Wireless Sensor Networks Cluster Head Selection using Fuzzy Logic

Report of the Project

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Abstract: - Wireless Sensor Networks (WSNs) are critical for real-time monitoring in smart systems, but energy-efficient cluster head (CH) selection remains a key challenge. This paper proposes a hybrid intelligent system that integrates Fuzzy Logic to evaluate CH probability based on residual energy, node density, and distance to the base station. A Python-based simulation environment leverages NumPy for computations and Matplotlib for visualizing node deployment and CH selection. The fuzzy controller assigns a CH probability score to each node, with the highest scorer elected as CH. The system incorporates a Streamlit-driven user interface and OpenCV for camera-based visualization, enabling real-time monitoring of the sensor environment. Experimental results demonstrate that this approach enhances energy efficiency, extends network lifetime, and improves data transmission reliability through intelligent CH selection.

1. Introduction

- **Wireless Sensor Networks (WSNs)** have emerged as a foundational technology in modern distributed monitoring systems. Comprising numerous sensor nodes distributed across a spatial area, WSNs autonomously collect and transmit data about environmental or physical parameters such as temperature, pressure, sound, and motion. These networks play a crucial role in a wide range of applications, from environmental monitoring to industrial automation and smart infrastructure.
- Each sensor node in a WSN is typically energy-constrained and equipped with limited computational resources. The nodes gather data from their surroundings and forward it—either directly or through intermediate nodes known as **Cluster Heads (CHs)**—to a central base station for further processing and analysis. The efficiency of communication and data aggregation within WSNs is vital, as it directly impacts the network's lifetime and overall stability.
- Recent advances in WSN research have explored the use of **fuzzy logic-based** techniques for CH selection. These methods leverage the ability of fuzzy systems to handle uncertainty and imprecise information, enabling more effective evaluation of sensor nodes based on multiple criteria such as residual energy, node density, and proximity to the base station. By adopting such intelligent approaches, WSNs can achieve more balanced energy consumption and improved communication efficiency, paving the way for robust and scalable monitoring solutions.

2. Problem Statement

Wireless Sensor Networks (WSNs) are increasingly deployed for monitoring and data collection in diverse environments, leveraging numerous resource-constrained sensor nodes. Efficient data aggregation and transmission are essential for maximizing network performance and longevity.Here are Problems -

1. **Energy Consumption Imbalance:** Sensor nodes possess limited battery resources, yet CHs are burdened with additional tasks such as data aggregation and long-range communication.
2. **Dynamic Network Conditions:** WSNs are subject to frequent changes in network topology, node density, and energy levels due to environmental factors or node mobility.
3. **Network Lifetime and Stability:** Without intelligent and adaptive mechanisms for CH selection, WSNs experience reduced stability and shortened operational lifetimes, compromising their reliability and effectiveness in critical applications.
4. **Communication Overhead:** Inefficient CH selection can cause redundant transmissions and increased communication overhead, further draining limited energy resources.
5. **Uncertainty and Imprecise Information:** The real-world deployment of WSNs introduces uncertainties and imprecise data regarding node energy, distances to the base station, and node distribution.

3. Objectives

The main goals behind deploying Wireless Sensor Networks (WSNs) in various environments

1. Real-Time Monitoring and Data Collection
2. Maximizing Coverage and Connectivity
3. Robustness and Fault Tolerance
4. Security and Data Integrity
5. Scalability and Cost Effectiveness

4. Literature Review

Wireless Sensor Networks (WSNs) are increasingly deployed for real-time monitoring in environmental, industrial, and urban contexts.a variety of methodologies have been developed to address this issue, each with distinct advantages and limitations-

1. **Stable Election Protocol (SEP)**:

Smaragdakis et al. introduced the Stable Election Protocol (SEP), which improves network lifetime in heterogeneous WSNs by assigning weighted election probabilities based on initial node energy. SEP selects CHs by considering both residual energy and average network energy, thereby stabilizing the election process. However, SEP fails to adapt to real-time changes in node density and varying distances to the base station, limiting its effectiveness in dynamic scenarios.

2. **Power-Efficient Gathering in Sensor Information Systems (PEGASIS):**

Lindsey and Raghavendra proposed PEGASIS, which organizes nodes into a chain, with each node communicating only with its nearest neighbor. A designated chain leader transmits aggregated data to the base station. PEGASIS significantly reduces transmission energy, it can introduce substantial delays in large networks due to long chain paths and does not support dynamic cluster formation

3. **Low-Energy Adaptive Clustering Hierarchy (LEACH):**

Heinzelman et al. developed LEACH, a protocol that randomly rotates CH roles to distribute energy consumption more evenly among nodes. LEACH is notable for its energy efficiency and scalability but does not account for residual energy, node density, or proximity to the base station when selecting CHs. As a result, its performance is suboptimal in real-world, dynamic environments.

4. **Density-Based Fuzzy Clustering Models:**

Sharma and Batra introduced a density-based fuzzy clustering model that considers not only residual energy but also local node density and communication overhead in CH selection. This model reduces redundant data transmission and enhances scalability, especially in dense networks.

5. **Fuzzy Logic-Based Clustering Protocols:**

Ameer et al. proposed a fuzzy logic-based clustering protocol that selects CHs using multiple parameters such as residual energy, node centrality, and distance to the base station. A Fuzzy Inference System (FIS) computes a suitability score for each node, and those with higher scores are chosen as CHs. This approach effectively handles uncertainty and variability in dynamic networks, resulting in improved energy balancing and network longevity.

5. System Architecture

Wireless Sensor Networks (WSNs) are distributed systems comprised of numerous sensor nodes that autonomously monitor physical or environmental conditions (such as temperature, pressure, or motion) and communicate the collected data to a central Base Station (BS). These sensor nodes are typically energy-constrained and possess limited computational and communication capabilities.

A critical challenge in WSNs is the selection of **Cluster Heads (CHs)**—special nodes that aggregate data from their cluster members and relay it to the BS. Traditional CH selection methods often fail to adapt to dynamic network conditions, leading to inefficient energy usage and reduced network lifetime.

1. Clustering in WSNs

Clustering is a widely-used approach to reduce communication overhead and conserve energy in WSNs. In this architecture:

- **Sensor nodes are grouped into clusters.**
- **Each cluster elects a Cluster Head (CH).**
- **CHs aggregate and forward data to the BS, reducing redundant transmissions and balancing**

2. Fuzzy Logic-Based Cluster Head Selection

Fuzzy logic is employed to handle uncertainties and imprecise information inherent in real-world WSN deployments. The system uses a **Fuzzy Inference System (FIS)** that evaluates each node based on:

- **Residual Energy: Remaining battery power of the node.**
- **Node Density: Number of neighboring nodes within communication range.**
- **Distance to Base Station: Proximity affects energy required for data transmission.**

3. System Components

- **Sensor Nodes:** Small, energy-limited devices deployed in the monitoring area.
- **Cluster Heads (CHs):** Nodes selected (via fuzzy logic) to manage clusters and communicate with the BS.
- **Base Station (BS):** Centralized node that collects aggregated data from CHs.
- **Fuzzy Inference System (FIS):** Decision-making engine for CH selection.
- **User Interface:** Streamlit-based GUI for real-time parameter adjustment and monitoring.
- **Visualization Tools:** Matplotlib for graphical representation, OpenCV for camera-based real-time visualization.

6. Fuzzy Logic Approach

Traditional cluster head (CH) selection algorithms in Wireless Sensor Networks (WSNs) often rely on fixed thresholds or deterministic rules. These methods struggle to adapt to real-world uncertainties, such as:

- **Dynamic energy levels.**
- **Varying node densities.**
- **Changing distances to the base station.**
- **Unpredictable environmental conditions.**

Input Parameters (Fuzzy Variables):

The fuzzy logic system evaluates each sensor node for CH candidacy based on three key parameters:

1. **Residual Energy**

   The remaining battery power of the node.

2. **Node Density**

   The number of neighboring nodes within communication range.

3. **Distance to Base Station**

   How far the node is from the central base station.

Each parameter is fuzzified which can converted into linguistic variables such as "Low," "Medium," or "High."

Fuzzy Inference System (FIS) Structure:

The FIS uses a set of if- then rules to combine these fuzzified inputs and assess the suitability of each node for becoming a CH.

For example:

- If residual energy is High and node density is High and distance to BS is Low, then suitability is Very High.
- If residual energy is Low or distance to BS is High, then suitability is Low.

Defuzzification:

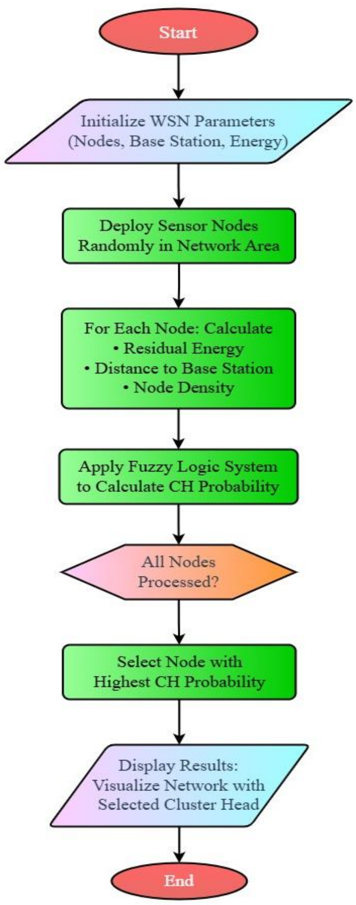
The FIS outputs a fuzzy suitability score for each node (e.g., between 0 and 1). This score is then "defuzzified" (converted to a crisp value), and nodes with the highest scores are selected as cluster heads.

Implementation Highlights:

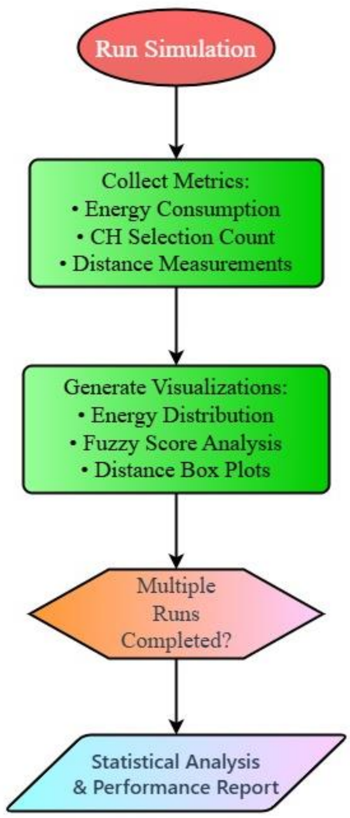
- Simulation Environment: Built using Python, NumPy, and Matplotlib for visualization.
- Real-Time Monitoring: Streamlit-based UI allows users to adjust parameters and see CH selection in real time.
- Camera Integration: OpenCV provides real-world visualization and overlays.

7. <u>Proposed Flowchart</u>

Main Algorithm Flowchart



Performance Evaluation Flowchart



8. <u>Tools and Technologies Used</u>

To build this simulation for cluster head selection in WSNs using fuzzy logic, a combination of Python libraries and development tools was used. Each tool played a specific role in bringing the logic and visuals to life:

1. **Python**: Python was the core language used throughout the project. Its simplicity and the vast availability of scientific libraries made it ideal for both implementing fuzzy logic and building the interface.
2. **NumPy**: NumPy was used for mathematical operations like generating random positions for nodes, calculating distances, and handling arrays efficiently.
3. **Matplotlib:** For plotting the Wireless Sensor Network, Matplotlib helped visualize node positions, the base station, and the selected cluster head in a clear and interactive way.
4. **Pandas**: Pandas was used to organize the simulation data into a structured table format, making it easier to display and understand node-wise results.
5. **scikit-fuzzy (skfuzzy)**: This library was central to the project. It enabled the implementation of fuzzy logic — defining membership functions, setting up fuzzy rules, and making decisions based on multiple parameters like energy, distance, and node density.
6. **Streamlit**: Streamlit provided a user-friendly web interface where the simulation runs dynamically. With sliders, buttons, and real-time charts, it became easy to interact with the model without needing any programming knowledge.
7. **Time & OS Modules:** These built-in Python modules helped manage the timing of simulation reruns and added basic system-level support like random seed initialization.
8. **Development Environment**: The code was run in a Python environment with all dependencies managed using a virtual environment. Streamlit also makes it possible to deploy this as a simple web app, even without a full backend setup.

9. <u>Experimental Setup</u>

A simulation has been conducted to analyze the performance of the suggested fuzzy logic-based Cluster Head (CH) selection system in Wireless Sensor Networks (WSNs). The goal is to measure CH selection efficiency, energy efficiency, and network lifetime enhancement under dynamic node placements.

A 100m × 100m square simulation area is assumed, with randomly distributed sensor nodes. The Base Station (BS) is fixed at point (50, 50). The number of sensor nodes ranges from 20 to 100, and each sensor node has an initial amount of 10 Joules of energy. Nodes are set to communicate at a distance of 25–40 meters and are presumed to be stationary during each simulation round.

Streamlit-based User Interface enables runtime modification of parameters like the number of nodes, energy levels, and weights of fuzzy rules. The OpenCV module serves for real-time frame grab and image overlay, visually representing sensor node status.

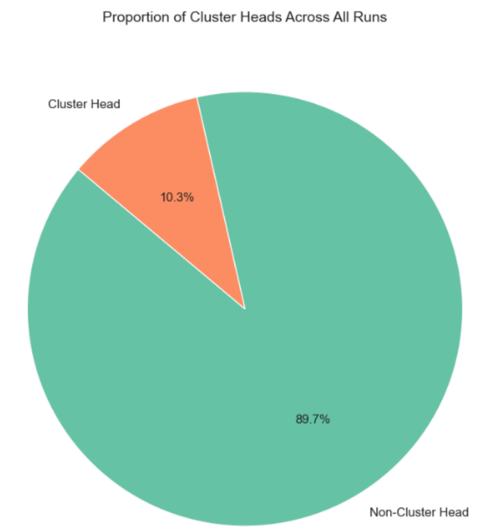
Simulation is performed utilizing Python 3.10, with the required libraries being NumPy (for numerical computation), Matplotlib (for plotting), OpenCV (for camera interfacing), and Streamlit (for web-based GUI development).

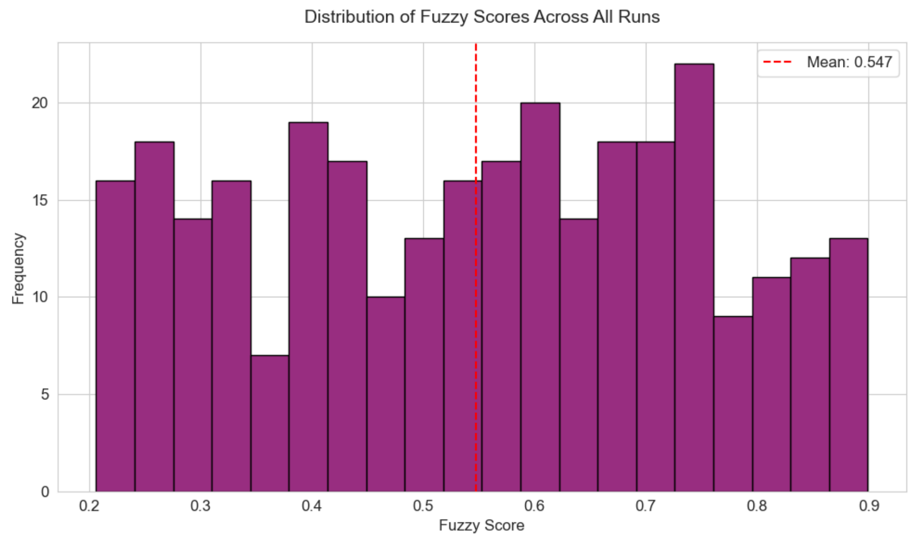
10. <u>Result and Analysis</u>

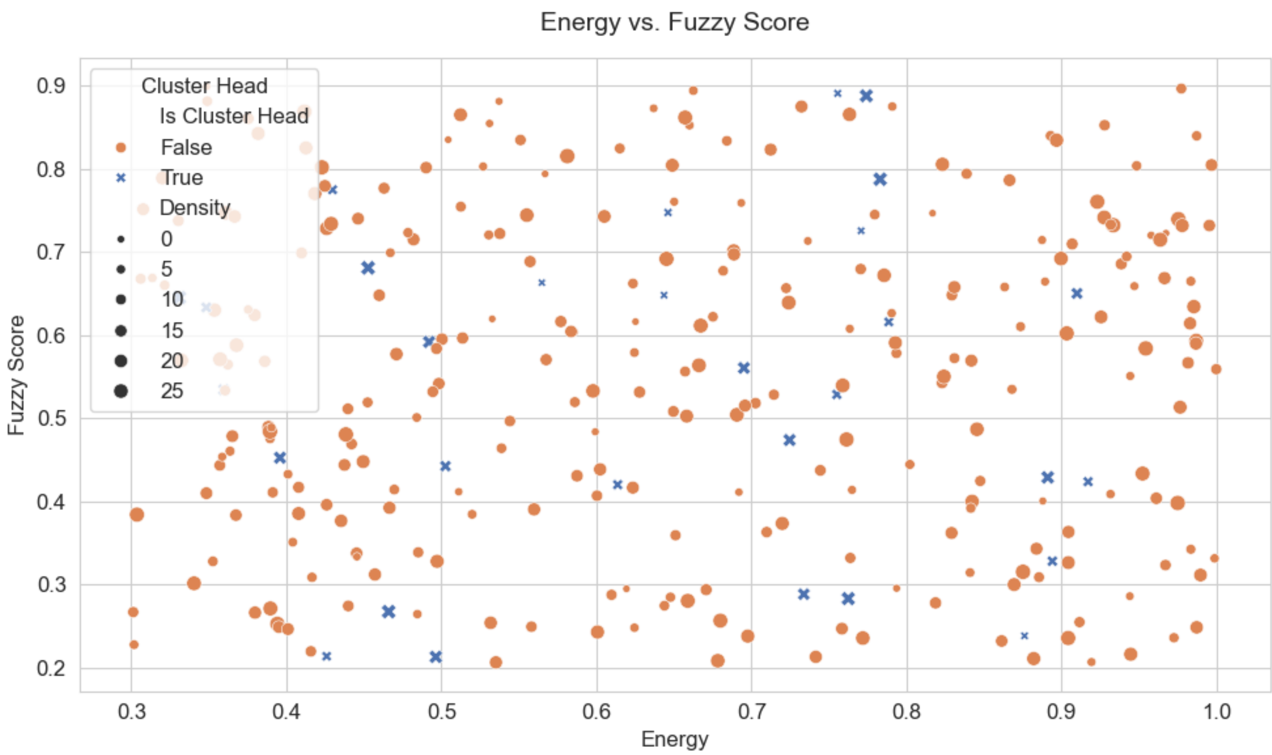
The analysis of the sensor network data across ten runs, as depicted in the provided graphs, reveals key insights into the performance metrics of the nodes. The "Average Energy per Run" bar graph indicates that the average energy levels fluctuate between 0.582 and 0.693, with Run 1 having the highest average energy (0.682) and Run 4 the lowest (0.582), suggesting variability in energy conservation across runs. The "Distribution of Fuzzy Scores Across All Runs" histogram shows a mean fuzzy score of 0.547, with a significant concentration of scores around 0.5, indicating that many nodes have a balanced suitability for cluster head selection, though a smaller group exhibits higher scores (0.7–0.9), reflecting better candidacy. The "Energy vs. Fuzzy Score" scatter plot highlights that nodes with higher fuzzy scores (above 0.6) often have

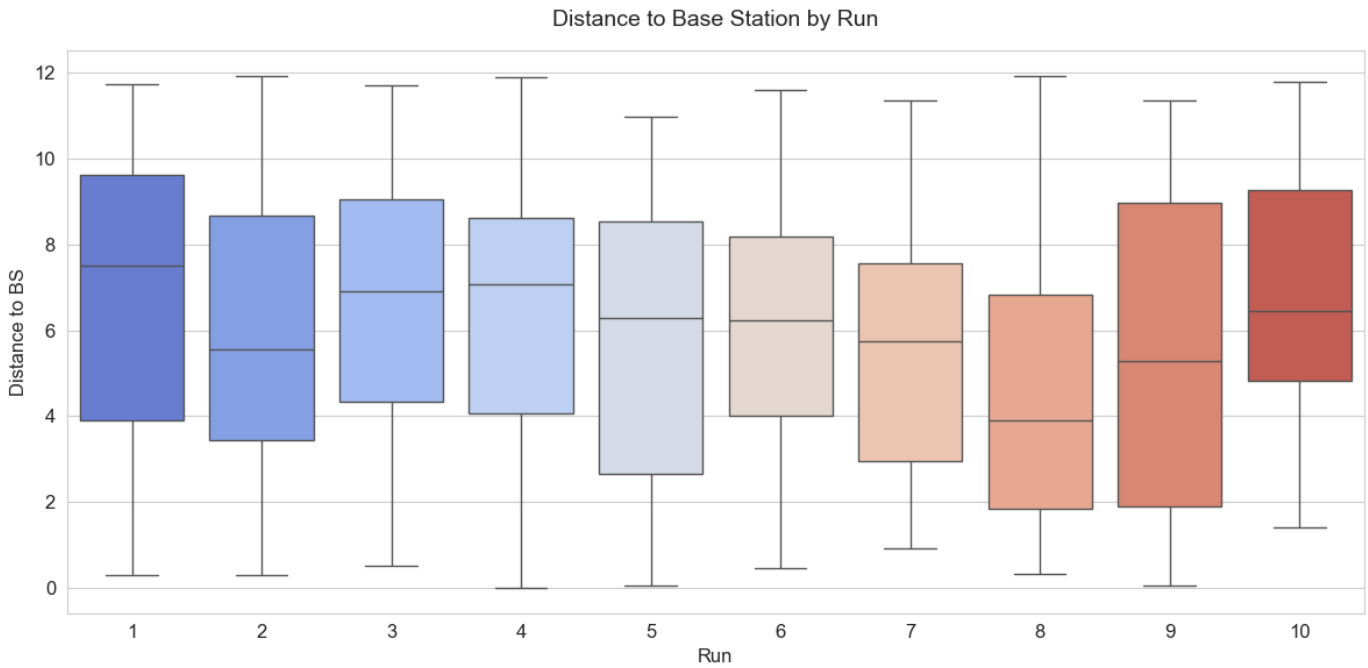
higher energy levels (above 0.7), and cluster heads (marked with blue 'x') are predominantly in this high-energy, high-fuzzy-score region, suggesting effective cluster head selection based on these metrics. The "Distance to Base Station by Run" box plot shows that the median distance to the base station varies between approximately 4 and 8 units, with Run 4 having the highest median (around 8) and Run 2 the lowest (around 4), indicating variability in node placement relative to the base station. Finally, the "Proportion of Cluster Heads Across All Runs" pie chart reveals that only 10.3% of nodes are selected as cluster heads, with 89.7% being non-cluster heads, reflecting a selective cluster head assignment strategy.

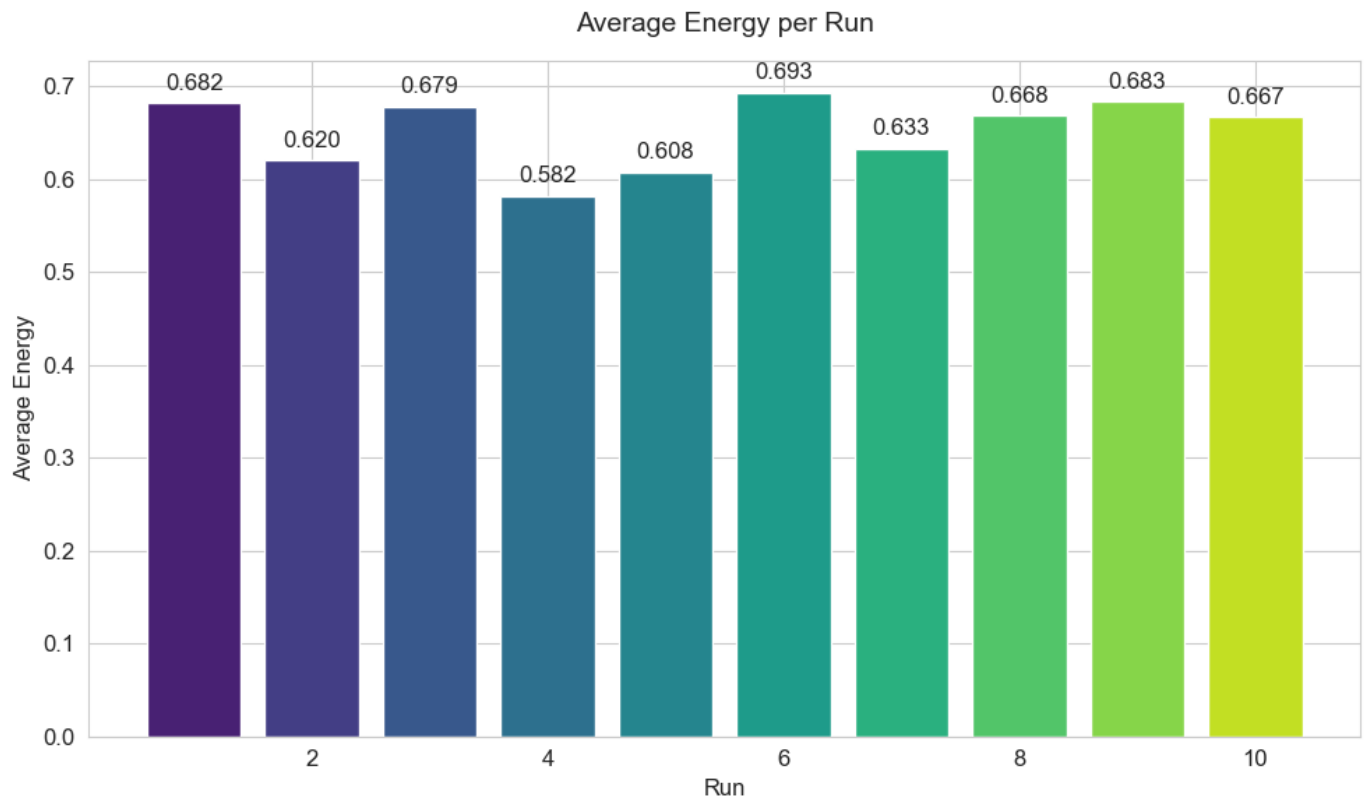
Some of the Graphs Based on the Data We've Collected:











11. Conclusion

The results indicate a strategic selection of cluster heads, favouring nodes with higher energy and fuzzy scores, as evidenced by the scatter plot, while maintaining a low proportion of cluster heads (10.3%) to optimize network efficiency. However, the variability in energy levels and distances to the base station across runs suggests potential inconsistencies in node deployment and energy management, which could be addressed to enhance overall network performance.

12. Future Scopes

This project lays the groundwork for intelligent cluster head selection using fuzzy logic, but there's plenty of room to grow and improve. Some promising future directions include:

1. **Real-Time Data Integration**: Instead of relying on simulated values, the model can be extended to work with real-time sensor data from actual WSN deployments, making it more practical and realistic.
2. **Adding More Parameters**: Future versions can include additional decision factors like node mobility, traffic load, or signal strength to improve the accuracy and efficiency of cluster head selection.
3. **Machine Learning Hybrid Models:** Combining fuzzy logic with machine learning techniques like reinforcement learning or genetic algorithms could allow the system to learn and adapt over time.
4. **Security-Aware Cluster Head Selection**: Integrating trust or security levels as a parameter could ensure that only reliable nodes become cluster heads—especially important for sensitive applications.
5. **Scalability and Real Deployment:** The system can be scaled to handle hundreds or thousands of nodes and deployed on real IoT or edge devices for smart cities, agriculture, or environmental monitoring**.**

13. References

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14. Individual Contribution

Group Members & their contributions:

- **Tushar Gupta**: Dataset Collections, Generating the data for the graphs, Graph Generation
- **Nitish Kumar Choubey**: Code & Working on the models, Documentation Work, Formatting
- **Harshit Singhal**: Contents for the Documentation, Draw.io Flow Chart Diagrams
- **Nikhil Nagar**: Exploring the research papers for reference.
- **Devansh Bansal:** Content for the various topics of the Documentation, Research Work, Word Format