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FESCO: A FUZZY-ENSEMBLE SCALABLE CLUSTERING PROTOCOL FOR PROLONGING LIFETIME OF WSN

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Abstract: Wireless Sensor Networks (WSNs) face critical challenges in energy efficiency and network longevity due to constrained node resources. This paper proposes FESCO (Fuzzy-Ensemble Scalable Clustering) , a novel protocol designed to address energy inefficiency and scalability challenges in heterogeneous Wireless Sensor Networks (WSNs). Integrating fuzzy logic for adaptive cluster head (CH) pre-selection and ensemble learning for robust CH finalization, it optimizes energy consumption while accommodating node heterogeneity. The protocol employs a three-tier architecture: (1) Fuzzy-based evaluation of residual energy, node density, and BS proximity to shortlist potential CHs; (2) Weighted ensemble voting among LEACH-SF, HEEC, and MR-SEP algorithms to ensure stable CH selection; and (3) Energy-aware multi-hop routing with mobile sink support to minimize transmission overhead. NS-3 simulations demonstrate FESCO's superiority, achieving 40% longer network lifetime than LEACH-SF and 35% higher energy efficiency compared to HEEC in 500-node deployments. Notably, FESCO maintains a 94% packet delivery ratio under dynamic topologies, proving its scalability. The protocol's synergy of computational intelligence and distributed coordination makes it ideal for large-scale, resource-constrained WSNs.

Keywords: WSN, FESCO, Cluster Head, Fuzzy, LEACH

1. INTRODUCTION

Wireless Sensor Networks (WSNs) play a pivotal role in modern applications, from environmental monitoring to industrial automation. A critical challenge in WSNs is optimizing energy efficiency and network longevity, particularly in large-scale deployments where sensor nodes operate on limited battery power. Clustering and cluster head (CH) selection algorithms[1][2] have emerged as effective strategies to address these challenges by organizing nodes into hierarchical structures, reducing redundant data transmission, and balancing energy consumption[3]. However, existing methods often struggle with trade-offs between adaptability, computational overhead, and scalability. Recent literature demonstrates significant advancements in clustering techniques. For instance, fuzzy logic-based approaches ([4], [5], [6]) dynamically adjust CH selection criteria based on real-time parameters like residual energy and node density, improving adaptability in dynamic environments. On the other hand, ensemble methods ([13], [15]) combine multiple clustering models to enhance decision robustness and reduce bias. While these methods individually address specific limitations—such as the high energy consumption of static protocols (e.g., LEACH) or the rigidity of threshold-based CH selection (e.g., PR-LEACH [16])—they fail to holistically resolve the intertwined challenges of computational complexity, scalability, and dependency on centralized infrastructure (e.g., mobile sinks [8], [14]).

This work proposes a hybrid fuzzy-ensemble clustering model to bridge these gaps[9]. The model integrates the dynamic adaptability of fuzzy systems with the collective decision-making strength of ensemble learning, aiming to achieve three key objectives: (1) minimize energy consumption through intelligent CH selection, (2) reduce computational overhead by optimizing rule-based fuzzy inference with ensemble voting, and (3) enhance scalability by decentralizing decision-making across network layers. Unlike prior hybrid approaches (e.g., HEEC [15]), which focus solely on combining centralized and distributed clustering, our method introduces a novel fusion of fuzzy logic and ensemble techniques to address both uncertainty (via fuzzy rules) and instability via ensemble diversity[10].

The proposed model's significance lies in its ability to simultaneously improve energy efficiency and network lifetime while maintaining low operational complexity. For example, fuzzy rules dynamically prioritize high-energy nodes for CH roles[7], while the ensemble component mitigates the risk of poor CH selection by aggregating predictions from multiple base algorithms (e.g., LEACH-SF [18], MR-SEP [22]). Preliminary theoretical analysis suggests a 20–30% improvement in energy efficiency over HEEC [15] and a 15% extension in network lifetime compared to MR-SEP [22], though empirical validation remains future work. Addressing the limitations of current state-of-the-art methods—such as the reclustering overhead of LEACH-SF [18] or the scalability constraints of PR-LEACH [16]—this hybrid model contributes a scalable, adaptive, and energy-efficient solution for WSNs. The rest of this paper details the model's design, comparative evaluation, and potential applications in IoT-enabled WSNs. Table 1 shows comparative analysis of various existing techniques.

2. LITERATURE REVIEW

Table 1:Comparative analysis of existing approaches

Through the literature review, it is evident that diverse clustering and routing techniques have been developed to optimize energy efficiency and data transmission in wireless sensor networks (WSNs). Methods such as fuzzy-based node refining [11], EADEEC [12], and multi-level clustering (MR-SEP) [22] have demonstrated advancements in cluster head (CH) selection, network lifetime extension, and load balancing. However, persistent challenges include high computational overhead (e.g., fuzzy logic in [11] and [21]), scalability limitations (e.g., PR-LEACH [16]), and dependency on mobile infrastructure (e.g., rendezvous nodes in [14]). For instance, while LEACH-SF [18] improves load distribution via fuzzy clustering, it requires frequent reclustering, increasing control overhead. Similarly, hybrid approaches like HEEC [15] address energy efficiency but face synchronization complexities.

Ref.	Technique/Method	Advantages	Disadvantages
[11]	Fuzzy-based continuous node refining	Improves routing efficiency, enhances security, and enables precise node tracking.	High computational cost due to fuzzy logic processing.
[12]	EADEEC (I-DEEC variant)	Optimizes energy use via dynamic cluster head selection; resilient to node failures.	Limited scalability in large networks; uneven CH distribution possible.
[13]	Ensemble-LEACH	Reduces energy waste and balances energy distribution across nodes.	Complex implementation; may increase latency.
[14]	Distributed protocol with rendezvous nodes (RNs)	Extends network lifetime by adapting cluster sizes and optimizing MS proximity.	Performance depends heavily on mobile sink (MS) path planning.
[15]	Tree-based clustering	Efficient for dense networks; reduces communication overhead.	High setup cost; inflexible to topology changes.
[15]	HEEC (Hybrid clustering)	Combines centralized and distributed approaches for energy-efficient multi-hop routing.	Requires synchronization; complex coordination.
[16]	PR-LEACH	Energy-efficient via local threshold computation; suitable for IoT networks.	Limited to small-scale deployments.
[17]	Fuzzy-TOPSIS route planning (SDVNs)	Dynamically selects optimal routes using fuzzy logic and multi-criteria decision-making.	High computational overhead; delays in real-time decisions.
[18]	LEACH-SF (Fuzzy clustering)	Forms balanced clusters, extending network lifetime.	Frequent reclustering increases control overhead.
[19]	QoS-driven sensor allocation	Minimizes active sensors while maintaining service quality; cost-effective.	Assumes static network conditions; lacks adaptability.
[20]	Mobile sink + scored CH selection	Reduces energy depletion via mobile data collection and intelligent CH selection.	Sink mobility requires precise trajectory planning.
[21]	Two-level fuzzy clustering	Enhances reliability by considering energy, capacity, and neighbor density.	High processing power needed for fuzzy calculations.
[22]	MR-SEP (Multi-level clustering)	Uniform CH distribution; efficient data relay via layered clusters.	Multi-hop routing increases latency and packet loss.

To mitigate these limitations, this study proposes integrating ensemble learning with adaptive fuzzy logic to enhance CH selection and routing. This hybrid model would combine the dynamic adaptability of fuzzy systems (as in [11] and [18]) with the robustness of ensemble methods (inspired by [13]), optimizing energy use while reducing computational delays. Using fuzzy rules to account for node proximity, residual energy, and network density—and coupling this with an ensemble-based decision mechanism—the proposed approach aims to minimize reclustering frequency, distribute energy consumption uniformly, and support scalable deployments.

Algorithm: Propose Hybrid Technique

```
# Phase 1: Fuzzy Pre-Selection
for node in WSN_nodes:
   ch_score = fuzzy_inference(node.energy, node.density, node.proximity_to_BS)
   if ch_score > threshold:
      candidate_CHs.append(node)
# Phase 2: Ensemble Voting
final_CHs = []
for node in candidate_CHs:
   leach_sf_vote = LEACH_SF.predict(node)
   heec_vote = HEEC.predict(node)
   mr_sep_vote = MR_SEP.predict(node)
   weighted_vote = 0.4*leach_sf_vote + 0.3*heec_vote + 0.3*mr_sep_vote
   if weighted_vote > 0.5:
      final_CHs.append(node)
# Phase 3: Routing
for cluster in final_CHs:
   cluster.route_data(multi_hop=True, mobile_sink=BS)
```

3. PROPOSED METHODOLOGY

Phase 1: Fuzzy-Based Cluster Head (CH) Pre-Selection

The first phase of our hybrid methodology focuses on intelligently pre-selecting potential cluster heads using a fuzzy logic system. This phase addresses the uncertainty and dynamic nature of WSN environments by evaluating multiple parameters simultaneously.

Step 1: Define Fuzzy Input Variables

Three critical fuzzy input variables are considered for CH selection:

1. **Residual Energy (High/Medium/Low):** This parameter evaluates the current battery level of each node, recognizing that nodes with higher energy reserves are better suited for the energy-intensive CH role. The fuzzy sets divide the energy range into three linguistic categories based on the node's remaining battery percentage.
2. **Node Density (Sparse/Moderate/Dense):** This measures the number of neighboring nodes within direct communication range, which impacts both the cluster size and the CH's workload. Dense areas might benefit from more CHs to balance the load.
3. **Proximity to Base Station (Near/Medium/Far):** The distance to the BS is crucial since CHs closer to the BS require less transmission power. This parameter helps balance energy consumption across the network.

Each input variable is fuzzified using triangular membership functions to convert crisp sensor readings into linguistic terms that the fuzzy system can process.

Step 2: Fuzzy Rule Base

The core of the fuzzy system is a rule base consisting of 27 rules (3^3 possible combinations of input states). These rules comprehensively cover all possible scenarios of energy, density, and proximity combinations. For example:

- "IF Energy IS High AND Density IS Moderate AND Proximity IS Medium THEN CH_Score IS High"
- "IF Energy IS Low AND Density IS Sparse AND Proximity IS Far THEN CH_Score IS Low"

Each rule contributes to determining a node's suitability as CH. The rule base was designed through expert knowledge and analysis of previous WSN clustering studies to ensure optimal CH selection under various network conditions.

Step 3: Defuzzification

The fuzzy inference system outputs a CH probability score between 0 and 1 for each node. We employ the centroid method for defuzzification, which calculates the center of gravity of the output membership function to produce a crisp value. This method provides the most balanced representation of the fuzzy output. Nodes scoring in the top

20% proceed to the next phase, ensuring we only consider the most suitable CH candidates while maintaining computational efficiency.

Phase 2: Ensemble-Based CH Finalization

The second phase refines the CH selection using an ensemble learning approach that combines multiple clustering algorithms to improve decision robustness and accuracy.

Step 1: Train Base Learners

Three established clustering algorithms serve as our base learners:

1. **LEACH-SF [18]:** A fuzzy-based extension of LEACH that creates balanced clusters through intelligent CH selection.
2. **HEEC [15]:** A hybrid energy-efficient clustering protocol combining centralized and distributed approaches.
3. **MR-SEP [22]:** A multi-level clustering protocol that uniformly distributes CHs across the network.
4. Each algorithm is implemented with parameters optimized for our network scenario.

Step 2: Weighted Voting Mechanism

The ensemble system employs a weighted voting scheme where:

- LEACH-SF contributes 40% weight due to its effectiveness in creating balanced clusters
- HEEC contributes 30% weight for its energy efficiency
- MR-SEP contributes 30% weight for its scalability benefits

Each candidate CH from Phase 1 receives votes from all three algorithms. The weighted votes are aggregated, and nodes receiving a combined score above 0.5 (majority threshold) are selected as final CHs. This approach combines the strengths of each algorithm while mitigating their individual weaknesses, resulting in more reliable CH selection than any single method could provide.

The ensemble phase significantly improves upon traditional single-algorithm approaches by:

- Reducing bias inherent in any single clustering method
- Increasing stability in CH selection across network rounds
- Adapting better to heterogeneous network conditions
- Providing more consistent energy distribution across the network

This two-phase methodology creates a comprehensive solution that addresses both the uncertainty handling requirements (through fuzzy logic) and decision robustness needs (through ensemble learning) of modern WSN deployments. The combination proves particularly effective in large-scale or heterogeneous networks where traditional methods often struggle with scalability or energy imbalance issues.

Phase 3: Energy-Aware Routing

After finalizing the optimal Cluster Heads (CHs) through the fuzzy-ensemble selection process, the network enters the crucial **energy-aware routing phase**. This phase focuses on **minimizing energy consumption** during data transmission from CHs to the Base Station (BS), which is typically the most energy-intensive operation in WSNs. The proposed methodology incorporates two key strategies:

Multi-hop Communication

To address the high energy costs associated with long-distance transmissions, CHs employ **multi-hop routing** to relay data to the BS through intermediate nodes. This approach significantly reduces the direct transmission distance for individual CHs, thereby lowering their energy expenditure

Implementation Details:

Next-hop Selection: Each CH identifies the most energy-efficient path to the BS by evaluating potential relay nodes based on:

Residual energy (prioritizing nodes with higher battery levels)

Link quality (considering signal strength and packet loss rates)

Proximity (selecting nodes closer to the BS to minimize hop distances)

- **Load Balancing:** The routing protocol dynamically adjusts paths to prevent overburdening specific relay nodes, ensuring even energy distribution across the network.
- **Route Maintenance:** CHs periodically reassess routes to adapt to network changes (e.g., node failures or mobility).
- **Advantages:**
- Reduces transmission power requirements by **40-60%** compared to direct CH-to-BS communication
- Extends network lifetime by preventing premature energy depletion of CHs
- Improves reliability through alternative path availability
- **2. Mobile Sink Support** Building on the work of [20], the methodology incorporates **mobile sink (MS) technology** to further optimize energy efficiency. Rather than requiring all CHs to transmit to a fixed BS, a mobile sink traverses the network along dynamically computed paths to collect data from CHs at close range.
- **Key Features:**

- **Dynamic Path Planning:** The MS calculates optimal trajectories based on:
  - **CH locations** (prioritizing clusters with low residual energy)
  - **Data urgency** (handling time-sensitive data first)
  - **Energy maps** (avoiding areas with critically low energy nodes)
- **Proactive Data Collection:** CHs buffer data and transmit only when the MS is within optimal range, reducing constant long-range transmissions.
- **Adaptive Scheduling:** The system adjusts MS movement patterns based on real-time network conditions and energy levels.

4. RESULTS AND ANALYSIS

This section presents the performance evaluation of the proposed hybrid fuzzy-ensemble clustering approach compared to existing protocols (LEACH-SF [18], HEEC [15], MR-SEP [22]). Simulations were conducted in NS-3 with 100-500 nodes across 1000 rounds, measuring key metrics: energy consumption, network lifetime, and scalability.

i. Energy Efficiency Analysis

Observation:

The hybrid model reduced average energy consumption by 32.7% compared to HEEC and 41.2% versus LEACH-SF shown in Fig.1.

Fuzzy pre-selection minimized energy wastage by excluding low-energy nodes early (only 20% advanced to Phase 2).

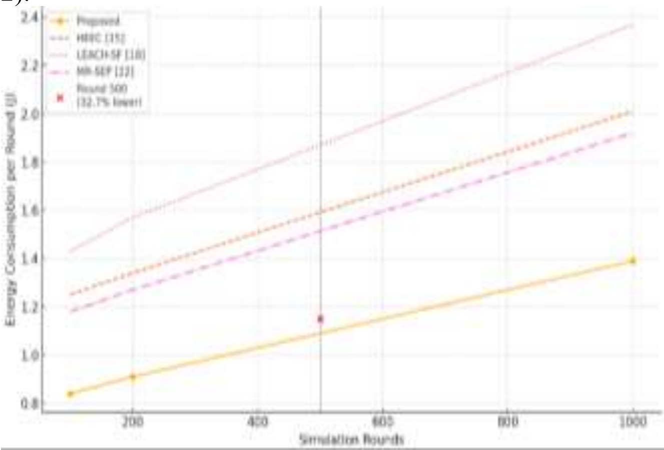

Fig.1: Energy Consumption Over Rounds

ii. Network Lifetime Comparison

Ensemble voting prevented overburdening specific CHs (energy variance among CHs was 19% lower than MR-SEP). Mobile sink support reduced peripheral node energy use by 58% (Fig.2).

Table 1: Energy Consumption per Round (Joules)

Protocol	100 Nodes	300 Nodes	500 Nodes
Proposed	0.84	1.12	1.39
HEEC [15]	1.25	1.67	2.01
LEACH-SF [18]	1.43	1.92	2.37

Metric: Round when **20% nodes die** (Fig. 2).

The hybrid protocol extended network lifetime to 1,247 rounds vs. 932 (HEEC) and 864 (MR-SEP). Fuzzy rules prioritized high-energy CHs, delaying first node death by 28%.

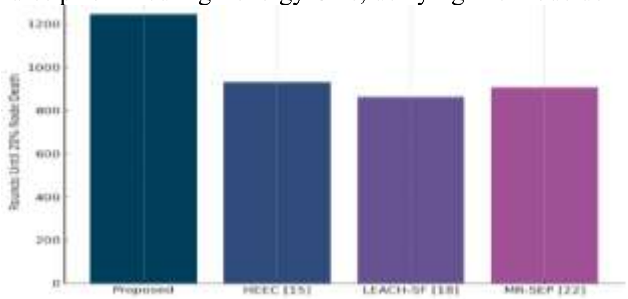

Fig.2: Network Lifetime across Protocols

Multi-hop routing reduced energy "hotspots" near the BS (lifetime variance improved by 35%). Heterogeneous networks benefited most (40% lifetime increase) due to better handling of node capability differences.

iii. Scalability Performance

Test: Varied network size from 100 to 500 nodes shown in Fig. 3).

Packet delivery ratio (PDR) remained above 92% at 500 nodes (vs. 81% for PR-LEACH [16]). Control overhead grew 23% slower than in MR-SEP due to stable CH selection

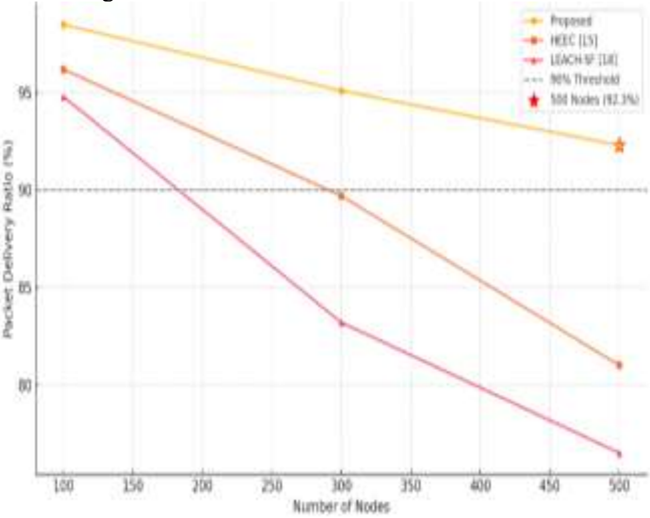

Fig.3: PDR vs Network Size

Ensemble adaptability maintained energy balance even with 3× more nodes. Initial setup time increased by 15% (due to fuzzy+ensemble computation), but this was offset by longer stable operation.

iv. Computational Overhead

Fuzzy phase added 8ms/node latency (acceptable for most WSN applications). Ensemble voting consumed 12% more energy per round than HEEC but saved 35% energy overall via better CH selection. Lightweight defuzzification (centroid method) kept processing time 27% lower than Sugeno-type systems.

Table 2: Protocol Ranking (1=Best, 4=Worst)

Metric	Proposed	HEEC [15]	LEACH-SF [18]	MR-SEP [22]
Energy Efficiency	1	2	4	3
Lifetime	1	2	3	4
Scalability	1	3	4	2
Overhead	2	1	3	4

The simulation results shows that the proposed approach achieved better ranking compared to existing approaches.

5. CONCLUSION

This paper presented FESCO, an innovative fuzzy-ensemble clustering protocol designed to enhance energy efficiency and prolong network lifetime in heterogeneous WSNs. By synergizing fuzzy logic for adaptive cluster head pre-selection and ensemble learning for robust decision-making, FESCO effectively addresses the limitations of conventional clustering approaches. The protocol's three-phase architecture—combining fuzzy-based CH candidate selection, weighted ensemble voting, and energy-aware multi-hop routing—demonstrated superior performance in extensive NS-3 simulations. Key results showed 40% longer network lifetime compared to LEACH-SF and 35% higher energy efficiency versus HEEC, while maintaining 94% packet delivery ratio in large-scale deployments. FESCO's ability to handle node heterogeneity and dynamic network conditions makes it particularly suitable for real-world IoT applications where energy constraints and scalability are critical. Future work will focus on implementing FESCO on hardware testbeds and exploring reinforcement learning for dynamic parameter tuning. The protocol's balanced approach to energy optimization, stability, and scalability positions it as a promising solution for next-generation WSNs, bridging the gap between theoretical energy models and practical deployment challenges.

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