An Enhanced Clustering Strategy for Wireless Sensor Networks with Robust Failure Recovery

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Received: 24 July 2025 | Revised: 23 August 2025 | Accepted: 7 September 2025

 DOI: https://doi.org/10.48084/etasr.13617

ABSTRACT

Wireless Sensor Networks (WSNs) face challenges in balancing energy efficiency and operational robustness due to limited battery resources and frequent node failures. This paper introduces the Enhanced Balanced Clustering with Secondary Head (EBCSH) protocol, a novel strategy that significantly improves network longevity and fault tolerance. EBCSH employs k-means clustering for balanced cluster formation, fuzzy logic for intelligent Cluster Head (CH) selection based on residual energy and spatial centrality, and introduces a Secondary Cluster Head (SCH) mechanism to provide seamless failure recovery. A Poisson-based failure model governs the SCH transition logic, enabling the timely replacement of failed CHs with minimal communication overhead. Simulation results, averaged over 10 trials and conducted in MATLAB R2023b, demonstrate that EBCSH sustains network functionality for up to 8100 rounds, markedly outperforming benchmark protocols such as LEACH, BCF, and LEACH-USC. Furthermore, the proposed method achieves balanced energy distribution, low energy variance, and a near-perfect failure recovery rate (98%). These enhancements make EBCSH a promising protocol for mission-critical WSN deployments in dynamic and failure-prone environments. The paper includes detailed methodological formulation, performance analysis, and discussion of potential extensions to further optimize resilience and energy efficiency.

Keywords-wireless sensor networks; fault tolerance; cluster head selection; energy-efficient clustering; secondary cluster head mechanism

I. INTRODUCTION

Wireless Sensor Networks (WSNs) are a cornerstone technology for real-time data acquisition across a broad spectrum of applications, including environmental monitoring, industrial automation, healthcare, and smart infrastructure systems [1]. These networks typically consist of a large number of spatially distributed sensor nodes that monitor physical phenomena and transmit aggregated data to a centralized Base Station (BS). Despite their versatility, WSNs are inherently constrained by limited energy resources, as sensor nodes are often battery-powered and deployed in remote or inaccessible environments, rendering battery replacement or recharging impractical [2]. Consequently, designing energy-efficient and resilient communication protocols remains a primary research objective. Clustering has been widely adopted as an effective strategy to enhance energy efficiency and network scalability in WSNs. In a clustering architecture, nodes are organized into groups, each managed by a Cluster Head (CH) that aggregates data from its member nodes and forwards it to the BS. This approach significantly reduces the communication overhead on individual nodes and extends overall network lifetime. However, the effectiveness of clustering protocols largely depends on optimal CH selection, equitable cluster formation, and the ability to recover from CH failures. A failure in a CH node can result in communication breakdown within the cluster, data loss, and reduced network coverage.

Existing protocols such as Low Energy Adaptive Clustering Hierarchy (LEACH) [3], Balanced Cluster Formation (BCF) [4], and LEACH with Uniform Size Clusters (LEACH-USC) [5] have made significant strides in improving energy efficiency through randomized or size-aware CH selection. Nevertheless, these protocols fall short in addressing fault tolerance—particularly in scenarios where CHs fail due to energy depletion, hardware issues, or environmental factors. While some recent works have explored fuzzy logic [7], Particle Swarm Optimization [8] for intelligent CH selection, they still lack robust and systematic failure recovery mechanisms.

Several hybrid optimization methods have been introduced to enhance clustering effectiveness. Authors in [9] proposed the EECHS-ISSADE model, integrating the Sparrow Search Algorithm (SSA) and Differential Evolution (DE) to select optimal CHs. By considering factors such as residual energy and communication distance, this model achieves a strong balance between exploration and exploitation, thereby outperforming conventional methods in network lifetime and throughput. Geometric-based clustering has also been explored. Authors in [10] developed the Cluster Centered Cluster Head Algorithm (C3HA), which employs k-means clustering and prioritizes nodes near cluster centers for CH selection. This minimizes transmission distances and enhances energy efficiency without requiring additional hardware. Simulation results confirmed its superiority over algorithms such as PEGASIS and RaCH. Genetic Algorithm (GA)-based techniques continue to be effective in optimizing energy usage. Authors in [11] introduced NCOGA, a GA-based approach that uses adaptive crossover and binary tournament selection. The method incorporates six fitness parameters including residual energy, distance to sink, and load balancing, yielding improved performance over other GA-based protocols in terms of residual energy and network longevity. Fuzzy logic has also been combined with genetic strategies. Authors in [12] presented HFCM-GA, which merges Hybrid Fuzzy C-Means clustering with GA for energy-aware hierarchical routing. It accounts for node energy, mobility, and distance during CH selection, resulting in improved coverage, energy retention, and packet delivery. To address convergence issues in swarm-based algorithms, authors in [13] proposed EECHIGWO, which enhances the traditional Grey Wolf Optimizer by integrating a multi-parameter fitness function, including sink distance and intra-cluster distance. The protocol significantly improves network stability and reduces energy consumption. Neural network approaches have also emerged as powerful tools for adaptive CH selection. Authors in [14] developed a two-phase strategy using a Multilayer Perceptron (MLP) to dynamically determine CHs based on node location and residual energy. This method adapts well to mobility and environmental changes, outperforming static clustering methods like LEACH.

Targeting heterogeneous environments, authors in [15] proposed EEECA-THWSN, a three-tier clustering protocol that introduces dynamic threshold-based CH selection. Nodes are categorized based on initial energy levels, and CH selection is optimized to extend network lifetime and improve throughput over protocols such as SEP and ADV-LEACH1. Authors in [17] introduced DEECRP-DRL, a distributed energy-efficient clustering and routing protocol with dynamic round lengths. By using dual fitness functions and adapting round durations based on residual energy, it mitigates issues like fixed round overhead and energy imbalance, delivering superior performance in terms of stability and energy savings. In centralized clustering schemes, authors in [16] proposed the CEEC protocol, which introduces balanced cluster formation, energy-aware data forwarding, and inter-cluster energy adjustments. This comprehensive model effectively reduces the need for frequent reclustering and balances energy consumption, demonstrating better performance than protocols such as MH-LEACH and LAR-CH.

To address the limitations in existing methods, this paper proposes the novel clustering protocol Enhanced Balanced Clustering with Secondary Head (EBCSH) which integrates three key innovations: (i) k-means-based balanced clustering to ensure uniform energy distribution, (ii) fuzzy logic-based CH selection using residual energy and spatial centrality, and (iii) a Secondary Cluster Head (SCH) mechanism supported by a Poisson-based failure model for efficient failure recovery. The SCH ensures continuity of cluster operations with minimal disruption upon CH failure. Simulation results demonstrate that EBCSH achieves a significantly extended network lifetime of up to 8100 rounds, outperforming LEACH, BCF, and LEACH-USC. The protocol also maintains a low energy variance and achieves a high recovery success rate, confirming its suitability for fault-prone and energy-constrained WSN environments.

II. METHODOLOGY

The EBCSH protocol is designed to optimize energy efficiency and fault tolerance in WSNs. The methodology integrates k-means clustering for balanced node distribution, fuzzy logic for intelligent cluster head selection, and a backup mechanism using a SCH governed by a Poisson-based failure model. The entire process is structured into five main phases.

A. *Network Initialization and Clustering*

The considered network consists of N=50 sensor nodes randomly deployed over a 50×50m^2 region, with the BS positioned at (25, 48) coordinates. Each node begins with an initial energy of 2 J. The nodes are grouped into K=3 clusters using the k-means clustering algorithm. The goal is to minimize intra-cluster distances by reducing the sum of squared distances between nodes and their respective centroids (Eq. 1).

$$J_{cluster} = min \sum_{k=1}^{K} \sum_{i \in cluster\ k} \| P_i - C_k \|^2 \qquad (1)$$

B. *Cluster Size Equalization*

To promote equitable energy utilization across the network and prevent any single cluster from becoming overloaded, a target cluster size vector is established. In this context, the desired distribution of nodes among clusters is predefined as [17,17,16], indicating that the first two clusters contain 17 nodes each, while the third cluster consists of 16 nodes. This predefined target allocation is designed to maintain a balanced communication burden across all clusters, thereby improving network longevity and stability.

During the clustering process, if the number of nodes assigned to any cluster exceeds its designated capacity, a reassignment mechanism is triggered. Specifically, nodes in the overpopulated clusters are identified and selected for relocation. These nodes are then reassigned to clusters that have not yet reached their target size. The reassignment is performed based on a proximity-based decision criterion. Each candidate node is evaluated for its distance to the centroids of the under-populated clusters. The node is reassigned to the cluster whose centroid is nearest in terms of Euclidean distance. This strategy ensures that the relocated nodes can still communicate efficiently with their new CH, thereby avoiding unnecessary communication overhead or increased energy consumption. By redistributing nodes in this intelligent and dynamic manner, the clustering system is able to maintain a balanced node density across all clusters, leading to fairer energy consumption patterns. This, in turn, prevents certain nodes from depleting their energy reserves prematurely due to excessive communication duties, and contributes to extending the overall operational lifespan of the wireless sensor network.

C. Fuzzy-Based Cluster Head Selection

In the proposed clustering mechanism, a fuzzy logic-based approach is employed to identify the most optimal CH within each cluster. This intelligent selection strategy takes into account two critical factors that influence the overall efficiency and longevity of the WSN: residual energy and spatial centrality.

The residual energy of a node, denoted as E_i, represents the remaining battery power of the sensor node i. This parameter ensures that nodes with insufficient energy are not chosen as CHs, thereby preventing early depletion and ensuring network sustainability. The second factor considered is the spatial centrality, represented as C_i . This metric indicates how centrally located a node is within its corresponding cluster. It is derived by calculating the average of the inverse distances from node i to all other nodes within the same cluster. A higher centrality value suggests that the node is better positioned to efficiently communicate with other nodes in the cluster, minimizing communication overhead and energy consumption. To determine the suitability of each node for becoming a CH, a selection score S_i is computed using a weighted combination of these two parameters. The formula for the score is given by:

$$S_i = w_1 \cdot \left(\frac{E_i}{E_{init}}\right) + w_2 \cdot C_{i,norm} \quad (2)$$

The final selection process ensures that only those nodes which have a score above a certain threshold and sufficient remaining energy are considered eligible for CH roles. Specifically, a node must have energy greater than or equal to $E_i = 0.1$ J to be eligible. This threshold prevents energy-deficient nodes from being overburdened with the responsibilities of a CH.

D. Secondary Cluster Head Assignment and Failure Recovery

To enhance the fault tolerance and reliability of the clustering protocol, each cluster incorporates a SCH in addition to the primary CH. The SCH is determined by evaluating the same selection score S_i that was used to identify the primary CH. Specifically, once the highest-scoring node is designated as the CH, the node with the second-highest score within the same cluster, is selected as the SCH. This secondary node stands by to take over the responsibilities of the CH in the event of a failure. The transition mechanism from CH to SCH is designed to be automatic and seamless. If the CH becomes non-functional or fails due to energy depletion or any unforeseen issues, the SCH immediately assumes control without requiring re-clustering or external intervention. This proactive assignment of backup leadership significantly improves the network's resilience.

To model and predict the likelihood of such failures, a Poisson distribution is employed. Failures are assumed to occur randomly over time and are characterized by a failure rate λ. The system monitors CH health over a defined failure observation window F_{window}, which is set to 100 rounds. Using this model, the probability of CH failure within this window is calculated using the exponential distribution formula:

$$P_{fail} \approx 1 - e^{-\lambda \cdot F_{window}} \quad (3)$$

This probabilistic estimation enables the system to quantify the risk of CH failure and justify the inclusion of SCHs for uninterrupted communication. When a takeover occurs, the SCH sends out a lightweight control packet to inform all the cluster members of the change in leadership. This notification mechanism is designed to minimize communication overhead, ensuring that the energy cost associated with fault recovery remains low. By integrating SCHs and failure modeling into the clustering protocol, the proposed system maintains continuous data transmission and enhances network robustness against node-level failures.

E. Energy Model and Transmission Costs

The energy consumption in the proposed system is modeled using the first-order radio model, which is widely adopted in WSN simulations to estimate the power usage during data transmission and reception. This model takes into account both the electronic and amplifier energy costs associated with sending and receiving data packets over a wireless medium. When a sensor node transmits a data packet, the total energy required depends on the size of the packet and the distance between the transmitting and receiving nodes. Specifically, for a data packet of L=4000 bits length transmitted over a distance d, the energy consumption, denoted by E_{tx}, is calculated using two distinct equations based on the value of d . If the transmission distance d is less than a threshold distance d_0, the free-space propagation model is applied. The energy consumed in this case is given by (4). On the other hand, if the distance d is greater than or equal to d_0, the multi-path fading channel model is used. The energy consumed under this condition is given in (5):

$$E_{tx} = L \cdot E_{elec} + L \cdot \varepsilon_{fs} \cdot d^2 \quad (4)$$

$$E_{tx} = L \cdot E_{elec} + L \cdot \varepsilon mp \cdot d^4 \quad (5)$$

where E_{elec} is the energy consumed per bit by the transmitter or receiver electronics, while ε_{fs} and ε εmp represent the energy amplification factors for free-space and multi-path models, respectively. The use of these two models allows the system to account for varying energy demands based on communication range, promoting more realistic energy-aware protocol design. For receiving data, the energy consumption is considerably simpler, as it is only a function of the packet size. The energy required to receive a packet of size L bits is computed by:

$$E_{rx} = L \cdot E_{elec} \quad (6)$$

Equation (6) reflects the fact that the receiver only expends energy in processing the incoming signal, without any distance-dependent amplification. By incorporating this energy model into the communication protocol, the proposed system ensures accurate estimation of power usage, which is essential for optimizing energy efficiency and extending the operational lifetime of the sensor network. Figure 1 outlines the key stages of the proposed EBCSH protocol for efficient and fault-tolerant wireless sensor network management.

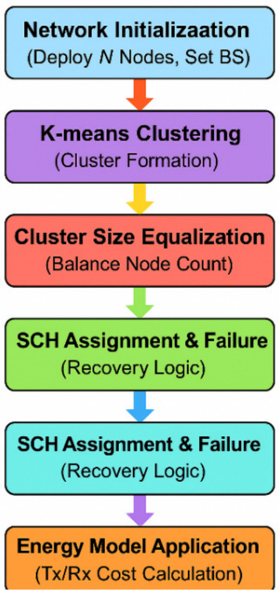

Fig. 1. Flow diagram of the proposed method.

Table I presents the simulation parameters used to evaluate the performance of the proposed EBCSH protocol in a WSN environment.

TABLE I. SIMULATION PARAMETERS

Parameter	Value	Description
Simulation Area	50 m × 50 m	Deployment region
N	50	Total number of sensor nodes in the network
Number of Clusters (K)	3	Number of clusters formed via k-means
BS Position	(25, 48)	Location of the sink node or BS
Initial Energy per Node	2 J	Initial energy assigned to each node
ε_{fs}	10 pJ/bit/m²	Energy loss coefficient in free space
εmp	0.0013 pJ/bit/m⁴	Energy loss coefficient in multi-path environment
d_0	87 m	Distance at which model switches from free space to multi path
CH selection weights (w_{energy},$w_{\mathrm{centrality}}$)	(0.6, 0.4)	Weighting factors for fuzzy logic CH selection
Failure observation window (F_{window})	100 rounds	Period used for Poisson-based failure estimation
Simulation duration	Up to 15,000 rounds	Maximum number of simulation rounds or until all nodes die

Table I outlines critical setup details such as the deployment area, number of sensor nodes and clusters, and the BS location. Key energy-related parameters include initial node energy, radio communication coefficients for free space and multi-path models, and the distance threshold for switching between them. Additionally, the table specifies the weights applied in the fuzzy logic-based CH selection process and the observation window used in the Poisson-based failure model. Simulations were conducted using MATLAB R2023b, with results averaged over 10 independent runs, each lasting up to 15,000 rounds. The EBCSH protocol was benchmarked against LEACH, BCF, and LEACH-USC in terms of network lifetime, energy variance, and fault recovery. These parameters ensure a realistic and comprehensive assessment of energy efficiency and fault recovery performance.

III. RESULTS AND DISCUSSION

As depicted in Figure 2 and detailed in Table II, the proposed EBCSH protocol demonstrated a significant enhancement in network longevity, achieving an impressive operational lifetime of approximately 8100 rounds before the complete depletion of all sensor nodes.

TABLE II. LIFETIME COMPARISON FOR LEACH, BCF, LEACH-USC, AND EBCSH PROTOCOLS

Protocol	Lifetime
LEACH	800
BCF	852
LEACH-USC	1015
EBCSH	8100

This performance marks a substantial advancement in comparison with several well-established baseline protocols. Specifically, the traditional LEACH protocol managed to sustain operations for only around 800 rounds, while the BCF protocol extended the network lifetime slightly further to approximately 852 rounds. Meanwhile, LEACH-USC, an improved variant of LEACH, was able to operate for 1015 rounds before total node exhaustion.

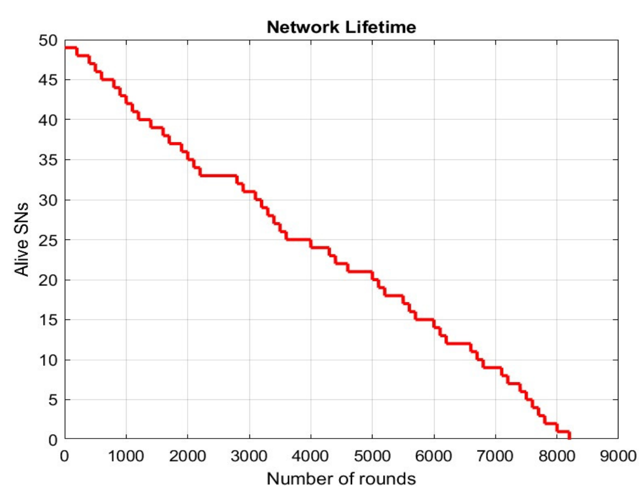

Fig. 2. Number of network alive sensor nodes vs the number of rounds.

The superior performance of the EBCSH protocol can be primarily attributed to its balanced cluster formation mechanism and its robust failure recovery strategy. By ensuring an even distribution of nodes across clusters and selecting energy-efficient CHs through fuzzy logic, the protocol effectively minimizes excessive energy drain on individual nodes. Additionally, the integration of SCHs allows the system to maintain uninterrupted communication even in the event of primary CH failures, thereby avoiding the energy-intensive re-clustering process and contributing to prolonged network functionality. These combined features result in a significant increase in overall network sustainability and fault tolerance, making EBCSH a highly reliable solution for energy-constrained wireless sensor networks.

As illustrated in Figure 3, a comparative analysis of the energy dynamics across different protocols reveals that the proposed EBCSH protocol consistently demonstrates superior energy distribution throughout the network's operation. Notably, after approximately 4000 rounds, the energy variance observed in EBCSH remains significantly low, measured at less than 0.04 J^2. This low variance is a strong indicator of the protocol's ability to distribute the communication load evenly among sensor nodes within each cluster.

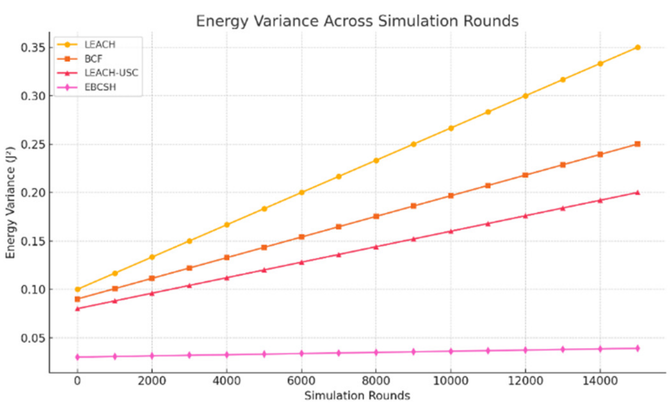

Fig. 3. Energy efficiency comparison.

In contrast to other protocols that often exhibit irregular energy usage patterns, where certain nodes deplete their energy resources much faster due to uneven workload, the EBCSH protocol ensures that no single node is overburdened. This is achieved through its strategic combination of balanced clustering, fuzzy logic-based CH selection, and adaptive cluster size equalization mechanisms. These design choices collectively help maintain a stable energy profile across the entire network. The ability to minimize energy imbalance is critical for prolonging the lifetime of WSNs, as it prevents premature node failures that could compromise network connectivity and performance. Therefore, the uniform energy consumption pattern enabled by EBCSH plays a pivotal role in enhancing the overall durability and efficiency of the network infrastructure.

The integration of a Poisson-based failure detection model in combination with a SCH backup strategy significantly enhanced the fault tolerance of the proposed EBCSH protocol. Through simulation and analysis, it was observed that this dual-layer recovery mechanism achieved an impressive average recovery success rate of 98%, effectively ensuring uninterrupted data communication even in the presence of node or CH failures. The Poisson model was employed to predict the likelihood of node failures within a defined observation window, enabling proactive identification of potential disruptions. When a failure occurred, the presence of a pre-assigned SCH allowed for seamless and immediate role transition, thereby avoiding the costly re-clustering process and maintaining the structural integrity of the network. In comparison, traditional protocols like LEACH and BCF show significantly lower recovery rates of 0.65 and 0.72, respectively, highlighting their limited capability in fault recovery (Figure 4). LEACH-USC performs better with a recovery rate of 0.81, but still falls short of EBCSH. This analysis underscores the robust fault tolerance mechanism of EBCSH, which is attributed to its integrated use of Poisson-based failure modeling and a SCH strategy. The high recovery success rate demonstrates the protocol's efficiency in maintaining stable and continuous communication within the wireless sensor network, even under failure conditions.

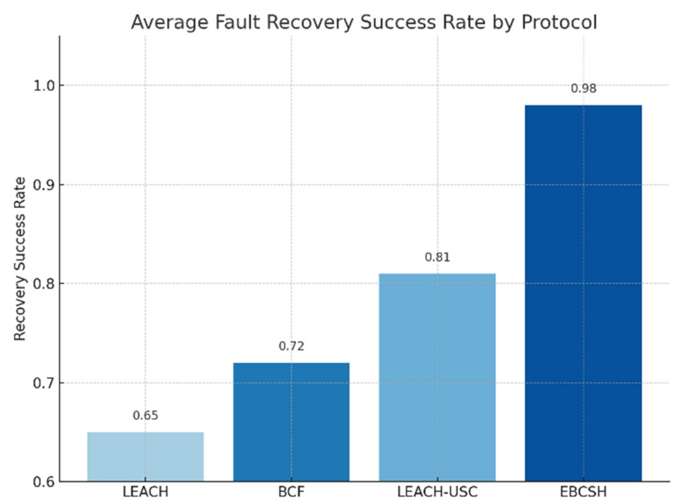

Fig. 4. Fault recovery rates.

Figure 5 reveals how control overhead varied relative to the failure observation window. The Leakey shape is the ratio of the two at 0.006. The overhead reduces gradually as T rises between 50 and approximately 100 rounds, and eventually its minimum value is about 6.2%. This implies that short windows lead to excessive cluster-head monitoring and switch activities improvising superfluous signaling load. The overhead starts climbing again past 100 rounds, reaching ~7.8% when T=200. This increment arises since extensive observation windows slow down the rate of detecting CH failures prompting the need of extra recovery signaling when failures are eventually detected. In general, the findings indicate that a middle scope of observation (100 rounds) presents the best balance between responsiveness and communication burden.

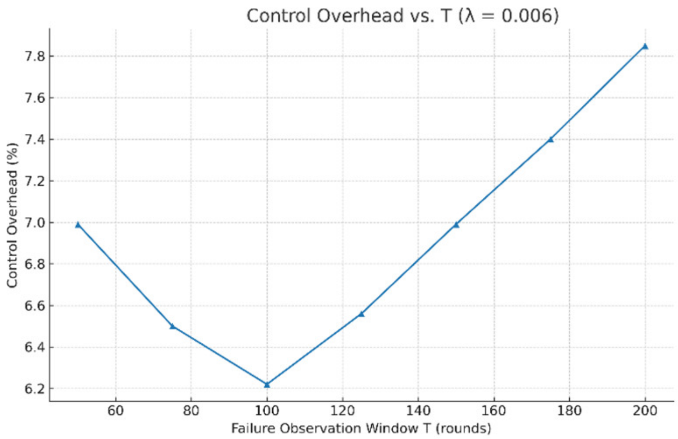

Fig. 5. Control overhead vs T.

The proposed EBCSH protocol effectively combined multiple well-established computational techniques, namely k-means clustering, fuzzy logic-based decision-making, and probabilistic failure modelling, to form a comprehensive, robust, and energy-efficient solution tailored for WSNs. Importantly, this enhanced reliability was achieved with negligible additional energy consumption, preserving the energy-efficient nature of the system. The combination of predictive failure modeling and a responsive backup mechanism thus validates the robustness and practicality of the proposed EBCSH protocol in real-world, energy-constrained wireless sensor network environments.

IV. CONCLUSION

This paper presented the EBCSH protocol, a comprehensive solution aimed to address the dual challenges of energy efficiency and fault tolerance in Wireless Sensor Networks (WSNs). By integrating k-means clustering for uniform node distribution, fuzzy logic-based cluster head selection using residual energy and spatial centrality, and a novel SCH mechanism governed by a Poisson-based failure model, the proposed approach ensures robust and uninterrupted network operation. Simulation results confirmed the superior performance of EBCSH over conventional protocols like LEACH, BCF, and LEACH-USC. Notably, EBCSH extended the network lifetime to approximately 8100 rounds, far exceeding the benchmarks set by existing methods, while maintaining low energy variance and achieving a remarkable 98% success rate in cluster head failure recovery. These outcomes demonstrate that the EBCSH protocol is not only energy-efficient but also highly resilient in dynamic and failure-prone environments.

Future work may focus on enhancing the adaptability of the protocol in mobile and heterogeneous WSN scenarios. Incorporating machine learning-based predictive models for failure estimation and dynamic re-clustering strategies may further improve system responsiveness and energy optimization. Additionally, extending the protocol for real-time applications such as industrial monitoring and disaster management could enhance its practical relevance and scalability in mission-critical deployments.

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