and efficient algorithm that optimizes CH selection while maintaining computational feasibility.

2.5. CLUSTERING IN MACHINE LEARNING AND ARTIFICIAL INTELLIGENCE

The integration of machine learning (ML) and artificial intelligence (AI) has significantly transformed clustering methodologies. Ref. [29] developed a Reinforcement Learning-Based Clustering Algorithm that dynamically adapts to changing network conditions, reducing energy consumption and improving data transmission rates. Similarly, Ref. [30] employed a Convolutional Neural Network (CNN) model for real-time CH prediction, demonstrating enhanced energy efficiency and scalability.

Although AI-driven clustering methods offer promising results, their reliance on extensive training data and computational power makes them challenging to implement in resource-constrained WSN environments. Our approach circumvents these challenges by combining lightweight optimization techniques (MGWO) with GT-driven routing, ensuring computational efficiency while maintaining adaptability.

2.6. HYBRID AND INTEGRATED METHODOLOGIES

Hybrid methodologies that integrate multiple clustering strategies have shown promising results. Ref. [31] combined grid-based clustering with fuzzy logic to dynamically adjust CH roles based on environmental factors, achieving balanced energy consumption. Additionally, Ref. [32] explored hybrid solar-powered WSNs, integrating renewable energy with clustering algorithms to extend network lifetime, particularly in remote areas.

While these hybrid approaches enhance energy efficiency, they do not fully address scalability and adaptability in dynamic networks. Our research improves upon these methods by integrating GT-based routing and MGWO-driven CH selection within a grid-based clustering framework, ensuring a scalable and adaptive solution for energy-efficient WSNs.

3. METHODOLOGY

The proposed methodology introduces a structured enhancement to the existing S-LEACH algorithm, focusing on efficient deployment, clustering, and energy management. This involves initializing network parameters, deploying nodes within defined boundaries, implementing optimized CH selection strategies, modifying the WSN architecture, simulating the proposed improvements in MATLAB, and evaluating the performance metrics. The methodology follows a systematic framework to ensure consistency across design, implementation, and evaluation phases.

3.1. GRID DIVISION AND SECTOR-BASED CLUSTERING

To organize the network effectively, the deployment area is divided into a structured grid of sectors. The grid division can be uniform or adaptive, depending on node density [33].

- Uniform grid: Ensures equal-sized sectors across the entire deployment area, simplifying implementation and management.
- Adaptive grid: Adjusts sector sizes dynamically based on sensor node density. Densely populated areas feature smaller grid cells to reduce intra-sector communication distances, while sparsely populated areas have larger cells to optimize resource use [34].

Each sector is further divided into clusters using the theory of line symmetry and square formation, which ensures optimal node distribution.

3.2. THEORY OF LINE SYMMETRY AND SQUARE FORMATION

The theory of line symmetry in WSN deployment refers to placing sensor nodes symmetrically along predefined axes to balance communication distances and minimize energy wastage. This method improves coverage efficiency and ensures even energy distribution. Square formation divides the area into quadrants or rectangular sectors, allowing nodes to be grouped systematically for better cluster formation.

The proposed sector-based clustering approach enhances energy efficiency by:

- Reducing the computational complexity of routing and clustering.
- Ensuring localized management within each sector.
- Minimizing energy consumption by balancing node communication loads.

3.3. ENERGY-EFFICIENT ROUTING

Energy-efficient routing is crucial for maintaining balanced energy consumption across the network. The routing strategy includes:

- Intra-sector communication: Nodes relay data to the closest neighbors or directly to the CH using a cost function that considers residual energy and communication distance [35].
- Inter-sector multi-hop routing: Communication between sectors relies on multi-hop transmission to distribute the load and prevent energy depletion at individual nodes [36].
- Fault-tolerant mechanisms: If a CH or relay node fails, alternative routes are dynamically selected to ensure uninterrupted data transmission.

By integrating these routing strategies, the proposed approach significantly reduces overall energy consumption while maintaining reliable data transmission.

3.4. CLUSTER FORMATION AND CLUSTER HEAD SELECTION

Each sector is divided into clusters based on proximity and energy availability. The CH selection process is dynamic, preventing premature energy depletion and balancing power consumption across the network [37]. The CH selection criteria include:

- Residual energy: Higher-energy nodes are prioritized as CHs.

- Proximity to Cluster Center: Nodes closer to the geometric center of a cluster minimize transmission energy.

- Historical energy Usage: Nodes that have not recently served as CHs are preferred to ensure fair energy distribution.

Periodic CH rotation is employed to distribute energy usage evenly among nodes, extending network lifespan. The clustering mechanism is adaptive, allowing clusters to adjust dynamically based on node density and energy levels.

3.5. SECTOR-BASED DATA AGGREGATION

To minimize communication overhead, data aggregation is performed within each sector. The process follows these steps:

1. CHs collect raw data from sensor nodes.
2. Redundant data is removed, and relevant information is aggregated.
3. Compressed data packets are forwarded across sectors via energy-efficient routing mechanisms.

Figure 1 illustrates a CH Selection and Data Transmission Process in a WSN, specifically incorporating the LEACH protocol with an energy-aware approach. The goal is to optimize energy consumption and extend network lifespan by selecting CHs efficiently.

3.6. ENHANCED S-LEACH ALGORITHM

The enhanced S-LEACH algorithm incorporates the following steps:

1. Initialization & node deployment: The network initializes parameters and deploys nodes while broadcasting sector information.
2. Distance computation & CH selection: Nodes calculate their distance to the Base Station (BS) and sectors are assigned. The first round of CH selection follows the traditional LEACH method.
3. CH operations: The CH performs TDMA scheduling to manage communication among CMs.
4. Subsequent Rounds Energy-Aware CH Selection: Nodes broadcast their energy levels and a random number to determine CH eligibility. If a node meets the threshold, it becomes a CH; otherwise, the node with the highest residual energy is selected.
5. Data collection & transmission:
    - CMs sense and transmit data to the CH based on TDMA scheduling to avoid collisions.
    - The CH aggregates collected data and forwards it to the BS.
6. Termination condition: The process iterates until the maximum number of rounds is reached, at which point the network stops functioning.

Table 1. Simulation parameters.

Parameter	Value
Simulation Area	250 x 250
Data Packet Length	6,400 bits
Routing Packet Length	64 bits
Initial Energy	0.5J
Base Station coordinates	125,350
Node Probability to become CH	0.10
Number of Nodes	100
Maximum Communication Range	40m
Energy for bit transmitting	5×10^{-8} J
Energy for bit receiving	5×10^{-8} J
Free space model energy	1×10^{-11} J
Amplification energy	1.3×10^{12} J
Energy Data Aggregation	5×10^{-9} J

4. RESULTS AND DISCUSSION

The nodes in a WSN can either be CH and CM. Equation 1 represents the mathematical model for the node. The total energy consumed by a CM node is given by:

$$E_{(k,d)} = E_{\text{Sleep}_{(k,d)}} + E_{\text{Idle}_{(k,d)}} + E_{\text{Transmit}_{(k,d)}} + E_{\text{Sense}_{(k,d)}}, \quad (1)$$

where k is the data packet sent, d is the distance between the CM and CH, $E_{\text{Sleep}_{(k,d)}}$ is the energy consumed by the node in sleep mode, $E_{\text{Idle}_{(k,d)}}$ is the energy consumed by the node in idle mode, $E_{\text{Transmit}_{(k,d)}}$ is the energy consumed during data transmission, $E_{\text{Sense}_{(k,d)}}$ is the energy consumed during data sensing.

The energy consumed by a CH node is primarily due to data aggregation, which is the main factor responsible for energy depletion. Therefore, the model for the CH node's energy consumption is given in equation 2 as:

$$E_{(k,d)} = E_{\text{transmit}_{(k,d)}} + E_{\text{recieve}_{(k,d)}} + E_{\text{aggregate}_{(k,d)}} + E_{\text{sense}_{(k,d)}} + E_{\text{process}_{(k,d)}}, \quad (2)$$

where k is the data packet sent, d is the distance between the CH and BS, $E_{\text{Transmit}_{(k,d)}}$ is the energy consumed during data transmission, $E_{\text{recieve}_{(k,d)}}$ is the energy consumed while receiving data packets, $E_{\text{aggregate}_{(k,d)}}$ is the energy consumed while aggregating data packets, $E_{\text{Sense}_{(k,d)}}$ is the energy consumed during data sensing, $E_{\text{process}_{(k,d)}}$ is the energy consumed while processing data packets.

4.1. NETWORK SIMULATION PARAMETERS

Table 1 outlines essential simulation parameters for assessing the energy efficiency of WSN.

After the simulation on MATLAB 2023a, the field or sensing area is given in Figure 2.

In this research, several factors contributed to the observed increase in network lifetime compared to the findings of Ref. [38]. The sharp drop in network lifetime for both algorithms just before round 600 indicates a significant amount of the network nodes exhaust their energy at this stage. This is attributable to the following factors:

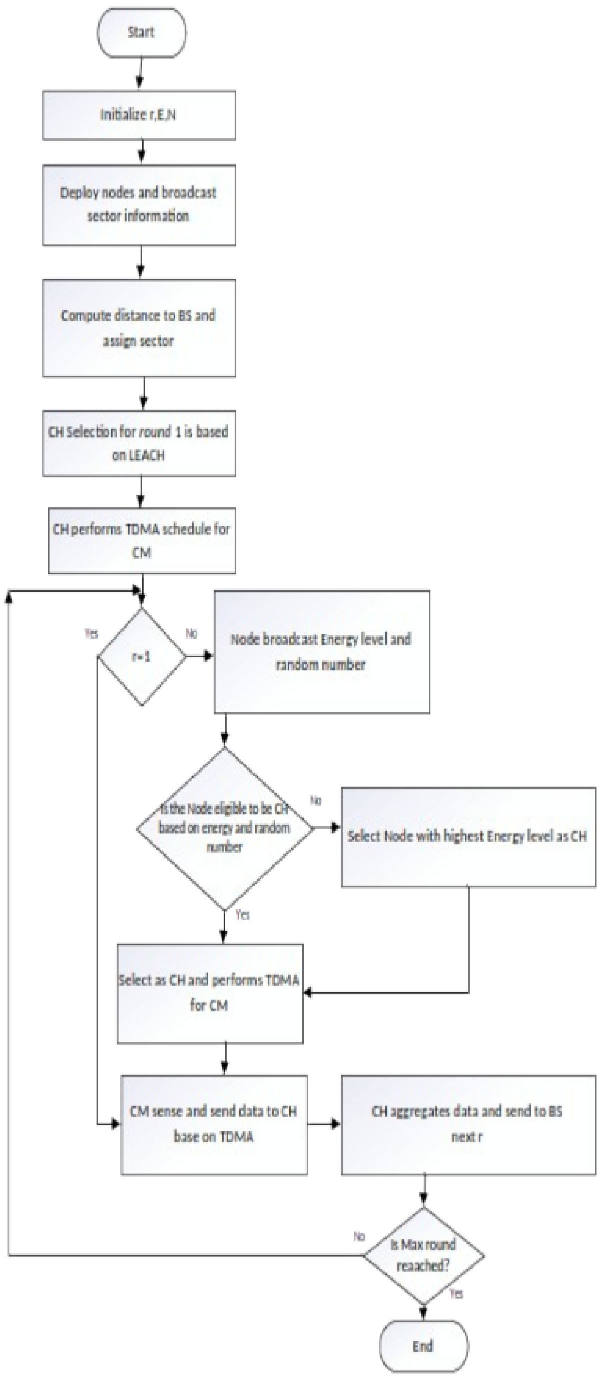

Figure 1. S-LEACH operation flow.

- Energy depletion of CH: the recurrent selection of specific nodes as CHs leads to accelerated energy depletion, resulting in network instability as in the case of S-LEACH.
- Energy harvesting: the ambient energy captured from RF sources serves as a supplementary or backup power source for the sensor nodes, enhancing the network lifetime of GWO-GT in comparison to S-LEACH.
- Uneven energy distribution: unequal energy consumption across nodes leads to some nodes failing earlier, impacting the overall network lifetime.

The downward trend is attributed to the consistent depletion of node energy in the network as the number of rounds grows, resulting in a diminished network lifespan. Initially, both algorithms exhibit stability due to the abundance of energy resources; but as rounds increase, the energy of nodes depletes, resulting in a significant reduction in lifespan. GWO-GT outperforms S-LEACH, evidenced by its gradual drop, signifying superior energy conservation efficiency.

Figure 3 illustrates that after one thousand (1,000) rounds

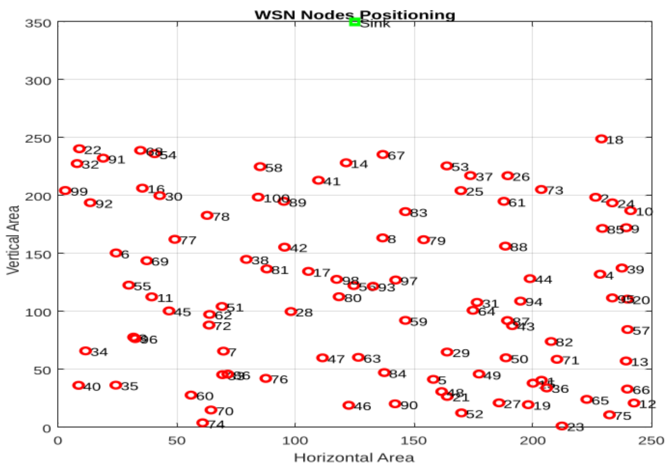

Figure 2. Node deployments.

of transmission, the network lifetime for S-LEACH was 565 seconds, whereas in this research, it increased to 582 seconds, demonstrating significant improvements in network longevity.

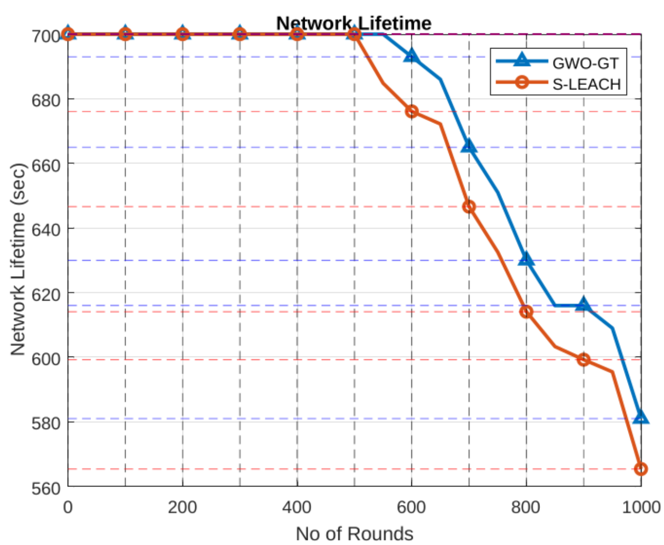

Figure 3. Network lifetime.

5. CONCLUSIONS

Energy management is a fundamental factor in ensuring the sustainability and longevity of WSNs. Extending network operational time enhances efficiency, as continuous data sensing and collection are crucial for numerous WSN applications. As WSNs evolve, efficient data gathering and increased throughput become increasingly important. This is particularly relevant in mission-critical scenarios such as environmental monitoring, disaster response, healthcare, and industrial automation, where timely and reliable sensor data directly impact decision-making and human well-being. The proposed enhancements to S-LEACH sector-based clustering, adaptive CH selection, and energy-efficient routing offer practical benefits in smart agriculture, healthcare monitoring, industrial IoT, and disaster management by reducing energy consumption and increasing network longevity. While simulation results demonstrate significant improvements in energy efficiency, future research could explore real-world hardware implementations to validate these findings. Additionally, integrating machine learning-driven adaptive clustering and testing in edge-computing and low-power IoT environments could further enhance network resilience and scalability. Addressing these areas will help bridge the gap between theoretical advancements and practical deployments, ensuring WSNs continue evolving to meet emerging challenges.

DATA AVAILABILITY

We do not have any research data outside the submitted manuscript file.

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