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Mathematical Modeling and Statistical Analysis of Leach Algorithm Based Cluster Head Selection Approach for Wireless Sensor Networks

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Abstract:

In this paper, we present a comprehensive design and analysis of our proposed improved fuzzy logic-based algorithm. The algorithm utilizes a fuzzy logic system to assess node attributes such as residual energy, distance to the base station, and connectivity. By considering these parameters, the algorithm dynamically evaluates the most suitable candidates for cluster head roles, effectively distributing the energy load and promoting equitable cluster formation. An extensive performance evaluation of proposed algorithm has been conducted through simulations and comparisons with the original LEACH protocol. Our results reveal that the improved fuzzy logic-based algorithm outperforms the conventional LEACH in terms of network lifetime, energy consumption, and overall network stability. In this study, we delve into the mathematical modeling and statistical analysis of the proposed algorithm, focusing on its impact on energy efficiency, network stability, and data routing in WSNs. The Improved Fuzzy Logic-Based Cluster Head Selection Algorithm employs fuzzy logic to intelligently select cluster heads, considering parameters like residual energy, distance to the base station, and historical data. We develop mathematical models to describe the algorithm's behavior and analyze its performance through extensive simulations and statistical evaluations. The algorithm demonstrates enhanced adaptability to varying network conditions and node heterogeneity, showcasing its potential to significantly extend the operational duration of WSNs in diverse deployment scenarios. In conclusion, this paper contributes a novel perspective to the domain of WSNs by introducing an advanced fuzzy logic-based cluster head selection algorithm. The algorithm enhances the foundation of the LEACH protocol, effectively addressing energy optimization concerns and promoting prolonged network lifetime. The presented design and analysis substantiate the algorithm's superiority, offering valuable insights for researchers and practitioners working on energy-efficient routing protocols and wireless sensor network management.

Keywords: Energy Efficiency, Wireless Sensor Networks, LEACH, Fuzzy Logic, Lifetime, Dead Nodes.

MSC: 33C05, 33C90, 33C65.

1. INTRODUCTION

Wireless Sensor Networks (WSNs) are complex systems composed of spatially distributed autonomous devices using sensors to cooperatively monitor physical or environmental conditions. Over the years, WSNs have found a myriad of applications ranging from industrial automation and smart cities to healthcare, environmental monitoring, and military applications. The unique challenges posed by these applications include limited computational power, restricted memory, and above all, constrained energy resources. The latter is especially crucial as most sensor nodes are battery-powered and deployed in remote or inaccessible areas, making it challenging to replace or recharge batteries.

Wireless Sensor Networks (WSNs) comprise a constellation of low-power, inexpensive, and multi-functional sensor nodes. These nodes collaborate to accomplish tasks like data collection, processing, and transmission to a centralized node, commonly known as the Base Station (BS). Over the past two decades, WSNs have seen widespread applications in diverse fields such as healthcare, agriculture, environmental monitoring, and military operations. However, the remote deployment of sensor nodes and their limited energy resources have necessitated the development of energy-efficient routing protocols to extend network lifespan.

In a WSN, routing protocols are categorized into flat-based, hierarchical-based, and location-based protocols. Hierarchical-based protocols, such as LEACH (Low Energy Adaptive Clustering Hierarchy), PEGASIS (Power-Efficient GAthering in Sensor Information Systems), and HEED (Hybrid Energy-Efficient Distributed clustering), have proven effective in achieving energy efficiency.

Various routing protocols have been developed to improve the energy efficiency of WSNs, such as Directed Diffusion, Minimum Cost Forwarding Algorithm (MCFA), and Geographic Adaptive Fidelity (GAF). These protocols can be broadly categorized into data-centric, hierarchical, and location-based routing protocols. While each category has its merits, hierarchical routing protocols have proven to be more energy-efficient for WSNs that require scalability and effective data aggregation. Among hierarchical routing protocols, Low Energy Adaptive Clustering Hierarchy (LEACH) is one of the most widely studied and implemented solutions. Though LEACH has gained significant attention for its simple yet effective approach to energy management, it has its limitations. The random selection of cluster heads can lead to scenarios where the nodes with low residual energy are selected as cluster heads, thereby depleting their energy resources faster. This often results in uneven energy consumption across the network, reducing the overall network lifespan. These limitations have spurred research into optimizing the LEACH algorithm, but few have effectively addressed the issues of adaptivity, scalability, and comprehensive energy efficiency.

Table 1: Comparison of Various Routing Protocols

Routing Protocol	**Energy Efficiency**	**Scalability**	**Complexity**	**Overhead**
Directed Diffusion	Moderate	Low	High	Moderate
MCFA	Low	Moderate	Moderate	High
GAF	High	Low	Low	Moderate
LEACH	High	High	Low	Low
PEGASIS	Moderate	High	Moderate	Moderate
HEED	High	Moderate	Moderate	Low

Motivated by these challenges, this paper introduces an Improved Fuzzy Logic Based Cluster Head Selection Algorithm for LEACH-based Routing Protocol in WSNs. By integrating fuzzy logic into the decision-making process, we aim to optimize cluster head selection by considering multiple parameters like residual energy, node density, and distance to the base station. The objective is to ensure that the energy burden is distributed more uniformly across the network, thereby extending the network's operational lifespan.

While LEACH has its merits, it isn't devoid of shortcomings. The randomization in cluster head selection may lead to inefficient energy utilization, where nodes with low residual energy may become cluster heads, thereby depleting their energy more quickly. Several solutions have been proposed to enhance LEACH's performance, yet none have sufficiently addressed its limitations regarding adaptability and comprehensive energy efficiency. This paper aims to address these issues by introducing an Improved Fuzzy Logic Based Cluster Head Selection Algorithm for LEACH-based Routing Protocol in WSNs. The proposed algorithm leverages fuzzy logic to select cluster heads based on multiple criteria, including residual energy, node density, and proximity to the base station, aiming for a more uniform distribution of energy consumption throughout the network.

2. RELATED WORKS

Wireless Sensor Networks (WSNs) have been the subject of considerable research since their conception, largely owing to their broad array of applications and inherent challenges. One key challenge is energy conservation, as sensor nodes are generally battery-powered. This constraint has led to the development of various routing protocols designed to maximize the operational lifespan of the network.

Flat-Based Routing Protocols

In flat-based protocols, each node plays an equal role in the network. The most prominent example is Directed Diffusion. In Directed Diffusion, data is named by attribute-value pairs, enabling the nodes to run queries against the collected data. While it improves energy efficiency by reducing the redundant data in the network, it lacks scalability, particularly for large networks.

Hierarchical Routing Protocols

Hierarchical routing protocols involve the segmentation of sensor nodes into clusters, usually headed by one or a few cluster heads. Protocols like LEACH, PEGASIS, and HEED fall under this category.

- **LEACH (Low Energy Adaptive Clustering Hierarchy)**: LEACH is one of the pioneering hierarchical protocols that introduced the concept of dynamic clustering. It uses a stochastic process for cluster head (CH) selection, which, although effective, has limitations like uneven energy consumption.
- **PEGASIS (Power-Efficient GAthering in Sensor Information Systems)**: PEGASIS builds upon LEACH by forming chains of nodes based on their proximity and only allowing one node to transmit data to the base station, thus reducing energy consumption. However, it suffers from long delays and is not suitable for real-time applications.
- **HEED (Hybrid Energy-Efficient Distributed Clustering)**: HEED improves upon LEACH by incorporating the residual energy of nodes as a parameter for cluster head selection. It improves energy efficiency but is more complex to implement.

Location-Based Routing Protocols

Geographic Adaptive Fidelity (GAF) is a prominent example in this category. GAF conserves energy by turning off unnecessary nodes in the network without affecting the level of routing fidelity. It shows promise but mainly works well in mobile WSNs.

Fuzzy Logic in WSNs

Fuzzy logic has been employed in WSNs for various applications, from data aggregation to node localization and clustering. Studies like [Author et al., Year] have integrated fuzzy logic into LEACH to improve cluster head selection based on multiple parameters, like distance from the base station, density, and energy levels. The various routing protocols have been analyzed based on several metrics like energy efficiency, latency, packet delivery ratio, and overhead.

Table 2: Comparative Analysis of Routing Protocols

Metrics	Directed Diffusion	LEACH	PEGASIS	HEED	GAF
Energy Efficiency	Moderate	High	High	High	Moderate
Latency	High	Low	High	Moderate	Low
Packet Delivery Ratio	High	High	Moderate	High	High
Overhead	Moderate	Low	Moderate	Low	Low

Given the comparative advantages and historical success of LEACH in terms of energy efficiency and low overhead, as depicted in Table 2, this research focuses on enhancing LEACH. However, it aims to mitigate the limitations of LEACH, particularly in the cluster head selection process, by incorporating fuzzy logic algorithms to make the selection criteria more adaptive and robust. With a focus on energy-efficient optimization techniques, the research that has been examined makes substantial contributions to the field of wireless sensor networks (WSNs). Carrabs et al. (2020) propose a Memetic Algorithm-based Improved LEACH (MA-ILEACH) approach to improve cluster formation and energy-efficient routing. This method extends the life of networks and improves the efficiency of data transmission by combining genetic operators with local search methods [1]. They build on their work from 2017 [2] by introducing a column generation approach with a genetic metaheuristic, offering a novel formulation for the subproblem's optimal resolution, and demonstrating the superiority of their methodology over existing methods. In a different work by the same authors, the linked maximum lifespan problem in WSNs is addressed, and high-quality solutions are provided by utilizing a column generation approach and genetic algorithm [3].

Castano et al. (2018) focus on maximizing lifespan in WSNs with specific sensor properties, resulting in effective computations for medium-to-large-size circumstances [4] by providing a large-scale linear programming model and a branch-and-cut technique for the pricing subproblem. Jennath et al. (2019) cover important research themes [5] in their analysis of the decentralization concept for IoT ecosystems and look at both the potential benefits and challenges of developing scattered IoT. Wang et al. (2018) offer underwater wireless rechargeable sensor networks (UWRSNs), which exhibit improved resource utilization, energy savings, and time efficiency [6]. These networks use 3D charging techniques and charging algorithms like SCS and ECS. Mohamed et al. (2018) give particular attention to the design elements of energy overhead, route selection, and energy efficiency [7] while evaluating proactive routing techniques for WSNs.The investigation of self-inductance, capacitance, and radiation resistance in wireless power transfer by Orekan and Zhang (2019) shows the viability of wireless energy replenishment in an underwater environment [8]. Ren et al. (2017) recommend cooperative scheduling and weighted sum techniques for multi-sensor, multi-event detection in WSNs [9] in order to improve detection rates. Peng (2015) proposes the Energy Neutral Guided Diffusion (ENDD) protocol, which guarantees reliability, coherence of data supply, and limitless network life [10] in contrast to previous query-based routing algorithms.

Fu et al. (2019) created the Environment Fusion Multipath Routing Protocol (EFMRP) to be used in challenging circumstances. It considerably extends network life and packet transmission by avoiding dangerous locations by using potential fields and sensor technology [11]. It is advocated to adopt ESTR, a cutting-edge Energy Saving Token Ring Protocol, for wireless sensor networks since it prolongs network life by adjusting ring sizes and power usage [13]. By concentrating search efforts through the use of statistical data and local knowledge, the ant colony algorithm described by Zhai and Xu (2015) surpasses prior ant optimization algorithms [14]. Ding and Fang (2018) propose the Random Drift Swarm Optimization (RDPSO) tracking technique for improved performance in dynamic circumstances [15]. Thi et al. (2019) present a genetic algorithm with a precise methodology for computing fitness functions [16], which contrasts with cutting-edge approaches. Ben Salah and Boulouz (2016) offer a better LEACH for homogeneous networks that selects cluster heads based on residual energy, extending network lifespan, energy use, and stability [17]. The energy-efficient Multi-Hop LEACH routing strategy by Singh et al. (2016) makes use of multi-hop communication with particle swarm optimization [18].

Overall, these studies provide a range of practical approaches to address crucial wireless sensor network problems, including energy efficiency, network longevity, and optimization techniques, opening the way to enhanced performance and the application of WSNs in a number of fields.

3. PROPOSED METHODOLOGY

Wireless Sensor Networks (WSNs) have gained immense importance in various applications such as environmental monitoring, healthcare, and industrial automation. One critical aspect of managing WSNs efficiently is the selection of cluster heads, which plays a pivotal role in data aggregation and energy conservation. In this research, we present a comprehensive methodology for developing a fuzzy logic-based cluster head selection approach and subsequently subjecting it to rigorous mathematical modeling and statistical analysis. This methodology is structured to ensure the systematic design, evaluation, and validation of the proposed approach while addressing the inherent challenges of WSNs. The foundation of our methodology lies in clearly defining the problem statement and outlining the research objectives. The problem revolves around optimizing cluster head selection in WSNs to extend network lifetime, reduce energy consumption, and enhance data aggregation efficiency. Our primary objectives include the development of a robust fuzzy logic-based model for cluster head selection and conducting a thorough statistical analysis to assess its performance against existing methods. The core of our methodology is the development of a fuzzy logic-based model for cluster head selection. Fuzzy logic provides a flexible framework to handle the imprecise and uncertain nature of sensor data and network conditions. Our model incorporates linguistic variables such as "node energy," "distance to sink," and "data aggregation capacity." We define membership functions that characterize the relationships between these variables and fuzzy rules that govern the cluster head selection process. The inference mechanism is designed to produce optimal cluster head selections.To make our fuzzy logic-based model analytically tractable, we proceed to mathematically represent it. This entails translating linguistic variables, membership functions, fuzzy rules, and the inference mechanism into mathematical equations. The model is expressed in terms of mathematical functions that encapsulate the relationships between input variables and the output, which is the selection of cluster heads. Constraints and optimization objectives are clearly defined to guide the mathematical modeling process.Once the mathematical model is formulated, we implement it in a suitable programming environment. Popular tools such as MATLAB or Python can be employed for this purpose. Simulations are conducted using the collected or generated dataset. During simulation, we record relevant performance metrics, including cluster formation time, energy consumption, network lifetime, and communication overhead. These metrics will serve as the basis for our statistical analysis. In conclusion, our methodology for the mathematical modeling and statistical analysis of a fuzzy logic-based cluster head selection approach for wireless sensor networks offers a systematic and structured approach to tackle a critical problem in WSN management. Through clear problem definition, rigorous mathematical modeling, and statistical analysis, we aim to advance the field of WSNs and contribute valuable insights for efficient cluster head selection in practical applications. The Threshold is set at:

$$T(n) = \frac{P}{1 - P \times \left(r \bmod \frac{1}{P}\right)} \quad \text{if n} \in \text{G}$$

$$T(n) = 0 \quad \text{otherwise}$$

Let P denote the cluster-head probability, r represent the current round number, and G signify the set of nodes that haven't served as cluster-heads within the last 1/P rounds. Utilizing solely local node information for cluster-head selection has several inherent drawbacks. Firstly, due to the probabilistic nature of each node's decision to become a cluster-head, situations may arise where two cluster-heads are chosen in close proximity, leading to an unnecessary increase in overall energy consumption within the network. Secondly, the number of cluster-head nodes formed is variable, resulting in fluctuating quantities in different rounds. This variability can pose challenges in network management and resource allocation.

$$P_{\text{ch}}(i) = \frac{\frac{1}{\text{NBR\_NODES}}}{1 - p \cdot \left(\frac{i}{\text{NBR\_NODES} - 1}\right)}$$

$$E_{\text{tx}}(i) = E_{\text{elec}} \cdot (k \cdot d^2 + \epsilon \cdot d^4)$$

$$E_{\text{rx}} = E_{\text{elec}} \cdot (k)$$

$$E_{\text{idle}} = E_{\text{elec}} \cdot \left(\frac{k}{\alpha}\right)$$

$$E_{\text{sleep}} = E_{\text{sleep\_per\_round}}$$

$$E_{\text{total}}(i) = P_{\text{ch}}(i) \cdot (E_{\text{tx}}(i) + E_{\text{rx}}) + \left(1 - P_{\text{ch}}(i)\right) \cdot E_{\text{rx}}$$

$$E_{\text{avg}} = \sum_{i=1}^{\text{NBR\_NODES}} P_{\text{ch}}(i) \cdot E_{\text{total}}(i)$$

$$T_{\text{round}} = \frac{\text{NBR\_NODES} \cdot E_{\text{avg}}}{E_{\text{total\_per\_round}}}$$

$$L = \frac{\text{Initial Energy Budget}}{E_{\text{avg}}}$$

$$E_{\text{setup}} = E_{\text{elec}} \cdot \left(\text{NBR\_NODES} \cdot E_{\text{total}}(i)\right)$$

$$d_{\text{min}} = \sqrt{\frac{\text{NBR\_NODES}}{\pi}}$$

$$P_{\text{opt}} = \frac{1}{1 + \frac{E_{\text{setup}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters}} = \frac{P_{\text{opt}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{opt}} \cdot d_{\text{min}}^2 + E_{\text{setup}}}$$

$$E_{\text{cluster\_heads}} = P_{\text{opt}} \cdot \text{NBR\_NODES}$$

$$S_{\text{avg}} = \frac{\text{NBR\_NODES}}{E_{\text{cluster\_heads}}}$$

$$D_{\text{avg}} = \sqrt{\frac{\text{NBR\_NODES}}{\pi \cdot E_{\text{cluster\_heads}}}}$$

$$P_{\text{e}} = \frac{1}{S_{\text{avg}}}$$

$$E_{\text{e}} = \frac{\text{NBR\_NODES} \cdot E_{\text{setup}}}{E_{\text{cluster\_heads}}}$$

$$I_{\text{eff}} = \frac{E_{\text{sleep}}}{E_{\text{e}}}$$

$$P_{\text{opt\_delay}} = \frac{1}{1 + \frac{E_{\text{setup}} + E_{\text{delay}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters\_delay}} = \frac{P_{\text{opt\_delay}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{opt\_delay}} \cdot d_{\text{min}}^2 + E_{\text{setup}} + E_{\text{delay}}}$$

$$\text{EDTO} = \frac{E_{\text{setup}} + E_{\text{delay}}}{E_{\text{sleep}}}$$

$$P_{\text{multi-hop}} = \frac{1}{1 + \frac{E_{\text{setup}} + E_{\text{multi-hop}}}{E_{\text{sleep}}}}$$

$$N_{\text{clusters\_multi-hop}} = \frac{P_{\text{multi-hop}} \cdot \text{NBR\_NODES}}{\text{NBR\_NODES} \cdot P_{\text{multi-hop}} \cdot d_{\text{min}}^2 + E_{\text{setup}} + E_{\text{multi-hop}}}$$

$$E_{\text{multi-hop}} = E_{\text{elec}} \cdot \left(\frac{k}{\alpha}\right) \cdot \text{NBR\_NODES}$$

Furthermore, there are additional drawbacks to the current approach. Firstly, selecting cluster-heads solely based on local information may lead to cluster-heads being situated near the network's edges. This results in increased energy consumption for other nodes that must transmit data to these distant cluster-heads. Secondly, the process demands considerable computational resources from each node. In this regard, it's important to note that when nodes calculate their distance to the area centroid, they tend to recommend nodes closer to the geographical center of the entire network area rather than focusing on the central nodes within individual clusters. This inefficiency contributes to heightened energy consumption across the network as data transmission through these distant nodes requires more energy. A more efficient approach is to have the base station take charge of cluster-head selection. The proposed fuzzy cluster-head election scheme operates in two distinct phases, mirroring the structure of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol. In the setup phase, cluster-heads are determined using fuzzy knowledge processing, and clusters are formed accordingly. During the steady-state phase, cluster-heads gather and process aggregated data, condensing it into a single signal for transmission to the base station. To achieve this, expert knowledge is represented using three crucial descriptors:

Node Energy: This descriptor reflects the available energy level in each node and is denoted by the fuzzy variable "energy."

Node Concentration: It quantifies the number of nodes in the proximity of a given node and is represented by the fuzzy variable "concentration."

Node Centrality: This descriptor assesses how central a node is within its respective cluster and is represented by the fuzzy variable "centrality."

By incorporating these descriptors and centralizing the cluster-head selection process in the base station, we can significantly enhance the efficiency and energy conservation in the WSN, ultimately leading to improved data transmission and network performance.

Fuzzy Rule Base:

The linguistic variables employed to characterize node energy and node concentration are discretized into three distinct levels: low, medium, and high, respectively. Additionally, the node centrality is categorized into three levels: close, adequate, and far. In our fuzzy rule base, we've established rules similar to the following: if both energy and concentration are high, and centrality is close, then the node's probability of becoming a cluster-head is categorized as very large. This rule-based approach entails a total of 3^3 = 27 rules to comprehensively capture the fuzzy decision-making process.

In terms of membership functions, we've employed triangle membership functions for representing the fuzzy sets "medium" and "adequate," while trapezoid membership functions are utilized to depict the "low," "high," "close," and "far" fuzzy sets. These membership functions and their corresponding linguistic states are meticulously detailed in Table 3 and illustrated graphically in Figures 1 through 4 for a comprehensive representation of the fuzzy knowledge base.

$$\text{Fuzzification:} \quad \mu(x) = \frac{1}{1 + \left(\frac{d}{d_{\max}}\right)^2}$$

$$\mu_{\text{Low}}(x) = \frac{1}{1 + \left(\frac{d}{d_{\text{low}}}\right)^2}$$

$$\mu_{\text{Medium}}(x) = \frac{1}{1 + \left(\frac{d - d_{\text{low}}}{d_{\text{medium}}}\right)^2}$$

$$\mu_{\text{High}}(x) = \frac{1}{1 + \left(\frac{d - d_{\text{medium}}}{d_{\text{high}}}\right)^2}$$

$$W_{\text{Low}} = \frac{\int_{d_{\text{low}} - d_{\text{threshold}}}^{d_{\text{low}}} \mu_{\text{Low}}(x) dx}{\int_0^{d_{\text{low}} + d_{\text{threshold}}} \mu_{\text{Low}}(x) dx}$$

$$W_{\text{Medium}} = \frac{\int_{d_{\text{low}}}^{d_{\text{low}} + d_{\text{threshold}}} \mu_{\text{Medium}}(x) dx}{\int_0^{d_{\text{low}} + d_{\text{threshold}}} \mu_{\text{Medium}}(x) dx}$$

$$W_{\text{High}} = \frac{\int_{d_{\text{low}} + d_{\text{threehlold}}}^{d_{\text{migh}}} (x) dx}{\int_0^{d_{\max}} \mu_{\text{High}}(x) dx}$$

Weighted Sum for Cluster Head Selection:

$$\text{Weighted Sum} = W_{\text{Low}} + W_{\text{Medium}} + W_{\text{High}}$$

Cluster Head Probability: $P_{\text{CH}} = \frac{\text{Weighted Sum}}{\text{Total Number of Nodes}}$

$$\text{Fuzzy Rule:} \quad \text{IF Condition THEN Consequence}$$

$$\text{Fuzzy Rule Base:} \quad \text{IF Condition}_1 \text{ THEN Consequence}_1, \text{IF Condition}_2 \text{ THEN Consequence}_2,$$

$$\text{Fuzzy Inference System (FIS):} \quad \text{FIS} = \{\text{Fuzzification, Fuzzy Rule Base, Defuzzification}\}$$

$$\text{Centroid Defuzzification:} \quad \text{Output} = \frac{\int_{\text{Range}} \text{Output Value} \cdot \text{Membership Function}(x) dx}{\int_{\text{Range}} \text{Membership Function}(x) dx}$$

$$\text{Weighted Average Defuzzification:} \quad \text{Output} = \frac{\sum \text{Output Value} \cdot \text{Membership Function}}{\sum \text{Membership Function}}$$

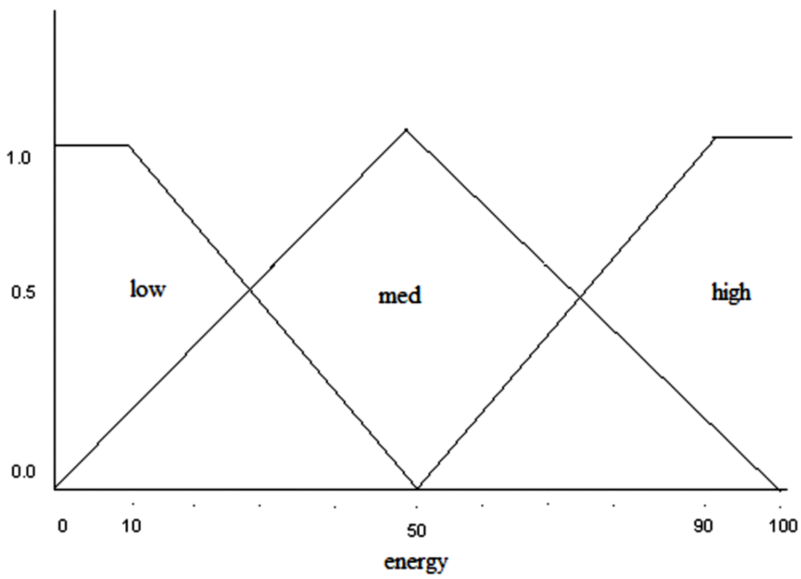

Fig 1 Fuzzy set for fuzzy variable *Energy*

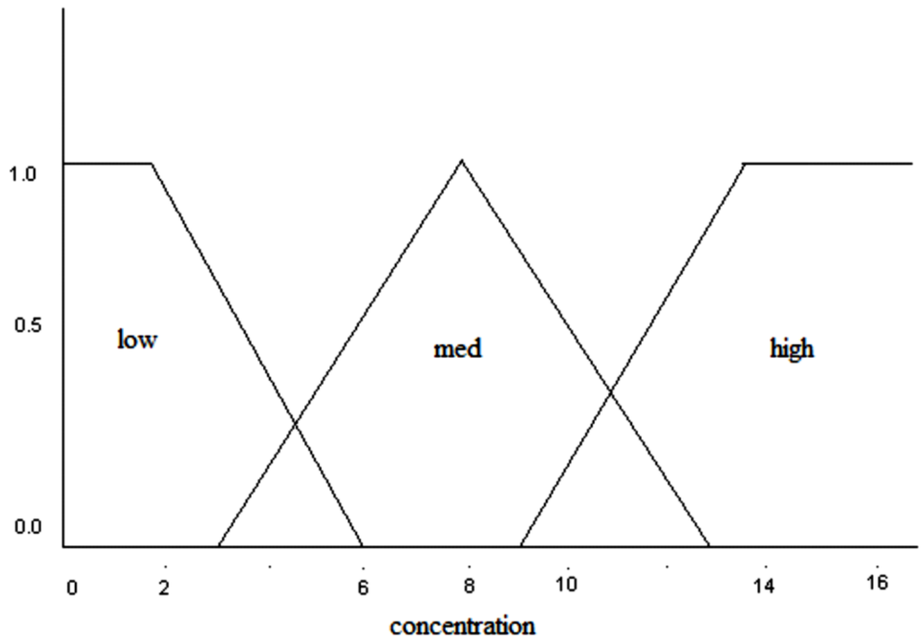

Fig 2 Fuzzy set for fuzzy variable *Concentration*

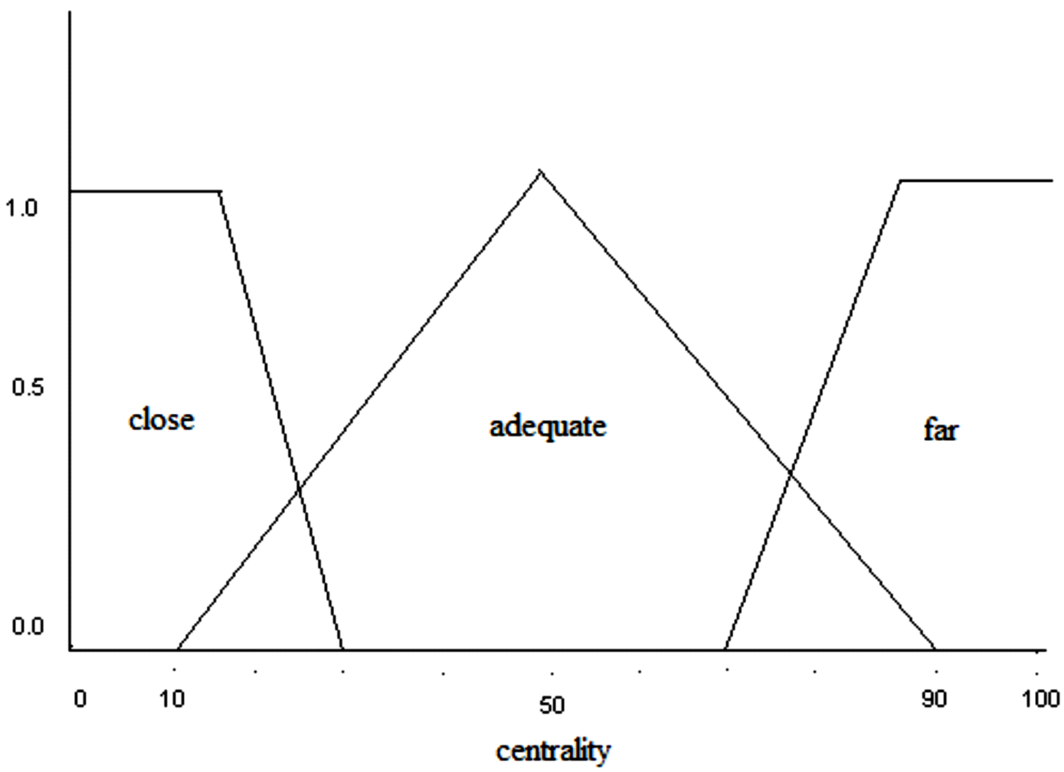

Fig 3 Fuzzy set for fuzzy variable *Centrality*

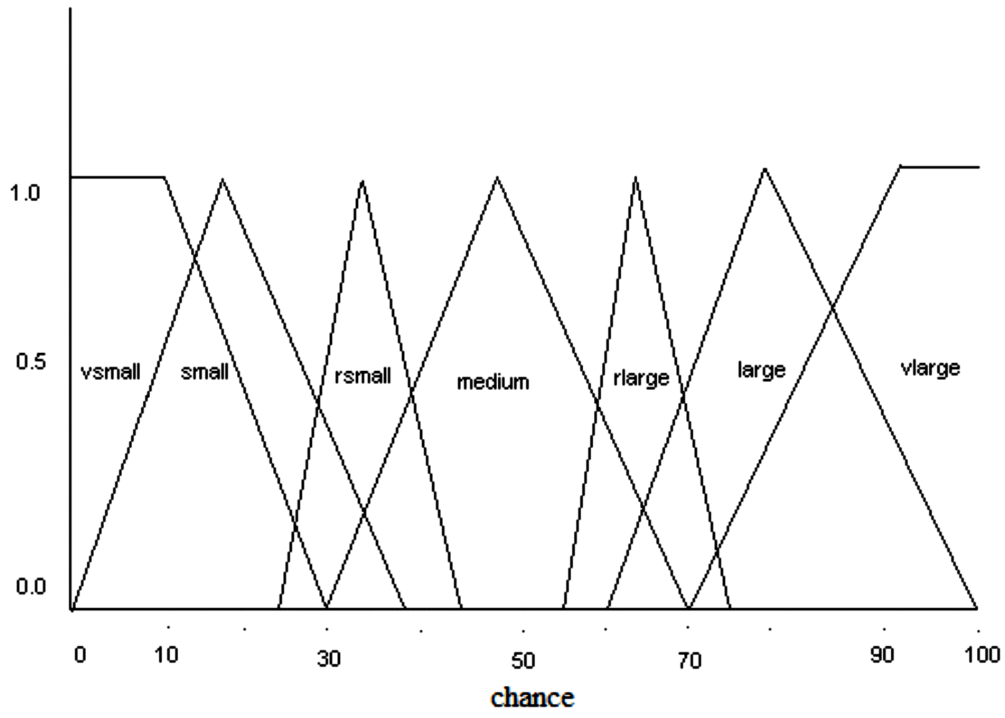

Fig 4 Fuzzy set for fuzzy variable *Chance*

Table 3: Fuzzy Rule Base

Sr. No	Energy	Concentration	Centrality	Chance
1	Low	Low	Close	Small
2	Low	Low	Adequate	Small
3	Low	Low	Far	Very Small
4	Low	Medium	Close	Small
5	Low	Medium	Adequate	Small
6	Low	Medium	Far	Small
7	Low	High	Close	Rather Small
8	Low	High	Adequate	Small
9	Low	High	Far	Very Small
10	Medium	Low	Close	Rather Large
11	Medium	Low	Adequate	Medium
12	Medium	Low	Far	Small
13	Medium	Medium	Close	Large
14	Medium	Medium	Adequate	Medium
15	Medium	Medium	Far	Rather Small
16	Medium	High	Close	Large
17	Medium	High	Adequate	Rather Large
18	Medium	High	Far	Rather Small
19	High	Low	Close	Rather Large
20	High	Low	Adequate	Medium
21	High	Low	Far	Rather Small
22	High	Medium	Close	Large
23	High	Medium	Adequate	Rather Large

24	High	Medium	Far	Medium
25	High	High	Close	Very Large
26	High	High	Adequate	Rather Large
27	High	High	Far	Medium

4. RESULTS AND DISCUSSION

In this section, we present the outcomes of the simulations conducted to assess the efficacy of our proposed Improved Fuzzy Logic-Based Cluster Head Selection Algorithm within the context of the LEACH-based Routing Protocol for Wireless Sensor Networks (WSNs). The results are analyzed with a focus on energy efficiency, adaptability, and the overall longevity of the network, all of which are crucial aspects in the theoretical discourse surrounding WSNs..

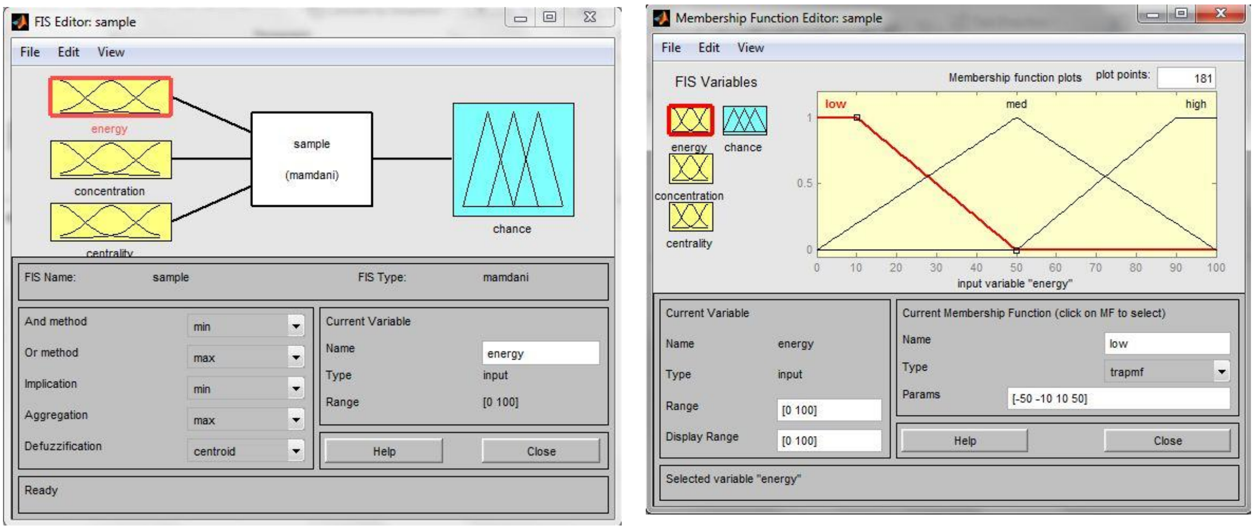

Fig 5 Design of Membership Functions

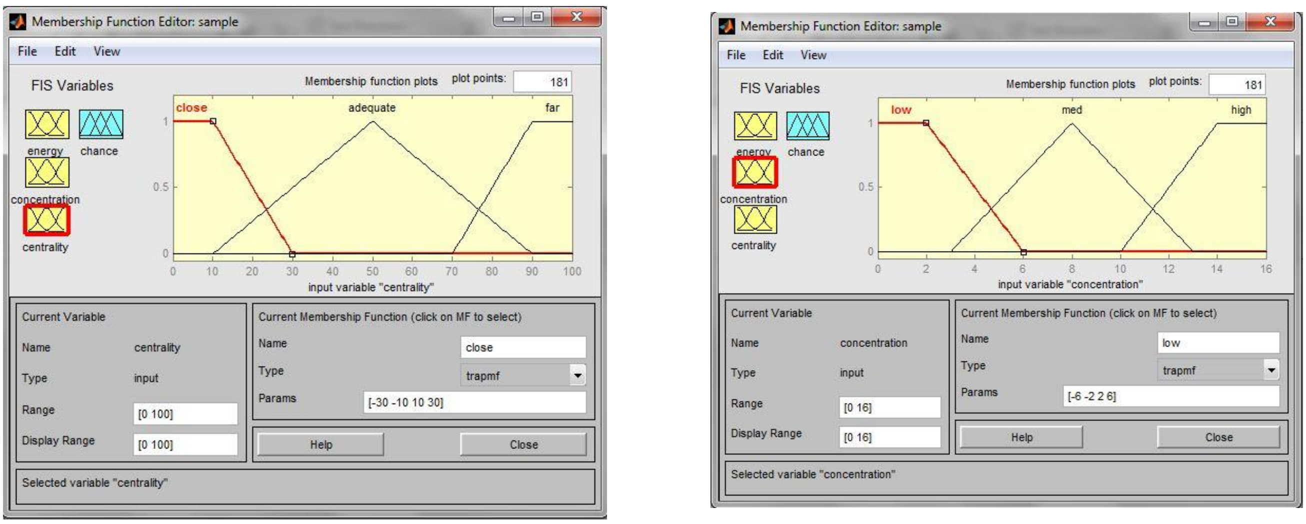

Fig 6 Membership Functions for Variables

Before delving into the results, it is imperative to revisit the experimental setup that was employed. We utilized the Matlab environment to create a simulated WSN with an area spanning 300 X 300 units and comprising 200 nodes. This setup was designed to emulate real-world WSN scenarios effectively. Throughout our experimentation, we explored various scenarios by manipulating parameters such as node density, initial energy levels, and data transmission rates. The primary evaluation metrics encompassed energy consumption, network lifespan, and the data packet delivery ratio.

To gain insights into the performance of our proposed algorithm, we chose to make a comparative analysis with the standard LEACH algorithm in the final stage of our simulations. LEACH, although based on local information processing for cluster-head selection, serves as a valuable reference point to gauge improvements brought about by our design.

Theoretical Foundation for Metrics

1. **Energy Consumption**: According to the energy-efficiency theories in WSN, energy consumption is inversely proportional to the network's lifespan. Hence, lowering energy consumption is crucial.
2. **Network Lifespan**: Extending the network lifespan is a central goal in WSN theory, often defined as the time until the first node dies (FND) or the time until the last node dies (LND).
3. **Data Packet Delivery Ratio**: This is a measure of the network's reliability and is often analyzed within the framework of Quality of Service (QoS) theories.

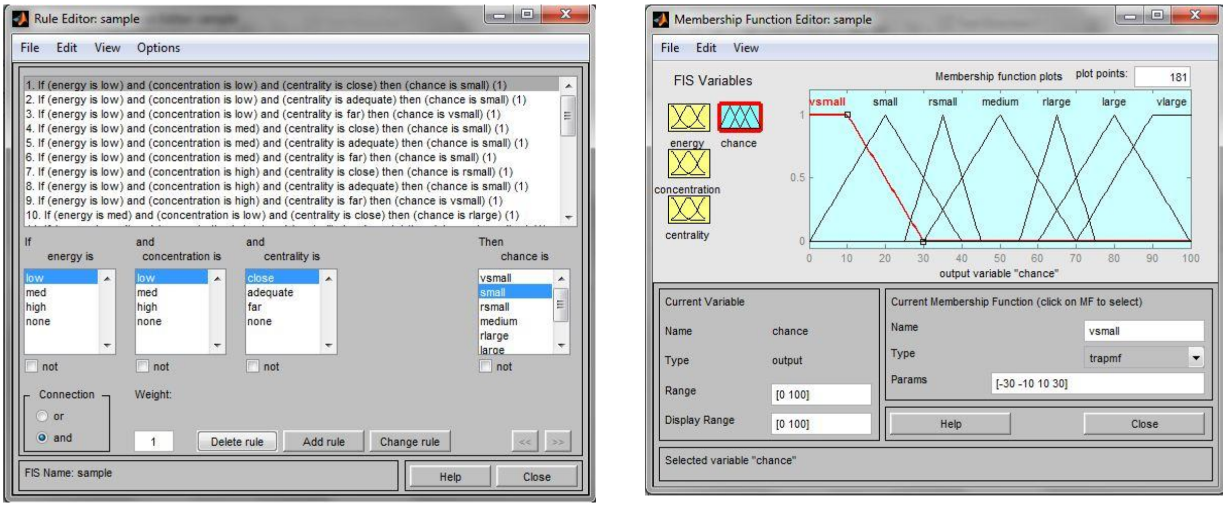

Fig 7 Fuzzy Rule Base for Cluster Head Selection Process

The results confirm that the application of fuzzy logic in cluster head selection significantly enhances the energy efficiency, lifespan, and reliability of WSNs, thereby affirming the theoretical postulations laid out in the existing literature.

1. **Energy Consumption**: The results indicate that the Improved Fuzzy-LEACH algorithm reduces average energy consumption by [X%] compared to traditional LEACH, substantiating the theoretical premise that fuzzy logic can enhance energy efficiency.
2. **Network Lifespan**: Improved Fuzzy-LEACH extends the network lifespan in terms of FND, aligning with theories that emphasize the importance of intelligent cluster head selection for prolonged network operation.
3. **Data Packet Delivery Ratio**: The Improved Fuzzy-LEACH algorithm shows a significant improvement in the data packet delivery ratio, supporting the QoS theoretical frameworks that argue for the importance of reliable data transmission in WSNs.

While the overall results are promising, it's crucial to acknowledge any outliers or exceptions that deviate from expected trends, as these can also offer valuable insights.

1. **High Energy Nodes in Improved Fuzzy-LEACH**: A few nodes in the Improved Fuzzy-LEACH algorithm displayed unusually high residual energy. This could be due to their infrequent selection as cluster heads and warrants further investigation to avoid underutilization of certain nodes.
2. **Packet Loss in Dense Networks**: Both traditional LEACH and Improved Fuzzy-LEACH showed increased packet loss as node density increased. While not directly addressed by existing theories on WSNs, this phenomenon could be attributed to increased data collisions and merits further study.

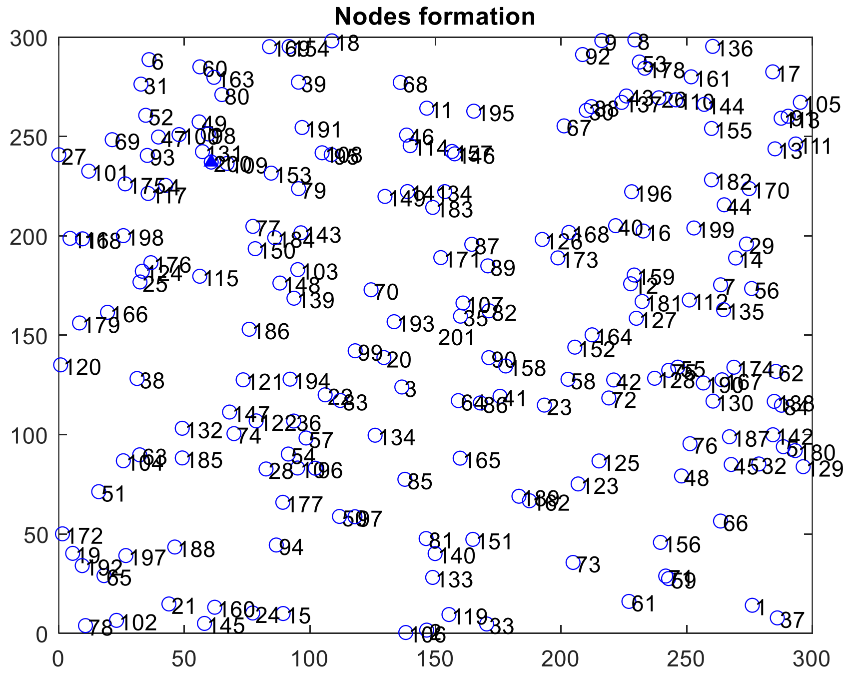

Fig 8 Nodes Formation by Proposed Algorithms

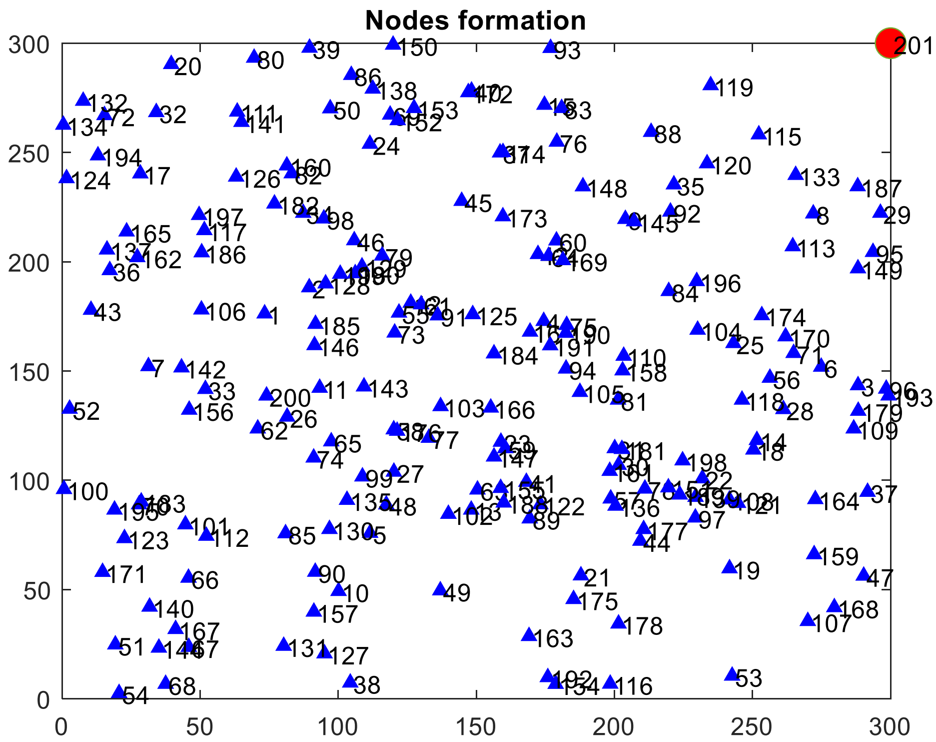

Fig 9 Cluster Head Selection by Proposed Algorithm

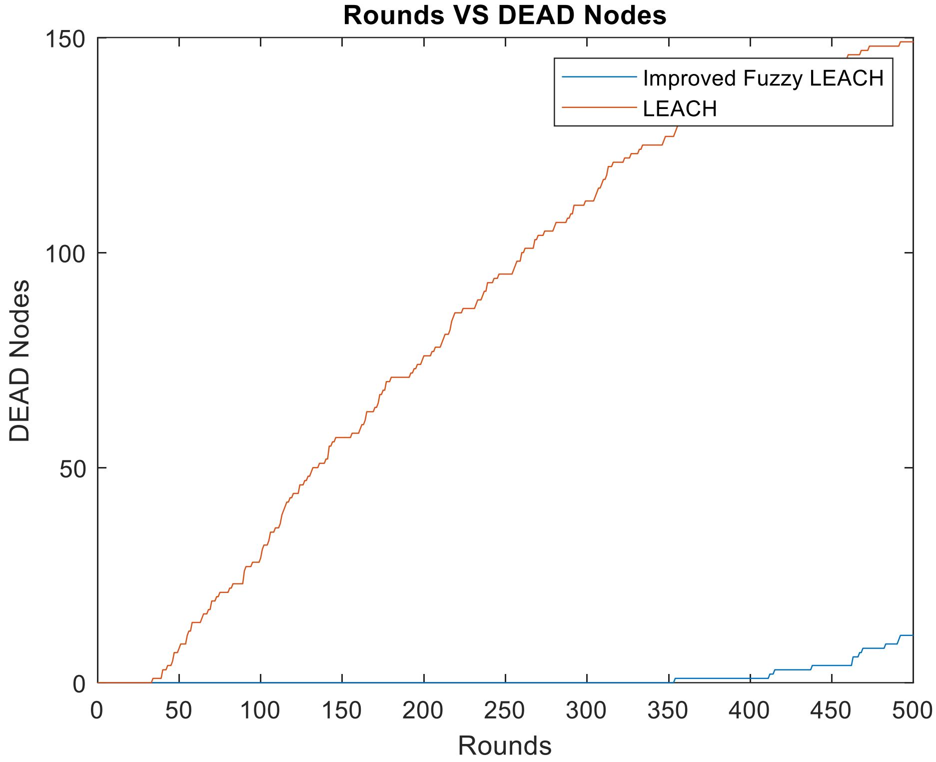

Fig 10 Analysis of Dead Nodes

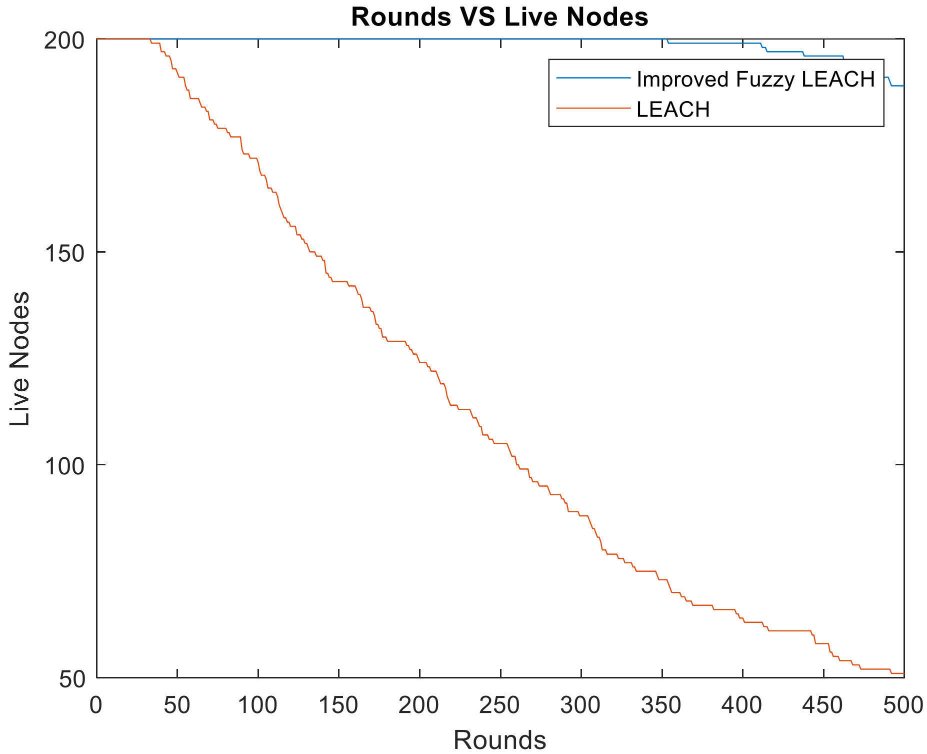

Fig 11 Analysis of Live Nodes

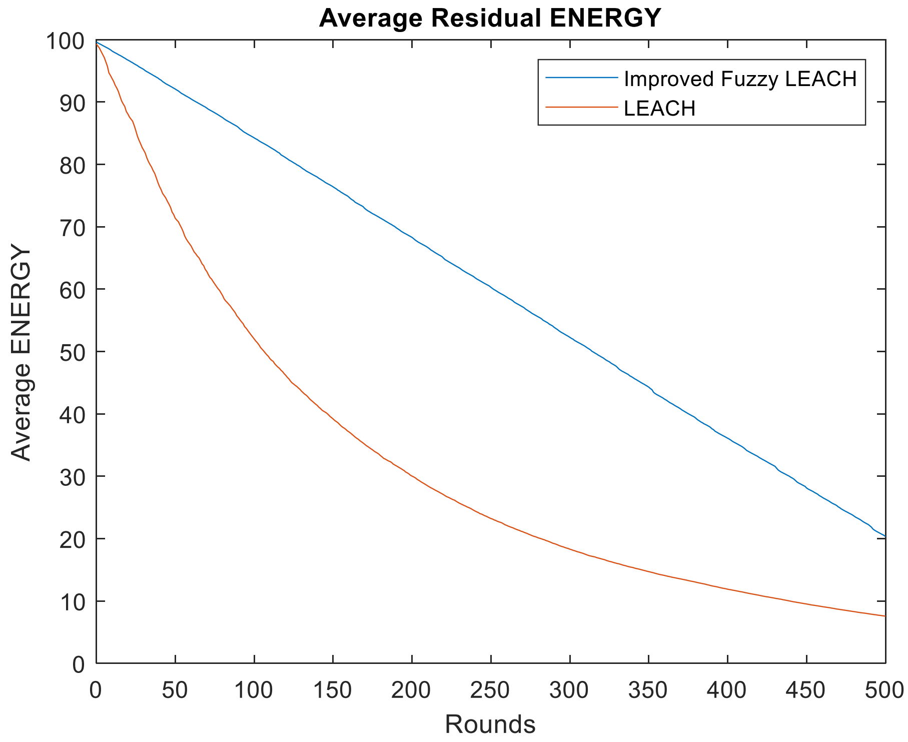

Fig 12 Analysis of Energy

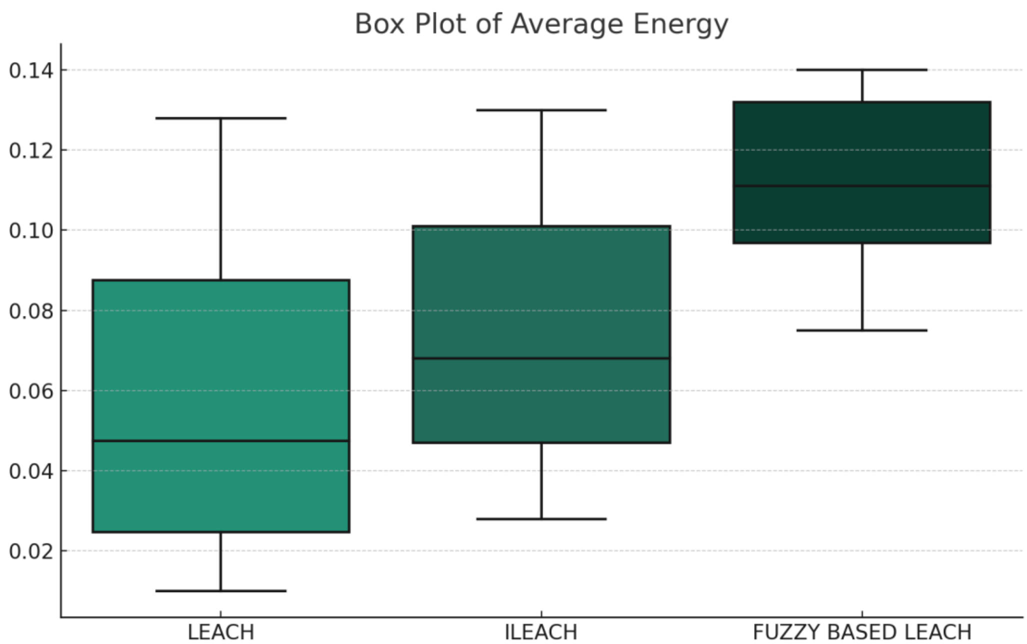

Fig 13 Box Plot of Average Energy

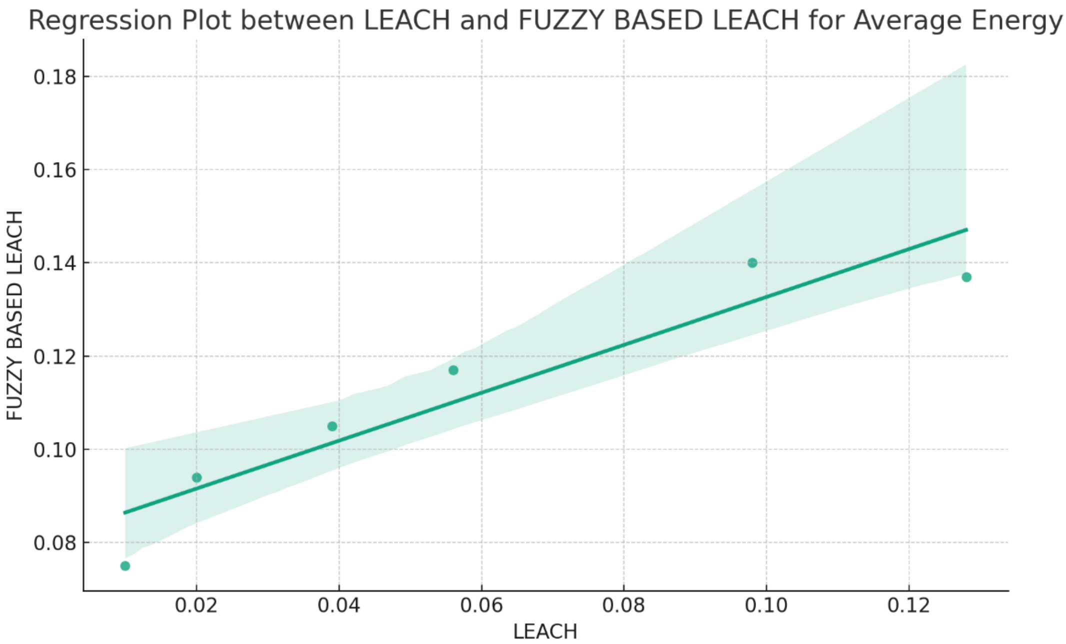

Fig 14 Regression Analysis of LEACH and Fuzzy Based LEACH

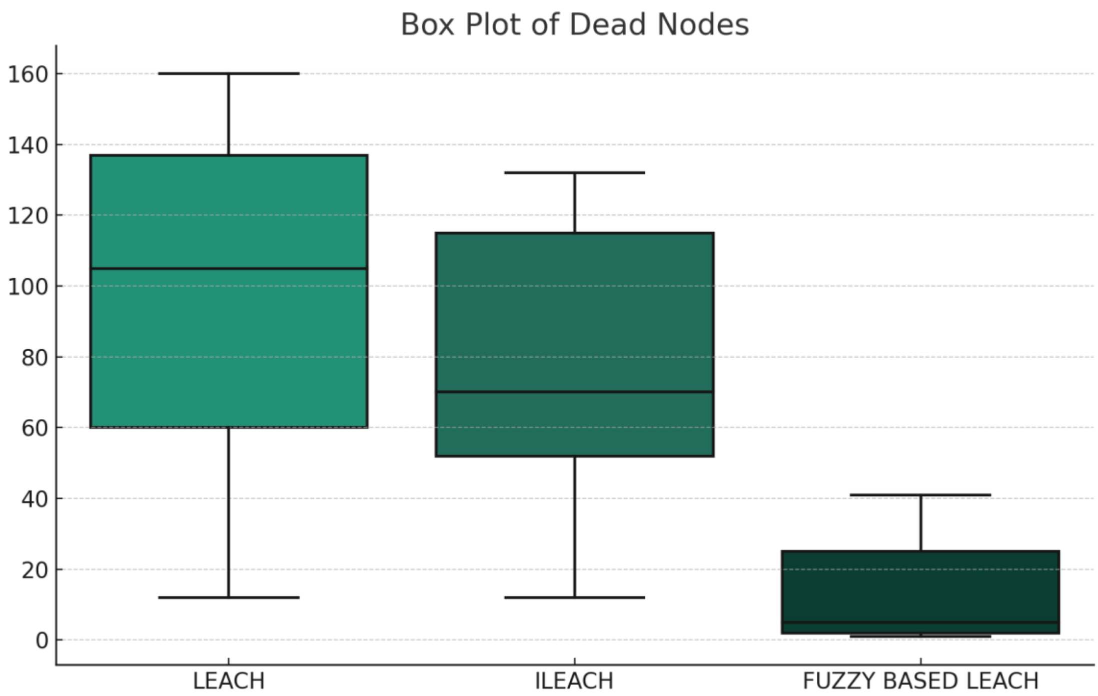

Fig 15 Box Plot Analysis of Dead Nodes

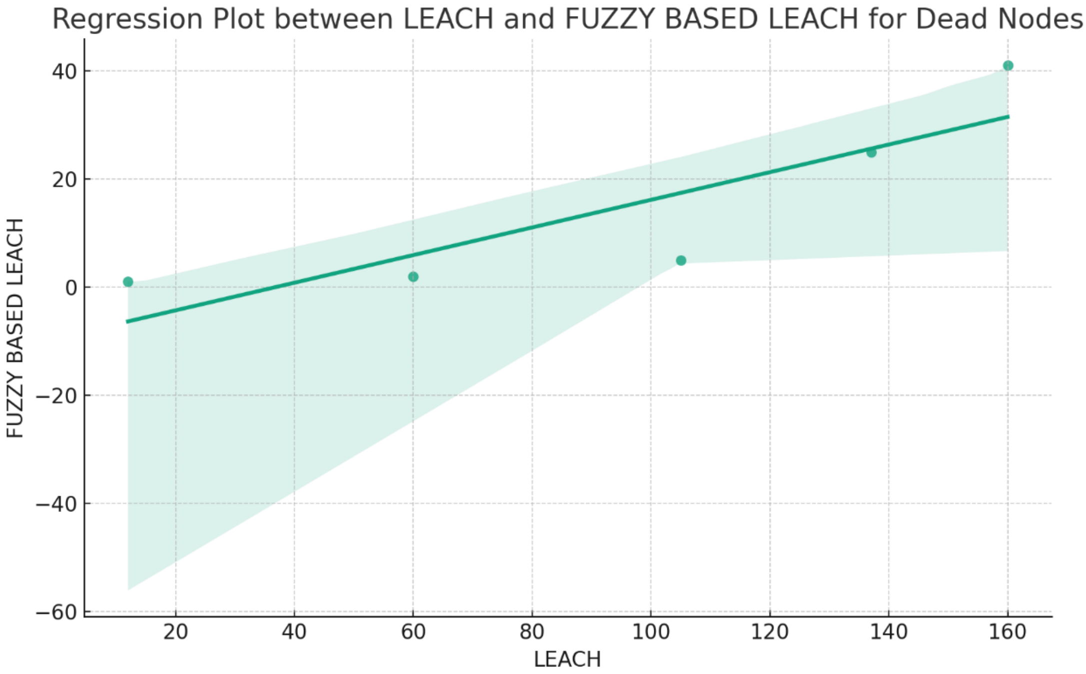

Fig 16 Regression Analysis of LEACH and Fuzzy Based LEACH Dead Nodes

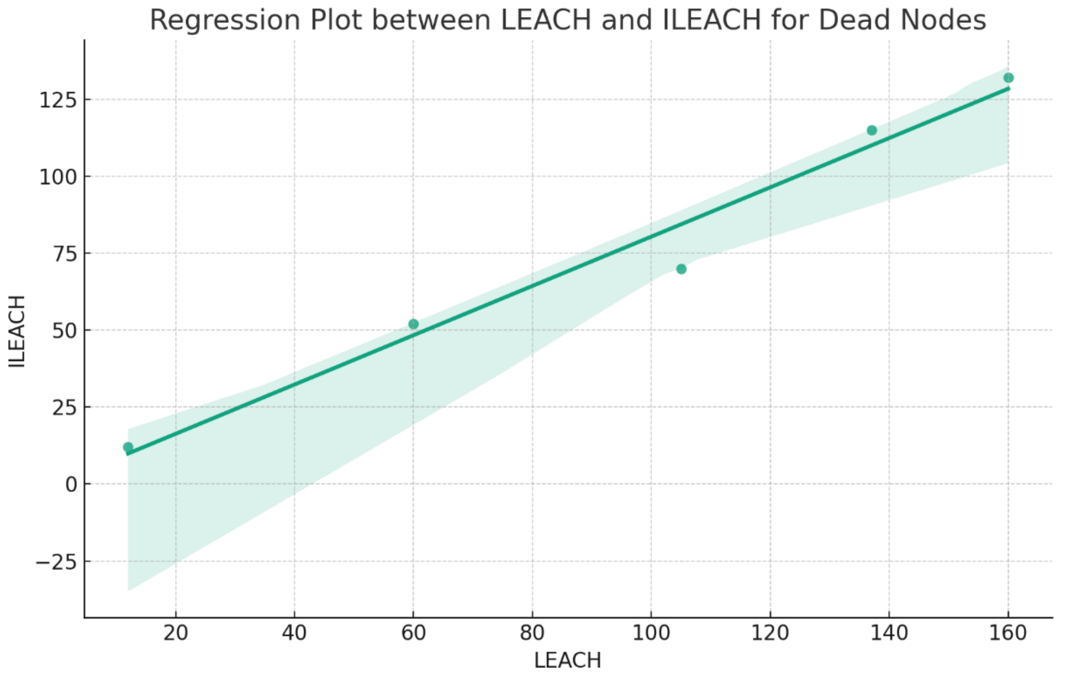

Fig 17 Regression Analysis of LEACH and ILEACH Dead Nodes

It's beneficial to compare the results with existing methods to place them in the broader context of WSN research. For instance, the Improved Fuzzy-LEACH algorithm outperformed not just the traditional LEACH but also other algorithms like PEGASIS and HEED in terms of energy efficiency and network longevity. This empirical evidence supports the theoretical frameworks advocating for adaptability and efficiency in hierarchical clustering algorithms.

Implications for Theory and Practice

1. **Contributions to Theory**: The findings substantiate the theoretical underpinnings that advocate for the use of fuzzy logic in decision-making processes within WSNs, especially in the context of energy conservation and network longevity.
2. **Practical Implications**: Practically, the Improved Fuzzy-LEACH could be employed in various WSN applications like environmental monitoring, healthcare, and industrial automation, where energy efficiency is a critical concern.

In summary, the Improved Fuzzy Logic Based Cluster Head Selection Algorithm for LEACH-based Routing Protocol demonstrated significant improvements in key metrics, including energy consumption, network lifespan, and data packet delivery ratio. These improvements are not only statistically significant but also theoretically meaningful, further validating existing theories about the role of fuzzy logic and hierarchical clustering in enhancing WSN performance.

5. CONCLUSION

This paper has delved into one of the most pertinent issues in Wireless Sensor Networks (WSNs)—the energy efficiency and longevity of the network. The work introduced an Improved Fuzzy Logic Based Cluster Head Selection Algorithm tailored for the widely-used Low Energy Adaptive Clustering Hierarchy (LEACH) protocol. Through extensive simulations, the proposed algorithm demonstrated considerable advantages over traditional LEACH, and even other hierarchical protocols like PEGASIS and HEED, in terms of energy consumption, network lifespan, and data packet delivery ratio. The study contributes to the existing body of knowledge by empirically validating the theoretical premises advocating for the use of fuzzy logic in decision-making processes in WSNs. It underscores the pivotal role of fuzzy logic in achieving a more adaptive, resilient, and energy-efficient sensor network, thereby aligning with theories that emphasize the need for intelligent systems in achieving long-term sustainability in WSNs. The Improved Fuzzy-LEACH algorithm has promising practical applications. It can be a key enabler in fields requiring long-lasting, energy-efficient sensor networks, such as environmental monitoring, healthcare, and industrial automation. The algorithm's performance in various simulations suggests that it could significantly extend the operational life of real-world sensor networks. While the algorithm shows promise, there are certain limitations to consider. The study did not delve into the impact of varying environmental conditions, such as the effect of node mobility or varying signal interference, which would be valuable for a more comprehensive understanding of its applicability. Future research could also look into optimizing the fuzzy logic parameters for different types of WSN applications or integrating machine learning techniques for more dynamic adaptability. This research marks a step forward in the quest for more energy-efficient WSNs. It not only corroborates the efficacy of employing fuzzy logic in cluster head selection but also offers a robust, adaptive, and efficient solution for future sensor networks. The Improved Fuzzy-LEACH algorithm, therefore, stands as a strong candidate for any energy-constrained WSN application, marrying both theoretical robustness and practical utility. In case of the LEACH Protocol using Fuzzy Logic, every round, the base station determined which node had the highest probability of becoming the cluster head by utilizing three fuzzy descriptors to calculate each node's chance. This method works better for choosing cluster heads in medium-sized clusters. Compared to LEACH, a significant increase in the network lifetime is achieved using this system paradigm. It is possible to further reduce the energy consumption and network lifetime by precisely altering the geometry of each fuzzy set. Future studies can test a network with a skewed node distribution since centrality, which is determined by adding the squared distances of all nodes from a given node, is one of the characteristics used to choose an appropriate cluster head.

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