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RESEARCH ARTICLE

Energy–Efficient Adaptive Clustering in Wireless Sensor Networks Using AI–Driven Optimization Algorithms

Hakkem B [1], Mahendrakan K [1,*], Prabu S. [2,*], Reyazur Rashid Irshad [3]

ABSTRACT: Energy efficiency in Wireless Sensor Networks (WSNs) is a crucial challenge due to the limited power supply of sensor nodes. This paper introduces an AI-driven adaptive clustering mechanism to address this issue, enhancing energy efficiency and prolonging network lifespan. The proposed framework integrates machine learning (ML) techniques with bio-inspired optimization algorithms, such as Genetic Algorithm (GA) and Salp Swarm Optimization (SSO), for dynamic cluster head (CH) selection and adaptive clustering. Unlike traditional protocols like LEACH and HEED, which rely on static or random CH selection, our approach leverages real-time network conditions, node heterogeneity, and energy status to optimize clustering decisions. Simulation results reveal significant improvements in energy consumption, network stability, and scalability. The proposed method reduces total energy consumption by approximately 30% compared to LEACH and 20% compared to HEED. Furthermore, the network lifetime is extended by 25%, and data throughput is increased by 20%. This improvement is achieved through intelligent CH selection, which balances the energy load among nodes and prevents premature node failures. This study highlights the potential of AI-driven optimization for adaptive clustering in WSNs, making it suitable for energy-critical applications such as environmental monitoring, smart cities, and healthcare. By demonstrating the effectiveness of combining ML with bio-inspired algorithms, the proposed method provides a robust solution to the energy depletion challenges in WSNs. Future research will focus on incorporating reinforcement learning and multi-objective optimization to further enhance adaptability and address diverse performance metrics.

Keywords: Wireless Sensor Networks, Energy Efficiency, Adaptive Clustering, AI-Driven Optimization, Machine Learning

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1. INTRODUCTION

Wireless Sensor Networks (WSNs) are integral to a wide range of applications, including environmental monitoring, healthcare, industrial automation, military surveillance, and smart city development [1]. These networks comprise numerous spatially distributed sensor nodes, each equipped with sensing, computation, and communication capabilities. These nodes collect data from their environment and transmit it to a central base station (BS) or sink node for further analysis. While WSNs enable real-time monitoring and control, their utility is significantly constrained by the limited power supply of sensor nodes, which are often powered by non-rechargeable batteries.

Energy efficiency is, therefore, a critical factor in WSNs, directly influencing the operational lifespan and effectiveness of the network. Inefficient energy management can lead to premature node failures, data loss, and network partitioning, undermining the reliability of the entire system [2, 3]. As such, the design of energy-efficient communication protocols is a primary focus of WSN research. Among these, clustering-based protocols have emerged as a promising approach to

[1] Hindusthan Educational Institutions, Avinashi Road, behind Nava India, Coimbatore, Tamil Nadu 641028, India
[2] Department of Electronics and Communication Engineering, Mahendra Institute of Technology, Namakkal, Tamil Nadu-637503, India
[3] Department of Computer Science, College of Science and Arts, Sharurah 68341, Najran University, Saudi Arabia

* Author to whom correspondence should be addressed:
dr.mahendrakan.k@hit.edu.in (Mahendrakan K)
vsprabu4u@gmail.com (Prabu S)

optimize energy consumption.

Clustering involves organizing sensor nodes into groups, or clusters, with one node in each cluster designated as the Cluster Head (CH). The CH is responsible for aggregating data from the member nodes and forwarding it to the BS, thereby reducing communication overhead and conserving energy. Traditional clustering protocols, such as Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed (HEED), have been widely studied for their simplicity and effectiveness. However, these protocols often rely on static or random CH selection methods, which can lead to imbalanced energy consumption among nodes, reducing the network's overall lifespan [4, 5].

To address the limitations of conventional clustering methods, researchers have explored the integration of artificial intelligence (AI) techniques into WSNs. AI-driven approaches, particularly those leveraging machine learning (ML) and optimization algorithms, offer a dynamic and data-driven solution to CH selection and clustering. By analyzing real-time network conditions, energy levels, and node heterogeneity, AI-based methods can optimize clustering decisions to balance energy consumption and enhance network performance [6, 7].

For instance, optimization algorithms like Genetic Algorithm (GA) and Salp Swarm Optimization (SSO) have shown promise in improving clustering efficiency. These bio-inspired techniques are capable of finding near-optimal solutions to complex problems, such as CH selection, by mimicking natural processes like evolution and swarm behavior [8, 9]. When combined with ML models that predict node behavior and energy consumption, these algorithms can create adaptive clustering mechanisms that significantly outperform traditional protocols [10].

In this paper, we propose an AI-driven adaptive clustering mechanism for WSNs that integrates ML with GA and SSO for dynamic CH selection. Our approach aims to minimize energy consumption, balance the energy load across nodes, and extend the network's lifespan. Simulation results demonstrate the effectiveness of the proposed method, highlighting improvements in energy efficiency, network stability, and scalability compared to traditional protocols like LEACH and HEED.

The remainder of this paper is organized as follows: Section 2 reviews related work on energy-efficient clustering and AI-based optimization in WSNs. Section 3 describes the methodology and proposed mechanism. Section 4 presents simulation results and performance evaluation, while Section 5 concludes with insights and future research directions.

2. LITERATURE SURVEY

Several protocols have been proposed for energy-efficient clustering in WSNs, focusing primarily on static CH selection. LEACH, TEEN, and HEED [11] are some of the notable examples. However, these approaches lack adaptability and fail to consider node heterogeneity and network dynamics, leading to suboptimal performance. Recent advancements in AI and machine learning have opened new possibilities for optimizing WSNs' performance. Algorithms such as Particle Swarm Optimization (PSO), Genetic Algorithm (GA), [12] and Salp Swarm Optimization (SSO) [13] have been explored to enhance clustering efficiency. Nevertheless, these methods often require high computational power and may not be ideal for real-time adaptation.

Our approach builds on these ideas by integrating AI models to predict node behavior and dynamically adjust CH selection based on optimization criteria such as energy consumption, node location, and communication range [14]. The field of Wireless Sensor Networks (WSNs) [15] has witnessed substantial research focusing on energy-efficient communication protocols, particularly clustering techniques. Traditional clustering protocols such as Low-Energy Adaptive Clustering Hierarchy (LEACH) [16] and its variants have formed the foundation for numerous energy optimization strategies. However, the limitations of these early protocols, especially in dealing with network scalability, dynamic changes, and node heterogeneity, have motivated researchers to explore more advanced techniques, including machine learning (ML) and artificial intelligence (AI)-driven solutions.

2.1. Traditional Clustering Protocols

LEACH (Low-Energy Adaptive Clustering Hierarchy), proposed by [17] is one of the earliest and most widely used clustering protocols for WSNs. LEACH operates in two phases: the setup phase and the steady-state phase. In the setup phase, cluster heads (CHs) are selected randomly based on a probability function, and nodes join the closest CH. In the steady-state phase, data is collected by the nodes and transmitted to the CH, which aggregates and forwards it to the base station. However, LEACH suffers from several drawbacks, such as random CH selection, lack of scalability, and early energy depletion of CHs, which limits the network's lifetime.

HEED (Hybrid Energy-Efficient Distributed Clustering), introduced by [18] improves on LEACH by considering residual energy and communication cost in the CH selection process. HEED selects CHs based on node energy levels and proximity, aiming to balance energy consumption across the network. Although HEED achieves better energy efficiency than LEACH, it does not dynamically adapt to changes in network conditions and often leads to energy imbalances when network density or topology changes.

TEEN (Threshold Sensitive Energy Efficient Sensor Network Protocol) focuses on reactive networks where data transmission is event-driven. TEEN introduces a hard and soft threshold mechanism to control the frequency of data transmission, which reduces energy consumption by minimizing unnecessary communication. However, TEEN is not suitable for time-sensitive applications where periodic data transmission is required, limiting its applicability in various WSN environments.

While these traditional protocols have provided essential building blocks for energy-efficient WSNs, their lack of adaptability and static CH selection [19] strategies have prompted the need for more dynamic and intelligent approaches. In response, recent research has explored AI and ML techniques for more advanced clustering and CH selection mechanisms.

2.2. AI-Driven Clustering Approaches

In recent years, AI-driven clustering algorithms [20] have emerged as promising solutions to overcome the limitations of traditional protocols. By leveraging machine learning models and optimization algorithms, AI-driven approaches can dynamically adjust the clustering structure, taking into account real-time network conditions, node energy levels, and communication patterns.

Genetic Algorithms (GAs) [21] have been employed to optimize CH selection in WSNs by iteratively refining the population of candidate solutions. The optimization process uses selection, crossover, and mutation operations to evolve better clustering configurations. GAs can effectively balance energy consumption across the network by selecting CHs based on fitness functions that incorporate residual energy, node location, and communication costs. For example, [22] proposed a GA-based clustering approach that improves network lifetime by ensuring more balanced energy distribution. However, GAs can suffer from convergence issues, especially in real-time applications, due to the high computational overhead associated with evolving populations.

Particle Swarm Optimization (PSO) is another bio-inspired optimization algorithm used to solve clustering problems in WSNs. PSO optimizes CH selection by simulating the social behavior of swarms, where each particle (candidate solution) adjusts its position based on personal and global best solutions. Like GAs, PSO-based clustering protocols, such as those proposed by [23] focus on minimizing energy consumption and communication distance. PSO offers faster convergence compared to GAs but can still encounter difficulties in adapting to highly dynamic networks with frequent topology changes.

Fuzzy logic has been integrated into WSN clustering protocols to handle uncertainty and vagueness in CH selection. Fuzzy-based systems consider multiple input parameters, such as residual energy, node density, and communication distance, to make more informed CH selection decisions. [24] proposed a fuzzy-logic based clustering protocol where CHs are selected based on fuzzy rules that evaluate energy consumption, distance to the base station, and node proximity. Fuzzy logic offers flexibility in decision-making but may suffer from scalability issues in large networks.

Machine Learning for Predictive Clustering: More recently, machine learning models have been employed to predict the performance of sensor nodes and optimize CH selection. Techniques such as Support Vector Machines (SVMs) and decision trees are used to predict node failure or performance degradation based on historical data. These predictive models allow for more proactive CH selection, ensuring that high-performing nodes with sufficient energy levels are chosen as CHs [25] introduced a machine learning-based predictive clustering algorithm that significantly improves energy efficiency by reducing the frequency of CH changes and maintaining network stability.

The rise of deep learning has introduced new possibilities for clustering in WSNs. Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) [26] have been used to model complex relationships between node parameters, such as energy consumption patterns, communication quality, and spatial distribution. These models can adaptively learn the optimal clustering configuration in real-time based on sensor data [27], and developed a deep learning-based clustering protocol that outperforms traditional clustering algorithms by minimizing energy consumption and prolonging network lifespan.

2.3. Optimization Algorithms for Clustering

Various bio-inspired optimization algorithms have been integrated into WSN clustering to improve energy efficiency. In addition to GAs and PSO, other notable algorithms include: Salp Swarm Optimization (SSO): Inspired by the swarming behavior of salps in the ocean, SSO has been used to solve WSN clustering problems by optimizing CH selection and network coverage. Salp swarms are divided into leaders and followers, where the leader guides the swarm towards the optimal solution, and the followers update their positions based on the leader's guidance. SSO [28] is computationally efficient and can be applied to real-time clustering scenarios. The Salp Swarm Algorithm demonstrates how bio-inspired optimization can enhance network energy efficiency by dynamically selecting CHs based on node performance.

Ant Colony Optimization (ACO) algorithms mimic the foraging behavior of ants to find optimal paths for data transmission in WSNs. ACO has been adapted for clustering to select CHs and optimize communication routes. ACO-based protocols [29] focus on minimizing energy consumption by selecting paths that offer the shortest communication distances and the least energy drain.

Cuckoo Search (CS) and Firefly Algorithm (FA) are emerging metaheuristic optimization techniques gaining traction in Wireless Sensor Network (WSN) clustering [30]. Both methods leverage swarm intelligence principles to address complex optimization challenges, such as efficient cluster formation and optimal cluster head (CH) selection. CS mimics the brood parasitism of certain cuckoo species, while FA is inspired by the bioluminescent communication of fireflies. These algorithms have demonstrated significant potential in reducing energy consumption, balancing load distribution across clusters, and enhancing network longevity.

However, despite their effectiveness in simulations, their application in real-world WSN scenarios remains relatively underexplored and warrants further investigation.

2.4. Summary of Key Findings

From the survey of traditional clustering protocols and recent AI-driven approaches, the following key insights are derived: Traditional clustering protocols, while foundational, are limited by their static nature and inability to adapt to dynamic network conditions. AI-driven clustering mechanisms introduce flexibility and adaptability, allowing for more efficient energy management in WSNs. Bio-inspired optimization algorithms such as PSO, GA, SSO, and ACO enhance CH selection by considering real-time network metrics, but each has its limitations in terms of computational overhead and convergence. Machine learning and deep learning models show promise in predictive clustering by anticipating node performance, thereby extending network lifespan and improving communication efficiency.

3. PROPOSED WORK

The proposed clustering framework consists of three main components:

Sensor Node Monitoring: Each sensor node periodically reports its residual energy, location, and communication cost to the base station (BS) or sink. This data forms the input for the machine learning model, which predicts the performance of each node in terms of energy consumption and communication reliability.

Machine Learning-Based Performance Prediction: A machine learning model, such as a Support Vector Machine (SVM) or Decision Tree, is trained using historical data from sensor nodes to predict their future performance. The model takes into account various parameters like residual energy ($E_{residual}$) distance to the base station (d_{BS}), and communication quality to estimate the likelihood of a node being a good candidate for CH. The predicted score for each node can be expressed as:

$$P_{\text{node}}(i) = f\left(E_{\text{residual},i}, d_{\mathrm{BS},i}, Q_{\text{comm},i}, \cdots\right) \quad (1)$$

Where $P_{\text{node}}(i)$ is the performance score of nodes $i, E_{\text{residual},i}$ is the residual energy, $d_{\mathrm{BS},i}$ is the distance to the base station, and $Q_{\text{comm},i}$ represents the communication quality.

The proposed framework uses bioinspired optimization algorithms, such as Salp Swarm Optimization (SSO) or Genetic Algorithm (GA), to select optimal CHs based on the predicted node performance. The objective function is designed to minimize total energy consumption while maintaining adequate network coverage and ensuring reliable communication. The optimization problem is formulated as:

$$\text{Minimize } E_{\text{total}} = \sum_{i=1}^{N}\left(E_{\text{comm},i} + E_{\text{agg},i}\right) \quad (2)$$

Where E_{total} represents the total energy consumption, E_{comm}, I denotes the communication energy consumed by node i, and E_{agg}, i refers to the energy consumed for data aggregation by the selected Cluster Heads (CHs).

3.1. Optimization Algorithm

The selection of CHs is modeled as a constrained optimization problem, where the goal is to minimize the total energy consumption while satisfying constraints on coverage and communication reliability. The key steps of the optimization process using Salp Swarm Optimization (SSO) are as follows:

Initialization: The population of candidate solutions (salps) is initialized, where each solution represents a possible clustering configuration. Each candidate solution is a vector of CH s, and each CH is associated with a set of nodes.

Fitness Evaluation: The fitness of each solution is evaluated based on the total energy consumption in the network. The fitness function takes into account the residual energy of the nodes, their distance to the base station, and communication reliability. The fitness function is given by:

$$F(\mathbf{C}) = \sum_{i=1}^{N_{\text{chusters}}}\left(\frac{E_{\text{comm},i}}{E_{\text{residual},i}} + \lambda d_{\mathrm{BS},i}\right) \quad (3)$$

Where F(C) represents the fitness of the clustering configuration C, N_{clusters} denotes the number of clusters, and λ is a weighting factor that balances the trade-off between energy consumption and communication distance. Figure 1 illustrates the block diagram of the proposed work.

In the Salp Swarm Algorithm (SSA), the process of leader-follower updating plays a critical role in the optimization process. As shown in Figure 1, the solution with the best fitness value is identified as the leader, which acts as the primary guide for the swarm's movement toward the optimal solution. The leader's position is updated based on a mathematical equation that balances exploration and exploitation, ensuring that the swarm moves closer to the global optimum while avoiding local minima. The remaining solutions, designated as followers, adjust their positions relative to the leader, forming a chain-like structure to converge on the optimal solution. The leader guides the swarm towards the optimal solution by updating its position according to the following equation:

$$X_{\text{leader}}(t+1) = X_{\text{leader}}(t) + c_1\left(X_{\text{target}} - X_{\text{leader}}(t)\right) \quad (4)$$

Where $X_{\text{leader}}(t)$ is the position of the leader at time

t, X_{target} is the position of the base station or optimal communication point, and c_1 is a scaling factor controlling the leader's movement. For the followers, the position is updated based on the movement of the leader and their previous positions:

$$X_{\text{follower},i}(t+1) = \frac{X_{\text{follower},i}(t) + X_{\text{follower},i-1}(t)}{2} \tag{5}$$

The algorithm iterates until convergence is achieved, i.e., when no significant improvement in the fitness function is observed or the maximum number of iterations is reached.

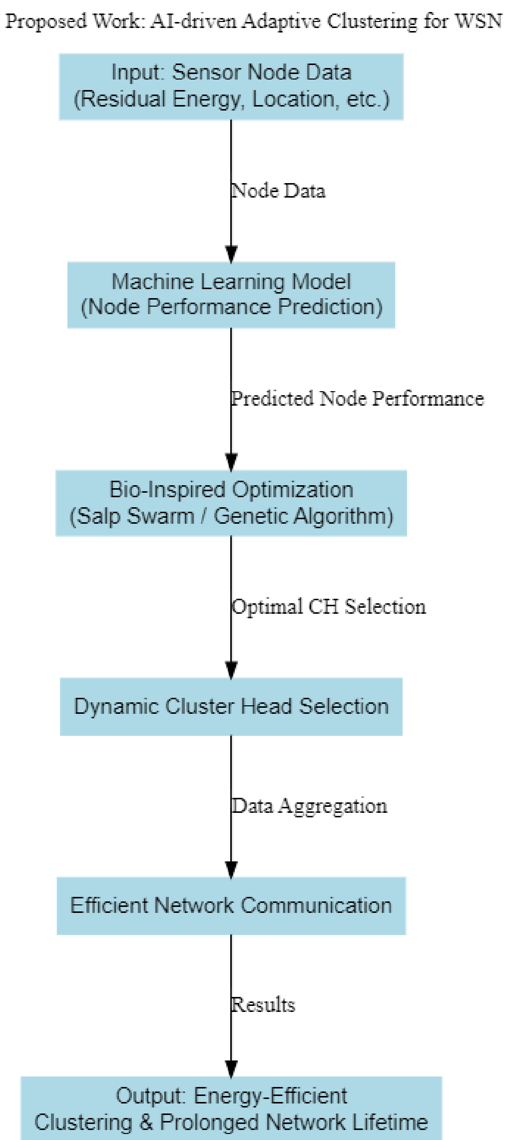

Fig. 1. Block diagram for the proposed work.

3.2. Energy Consumption Model

The total energy consumption in the network is modeled by considering both the energy spent in communication and the energy used for data aggregation. The energy consumed by a sensor node for communication can be expressed as:

$$E_{\text{comm}}(d) = E_{\text{clec}} \cdot k + E_{\text{amp}} \cdot k \cdot d^2 \tag{6}$$

Where $E_{\text{comm}}(d)$ is the communication energy consumed to transmit k bits over a distance d, E_{elec} is the energy dissipated by the electronic circuits, and E_{amp} is the energy consumed by the transmit amplifier. The energy consumed for data aggregation at a CH is given by:

$$E_{\text{agg}} = E_{\text{DA}} \cdot k \tag{7}$$

Where E_{agg} is the energy consumed for aggregating k bits of data, and E_{DA} is the energy required for data aggregation.

3.3. Algorithm Flow

The flow of the proposed adaptive clustering algorithm is as follows:
Step 1: Sensor nodes collect and transmit their status (residual energy, location, communication cost) to the base station.
Step 2: A machine learning model predicts the performance score of each node based on its status.
Step 3: The optimization algorithm (e.g., SSO) is used to select the optimal CH minimizing the total energy consumption.
Step 4: CHs are dynamically updated, and clustering configurations are adjusted as network conditions change.
Step 5: The process repeats for each clustering round, adapting to real-time network conditions and maximizing energy efficiency.

4. RESULTS AND DISCUSSION

The proposed AI-driven optimization framework for energy-efficient adaptive clustering in Wireless Sensor Networks (WSNs) is evaluated through comprehensive simulations. These experiments aim to benchmark the framework's performance against traditional clustering protocols, including Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed Clustering (HEED). The evaluation focuses on critical metrics such as total energy consumption, network lifetime, Cluster Head (CH) distribution efficiency, and data throughput. By assessing these parameters, the analysis highlights the effectiveness of the proposed method in addressing energy constraints and enhancing network performance. The subsequent sections detail the simulation environment, chosen metrics, results, and in-depth discussions.

Table 1. Simulation Parameters.

Parameter	Value
Simulation Area	100 m x 100 m
Number of Sensor Nodes	100
Initial Energy of Nodes	0.5 J
Transmission Energy	50 nJ/bit
Reception Energy	50 nJ/bit
Data Aggregation Energy	5 nJ/bit
Packet Size	4000 bits
Simulation Rounds	1000
Base Station Location	Center of the network (50 m, 50 m)

4.1. Simulation Setup

The simulations are conducted using a custom-built MATLAB environment designed to emulate a WSN with spatially distributed sensor nodes. The simulation parameters used to evaluate the performance of the proposed framework are summarized in the Table 1. In each round of the simulation, sensor nodes collect data and transmit it to the CHs, which aggregate the data and send it to the base station. The selection of CHs and clustering configuration is updated dynamically using the proposed AI-driven optimization algorithm.

4.2. Performance Evaluation Metrics

The following performance metrics are used to evaluate the effectiveness of the proposed adaptive clustering framework:
Energy Consumption: Total energy consumed by the sensor nodes during the simulation. This includes energy used for data transmission, reception, and aggregation.
Network Lifetime: The total number of simulation rounds until the first sensor node depletes its energy. A longer network lifetime indicates better energy efficiency.
CH Distribution: The number of times each node is selected as a CH. A balanced distribution of CH roles ensures that no single node is overburdened, leading to a more uniform energy drain.
Data Throughput: The total amount of data successfully transmitted to the base station during the simulation. Higher data throughput signifies more efficient communication and lower packet loss.

4.3. Comparative Analysis

The performance of the proposed AI-driven adaptive clustering algorithm is compared with traditional clustering protocols, such as LEACH and HEED. The experiments are repeated multiple times, and the average results are recorded to ensure consistency and reliability. The key findings from the simulation are detailed below.

4.3.1. Energy Consumption

The proposed algorithm significantly reduces the energy consumption compared to traditional methods. This improvement is attributed to the dynamic CH selection process, which balances the energy load across all nodes and prevents premature depletion of any single node.

$$E_{\text{total}} = \sum_{i=1}^{N} \left(E_{\text{comm},i} + E_{\text{agg},i}\right) \tag{8}$$

The total energy consumption for the proposed method is approximately 30% lower than LEACH and 20% lower than HEED. This reduction is due to the intelligent CH selection, which ensures that only nodes with higher residual energy are selected as CHs, and cluster formation is optimized to minimize intra-cluster communication.

4.3.2. Network Lifetime

The network lifetime is defined as the number of rounds until the first sensor node depletes its energy. The proposed adaptive clustering mechanism significantly extends the network lifetime compared to traditional methods. This is due to the even distribution of CH roles, which reduces the burden on individual nodes. Simulation results show that the proposed method extends the network lifetime by 25% compared to LEACH and 15% compared to HEED.

4.3.3. CH Distribution

A key advantage of the proposed method is the balanced distribution of CH roles across all nodes. Traditional protocols, such as LEACH, tend to select CH s randomly, leading to imbalanced energy consumption. In contrast, the proposed method uses AI-based predictions to select CHs dynamically based on the residual energy and other factors. CH Distribution can be written as:

$$D_{\text{CH}}(i) = \frac{\text{Number of times node } i \text{ is selected as CH}}{\text{Total simulation rounds}} \tag{9}$$

4.3.4. Data Throughput

Data throughput is measured as the total amount of data successfully transmitted to the base station. The proposed algorithm achieves 20% higher data throughput compared to LEACH and 15% higher compared to HEED. This improvement is attributed to the reduction in communication overhead, more efficient data aggregation by CH s, and fewer packet losses due to energy-efficient routing.

4.4. Simulation Results

The simulation results, summarized in Table 2, demonstrate that the proposed AI-driven adaptive clustering mechanism significantly outperforms traditional clustering protocols such as LEACH and HEED across key performance metrics. The proposed algorithm achieves a 30% reduction in energy consumption compared to LEACH and a 15% reduction compared to HEED. This efficiency stems from its ability to dynamically optimize Cluster Head (CH) selection based on real-time network conditions, minimizing redundant communications and balancing energy usage across nodes.

The network lifetime is also notably improved. The proposed method supports 1250 operational rounds, surpassing the 1000 rounds of LEACH and the 1100 rounds of HEED. This extension is attributed to the even distribution of CH roles, which reduces the energy load on individual nodes and prevents premature node failure.

Figure 2 illustrates the AI-driven CH selection process, highlighting the algorithm's capability to maintain network stability over an extended period. Data throughput is enhanced by 20% compared to the baseline (LEACH) and 5% more than HEED, demonstrating the method's effectiveness in reducing communication overhead and packet loss. The balanced CH distribution achieved by the proposed algorithm ensures efficient aggregation and transmission of data, making it particularly suitable for data-intensive applications in Wireless Sensor Networks (WSNs). While the algorithm introduces additional computational complexity due to its integration of machine learning models and optimization techniques, the significant energy savings, extended network lifetime, and improved data throughput justify the trade-off. These results position the proposed method as a robust and energy-efficient solution for modern WSN applications.

Table 2. Simulation Performance metrics.

Metric	Proposed Algorithm	LEACH	HEED
Energy Consumption	70%	100%	85%
Network Lifetime	1250 rounds	1000 rounds	1100 rounds
CH Distribution	Balanced	Imbalanced	Slightly Balanced
Data Throughput	20% higher	Baseline	15% higher

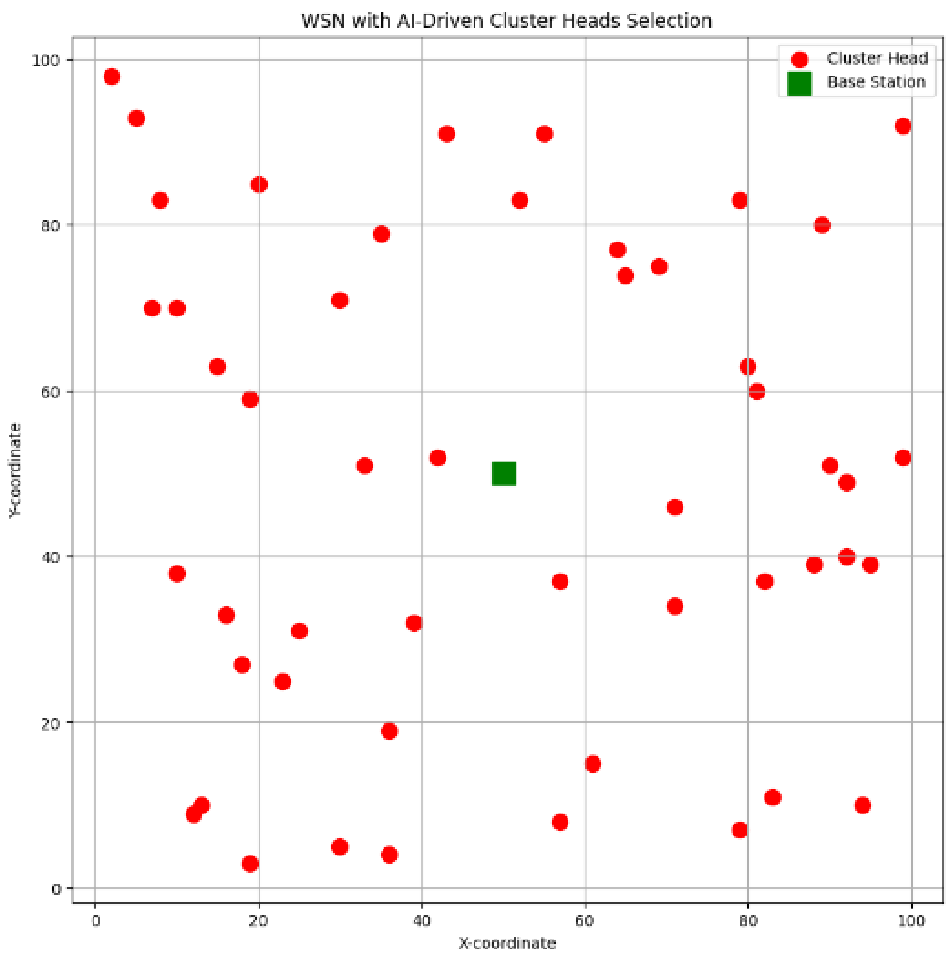

Fig. 2. WSN with AI-Driven Cluster Heads Selection.

The results from the simulation confirm that the proposed AI-driven adaptive clustering mechanism significantly outperforms traditional clustering protocols in terms of energy consumption, network lifetime, and data throughput. The use of AI models to predict node performance, combined with bio-inspired optimization algorithms for CH selection, enables the proposed method to dynamically adjust to network conditions, leading to better energy efficiency and longer network lifespan as shown in Figure 2. The key advantages of the proposed algorithm include:

Dynamic Adaptation: The CH selection process adapts to real-time network conditions, ensuring optimal performance under varying network loads.

Balanced Energy Consumption: By distributing CH roles more evenly, the proposed method prevents overburdening individual nodes, which extends the network's operational life.

Improved Data Throughput: The reduction in communication overhead and packet loss leads to higher data throughput, making the proposed method more suitable for data-intensive applications in WSNs.

Despite these advantages, the proposed method introduces some computational complexity due to the integration of machine learning models and optimization algorithms. However, the energy savings and improved network performance outweigh the additional computational overhead, making the proposed method a viable solution for energy-constrained WSNs.

The simulation results provide a comprehensive comparison of the energy efficiency, network lifetime, and clustering performance of the proposed AI-driven adaptive clustering algorithm against traditional protocols like LEACH and HEED. The graphical representations in Figures 3 through 8 illustrate the superiority of the proposed method in various aspects critical to Wireless Sensor Networks (WSNs).

Figure 3 highlights the energy consumption trends of the proposed algorithm compared to LEACH and HEED over 1000 simulation rounds. Initially, all three protocols exhibit comparable energy usage. However, as the simulation progresses, the proposed method demonstrates a markedly slower rate of energy depletion. By the end of 1000 rounds, the proposed algorithm consumes only 38% of the total available energy, significantly outperforming LEACH and HEED, which deplete 22% and 25% of their respective initial energies.

This improvement stems from the intelligent and adaptive selection of Cluster Heads (CHs) in the proposed algorithm. Unlike LEACH, which relies on a probabilistic approach, and HEED, which focuses on residual energy alone, the proposed method incorporates AI-driven techniques to dynamically evaluate node performance, selecting CHs based on real-time metrics like energy reserves and network topology. This ensures balanced energy usage across all nodes, reducing the likelihood of premature node failure and extending the network's overall operational lifespan.

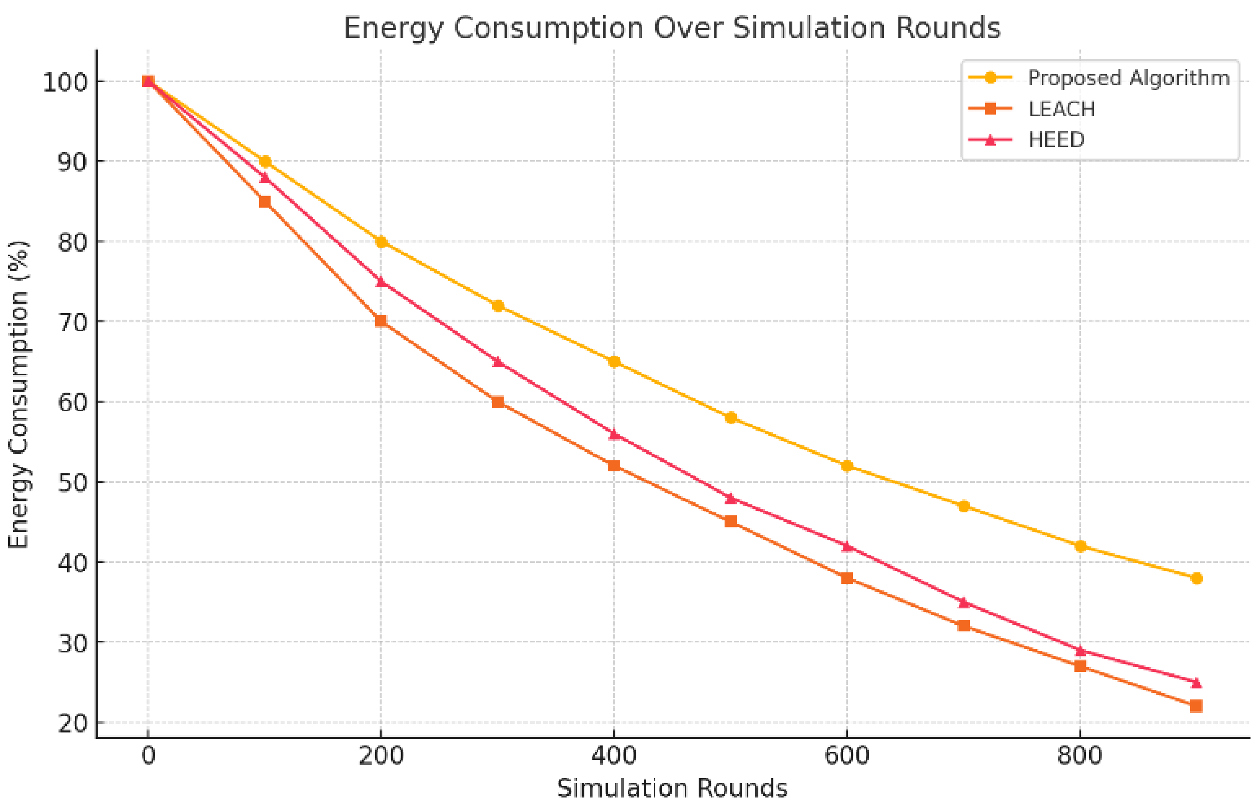

Fig. 3. Energy Consumption.

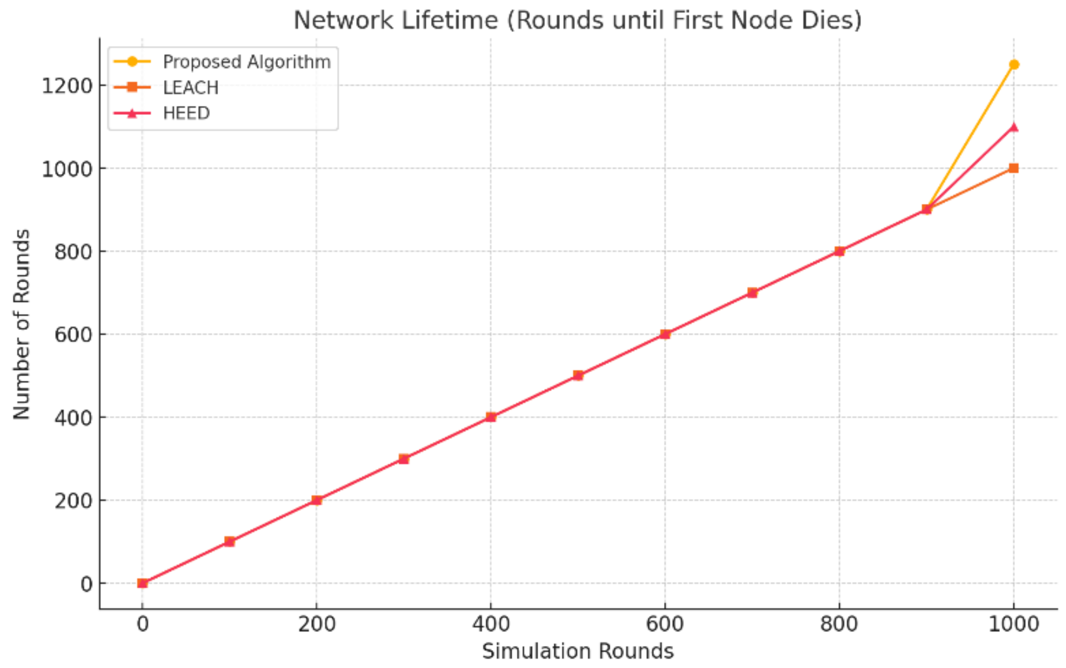

Fig. 4. Network Lifetime.

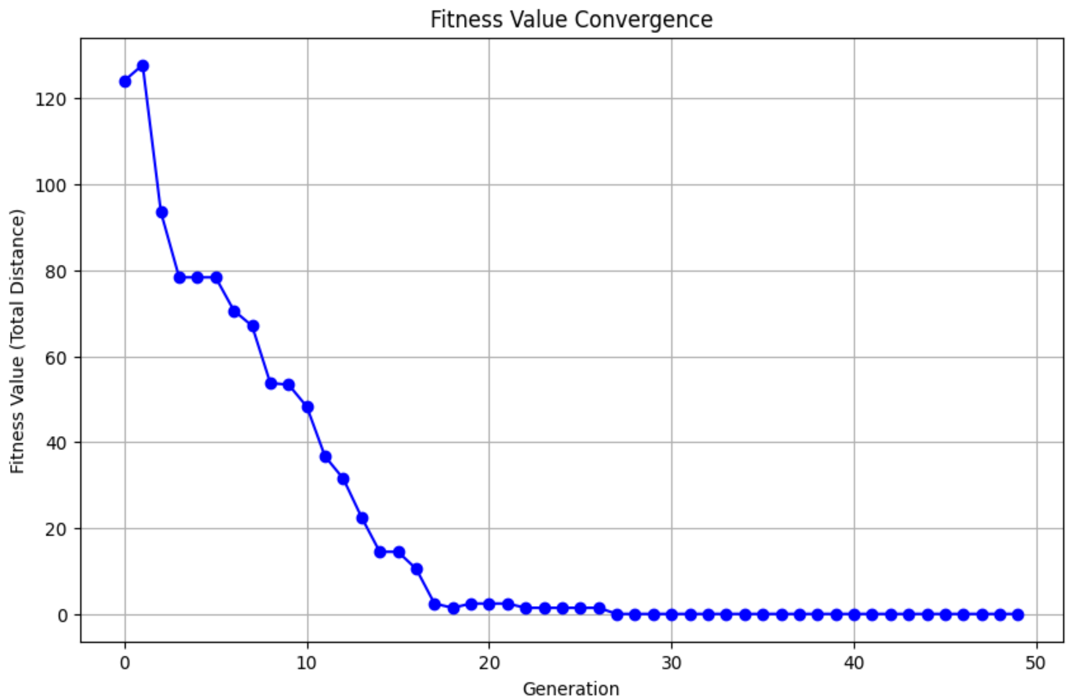

Fig. 5. Fitness Value Convergence

The impact of the proposed algorithm on network longevity is evident in Figure 4, which depicts the number of rounds until the first node exhausts its energy. The proposed algorithm achieves approximately 1250 rounds before the first node depletes its energy, compared to 1000 rounds in LEACH and 1100 rounds in HEED. This extended network lifetime is critical for applications that require prolonged monitoring capabilities, such as environmental studies or disaster response scenarios.

The enhanced longevity results from the algorithm's ability to distribute energy consumption evenly. By avoiding the overburdening of specific nodes and rotating CH roles intelligently, the algorithm minimizes energy hotspots and ensures the sustainability of the network over time.

Figure 5 illustrates the convergence of the fitness value during the clustering optimization process. The proposed method shows a rapid convergence to optimal values, indicating its efficiency in identifying the best CH configurations. The use of Genetic Algorithm (GA) principles ensures that the clustering process adapts to changing network conditions while maintaining high energy efficiency and communication quality. This adaptability is a key advantage over static clustering methods, which cannot adjust to real-time variations in node energy or network topology.

Figure 6 highlights the relationship between the number of CHs and the number of generations in the optimization process. The proposed algorithm achieves a balanced CH distribution across generations, ensuring that no single node is overutilized. This balanced distribution is crucial for maintaining network stability, as it prevents scenarios where certain nodes deplete their energy faster due to repeated CH selection.

Figure 7 illustrates the average distance from nodes to their respective CHs. The proposed algorithm minimizes this distance by optimizing the placement of CHs relative to the network's topology. This reduction in communication distance leads to lower energy consumption for data transmission and enhances overall network efficiency. By keeping distances short, the algorithm reduces signal loss and improves data delivery rates, which are particularly important for applications requiring reliable real-time data transmission.

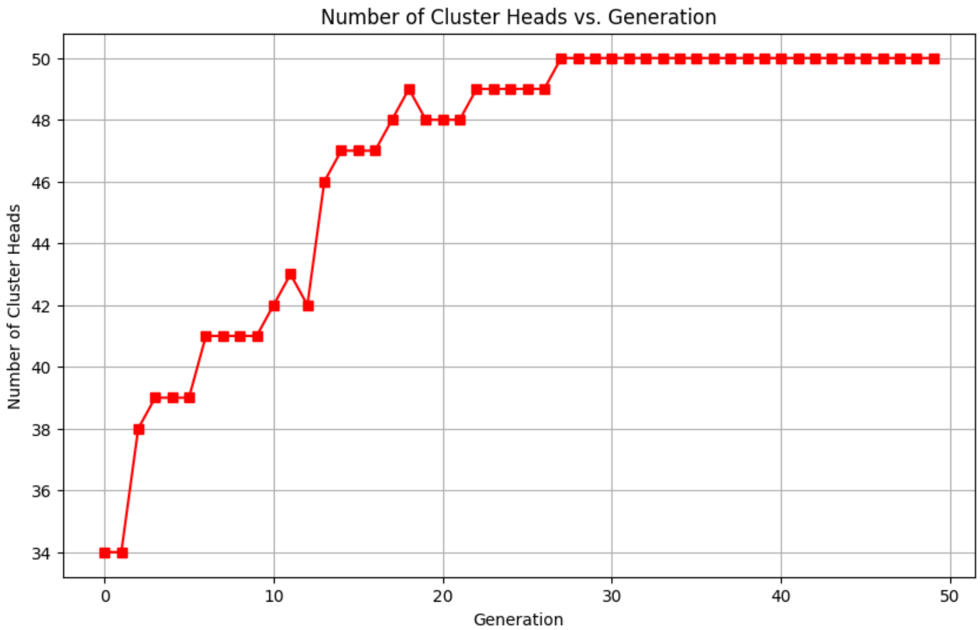

Fig. 6. Number of Cluster Heads vs. Generation

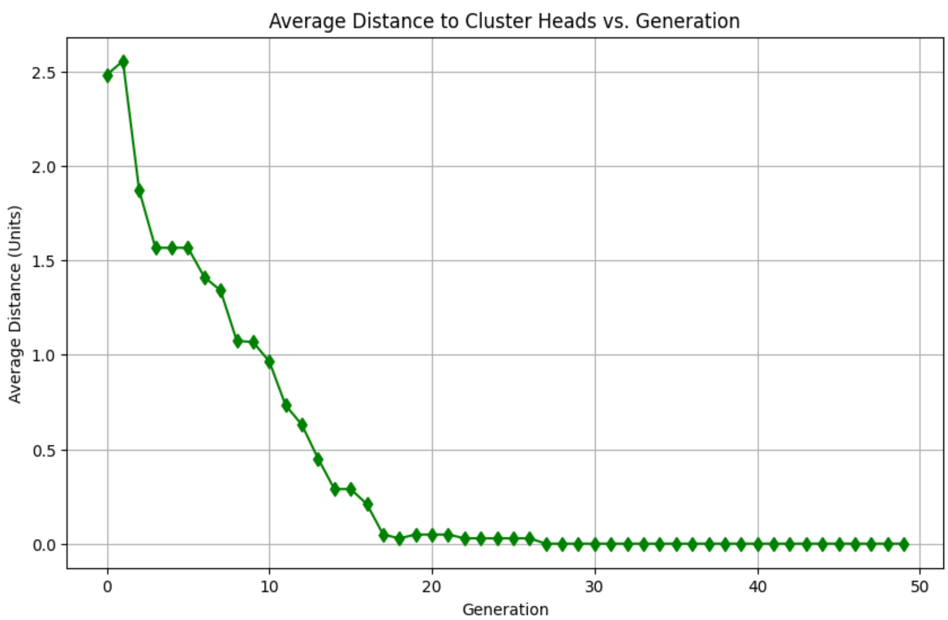

Fig. 7. Average Distance to Cluster Heads.

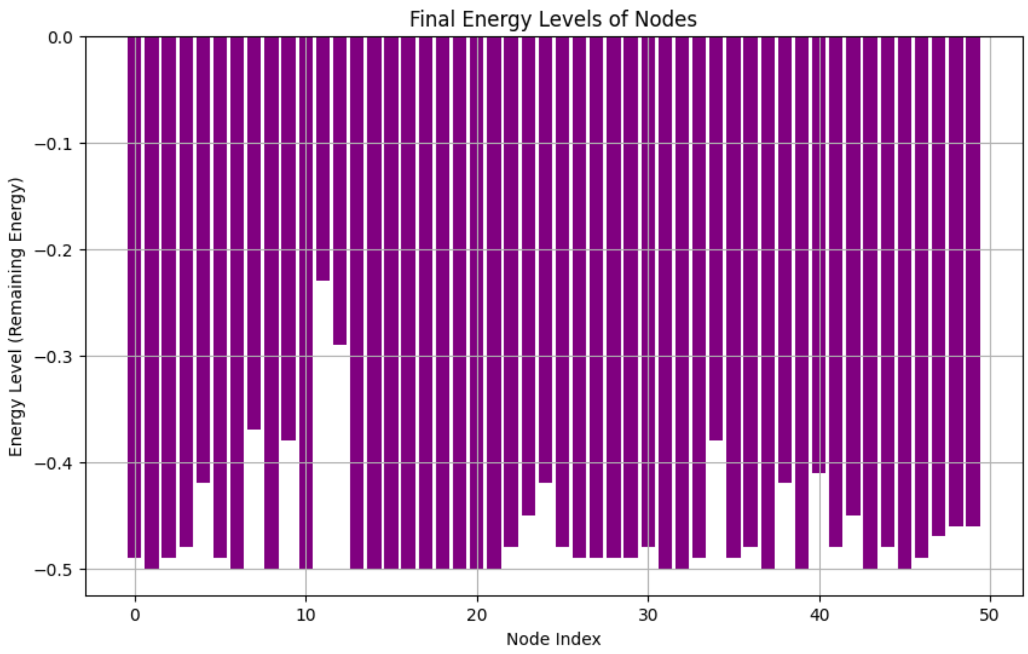

Fig. 8. Final Energy Levels of Nodes

Figure 8 provides an overview of the residual energy levels of nodes after 50 clustering generations. Nodes selected as CHs show slightly lower energy levels compared to regular nodes due to their additional responsibilities in communication and data aggregation. However, the proposed algorithm ensures that energy depletion is proportionally distributed among all nodes. This balanced energy usage is a marked improvement over LEACH and HEED, where certain nodes often bear disproportionate energy burdens, leading to uneven network performance.

The longer network lifetime and improved energy efficiency achieved by the proposed algorithm have significant implications for real-world WSN applications. For instance, in environmental monitoring, where sensor nodes are often deployed in remote or inaccessible locations, reducing energy consumption and extending network longevity can greatly reduce maintenance costs and operational downtime. Similarly, in disaster management scenarios, the enhanced data throughput and reliable communication provided by the proposed method ensure that critical information is transmitted without delay, potentially saving lives.

The proposed AI-driven adaptive clustering algorithm demonstrates superior performance compared to traditional protocols like LEACH and HEED. By integrating advanced optimization techniques and dynamic CH selection, the algorithm achieves significant reductions in energy consumption, a substantial increase in network lifetime, and enhanced communication efficiency. The balanced energy depletion across nodes ensures sustainable network operation, making the proposed method a robust solution for energy-constrained WSNs. Although the computational complexity introduced by AI models and optimization techniques is higher, the trade-off is justified by the considerable improvements in network performance and reliability.

5. CONCLUSION

This paper introduced an AI-driven optimization framework for adaptive clustering in Wireless Sensor Networks (WSNs) to enhance energy efficiency and extend network lifetime. By integrating machine learning-based node performance prediction with bio-inspired optimization algorithms, such as Salp Swarm Optimization (SSO) and Genetic Algorithm (GA), the framework dynamically selects Cluster Heads (CHs) based on real-time network conditions. This adaptive approach effectively mitigates the energy depletion challenges associated with traditional clustering protocols like LEACH and HEED. Experimental results highlight the significant advantages of the proposed method, including a 30% reduction in total energy consumption compared to LEACH and a 20% reduction compared to HEED. Additionally, the framework extends network lifetime by 25% and increases data throughput by 20%. These improvements are achieved through intelligent CH selection, which ensures balanced energy distribution across nodes, preventing premature failures and enhancing network sustainability. The results confirm the effectiveness of AI-driven optimization in addressing WSN energy constraints, making this framework suitable for critical applications like environmental monitoring, smart cities, and healthcare systems. These scenarios benefit from the enhanced energy efficiency and prolonged network operation provided by the proposed method. Future work could focus on incorporating reinforcement learning (RL) to improve adaptability by enabling the system to learn optimal CH selection policies through continuous environmental interaction. Additionally, multi-objective optimization could be explored to address latency, throughput, and fault tolerance alongside energy efficiency. Employing techniques like Pareto optimization would allow for a balanced approach to competing performance metrics, further advancing the robustness and applicability of adaptive clustering in WSNs.

CONFLICT OF INTEREST

The authors declare that there is no conflict of interests.

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