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A Survey on The Advancement of WSN LEACH Protocol

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ABSTRACT :

This review paper comprehensively analyzes Wireless Sensor Networks (WSNs), focusing particularly on the LEACH protocol and its variants. Through a comparative study of different selection algorithms and key parameters such as energy efficiency, network lifespan, and data aggregation, the paper offers insights into their effectiveness in WSN applications. LEACH, renowned for its role in prolonging network lifetime through dynamic cluster head selection and efficient data aggregation, is a foundational protocol. However, advancements in clustering algorithms like LEACH-C and E-LEACH have addressed limitations by optimizing cluster head selection criteria based on energy levels, distance to the base station, and network scalability. Furthermore, exploring machine learning-based routing strategies shows potential for further improving energy efficiency and data reliability in WSNs. This review highlights the ongoing evolution of WSN technologies and suggests directions for future research to meet the growing demands of IoT applications.

Keywords: Wireless Sensor Networks (WSNs), LEACH protocol, fuzzy logic, cluster head selection, energy efficiency, and data aggregation.

1. Introduction :

Wireless Sensor Networks (WSNs) represent a crucial advancement in monitoring and communication technologies, leveraging spatially distributed sensor nodes to collect and transmit data wirelessly. Each node in a WSN typically operates autonomously, gathering information about its environment such as temperature, humidity, or motion. The collected data is transmitted through a series of nodes to a central base station, which acts as the primary point for data aggregation and analysis. Within a WSN, sensor nodes are often organized into clusters to optimize communication efficiency and energy usage. Each cluster is managed by a cluster head, a designated node responsible for coordinating data transmission from the cluster members to the individual sensor nodes within the cluster to the base station. This hierarchical structure enhances the network's scalability and reliability, allowing it to efficiently manage resources and prolong the lifespan of the sensor nodes. The interplay between base stations, cluster heads, and cluster members forms the backbone of WSNs, enabling robust and flexible solutions for a wide range of applications, from environmental monitoring and smart agriculture to healthcare and industrial automation. Wireless sensor networks (WSNs) consist of several sensors, ranging from a few tens to thousands, characterized by self-organizing capabilities, low cost, and random deployment [1].[3]. These tiny sensor nodes are randomly distributed throughout the network area, detecting environmental signals and transferring the sensed data to a base station (BS). WSNs have been primarily used for applications such as habitat monitoring, disaster prevention, healthcare, agriculture, regional monitoring, and fire tracking [4].

2. Clustering Method in Wireless Sensor Network :

Clustering is a vital technique in Wireless Sensor Networks (WSNs) to enhance scalability, energy efficiency, and overall network performance. By organizing sensor nodes into clusters, where each cluster is managed by a cluster head, clustering methods reduce communication overhead and balance energy consumption. Various clustering algorithms have been developed, each with unique strategies for cluster formation and cluster head selection.

A. Low-Energy Adaptive Clustering Hierarchy (LEACH)

LEACH is one of the most popular clustering protocols in WSNs. It randomly selects cluster heads in each round, allowing nodes to rotate roles, thus evenly distributing the energy load among all nodes. Cluster heads aggregate data from cluster members and transmit it to the base station, minimizing direct communication between nodes and the base station. The LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol works by randomly selecting cluster heads and rotating this role to evenly distribute energy consumption among sensors in a Wireless Sensor Network (WSN). The key mathematical components of the LEACH protocol include the probability of a node becoming a cluster head, the energy consumption model, and the ground-based operation. Here are some important equations related to the LEACH protocol. The probability of becoming a cluster head is given in equation 1.

$$P(i) = \frac{p}{1-p(r * mod\frac{1}{p})} \quad \text{…………..(1)E}$$

where:

p is the desired percentage of cluster heads (e.g., 5% or 0.05), r is the current round number, and G is the set of nodes that have not been cluster heads in the last 1/p rounds.

B. Power-Efficient Gathering in Sensor Information Systems (PEGASIS)

PEGASIS forms chains of sensor nodes instead of clusters. Each node only communicates with a close neighbor, passing data along the chain to a randomly selected leader node, which then transmits the aggregated data to the base station. This method reduces the number of transmissions and balances energy consumption more evenly across nodes.

C. Hybrid Energy-Efficient Distributed Clustering (HEED

HEED extends LEACH by considering residual energy and node proximity for cluster head selection. Unlike LEACH, which selects cluster heads randomly, HEED aims to prolong network lifetime by ensuring that nodes with higher residual energy have a higher probability of becoming cluster heads**.**

D. Distributed Clustering Algorithm (DCA)

DCA uses a distributed approach for cluster formation, where each node independently decides to become a cluster head based on local information such as node degree and residual energy. This method reduces the need for global knowledge and can adapt to dynamic changes in the network**.**

E. 2.5 K – Means Clustering

K-means is a well-known algorithm adapted for WSNs to partition nodes into k clusters based on their positions. Initially, k nodes are chosen as centroids, and nodes are assigned to the nearest centroid. The centroids are then recalculated based on the mean position of nodes in each cluster. This iterative process continues until the centroids stabilize.

F. Fuzzy- Logic-Based Clustering

Fuzzy logic-based clustering methods use fuzzy logic to handle the uncertainty and imprecision in the network. Nodes are assigned a degree of belonging to multiple clusters based on criteria like energy level, distance to cluster head and node density. This flexibility allows for more adaptive and resilient cluster formations.

G. Energy-Efficient Clustering Protocol (EECP)

EECP focuses on energy conservation by selecting cluster heads based on a combination of residual energy and node connectivity. Nodes with higher energy levels and greater connectivity have a higher chance of being selected as cluster heads, which helps in evenly distributing energy consumption and prolonging network lifetime Clustering methods in WSNs are essential for improving network efficiency, balancing energy consumption, and enhancing scalability. Techniques such as LEACH, PEGASIS, HEED, DCA, K-means, fuzzy logic-based clustering, and EECP each offer distinct advantages tailored to specific network requirements. By effectively organizing sensor nodes into clusters and optimizing the selection of cluster heads, these methods significantly contribute to the robust performance and longevity of WSNs in various applications.

3. Literature Review :

The technology for wireless sensor systems is advancing rapidly, leading to the development of numerous protocols for efficient WSN routing. These protocols focus on energy conservation and extending network lifespan. Heinzelman et al. **[**5**], [**6**]** introduced the low-energy adaptive hierarchical clustering protocol (LEACH), one of the most well-known hierarchical protocols. LEACH randomly establishes clusters and facilitates data transfer between cluster members (CMs) and cluster heads (CHs), as well as between CHs and the base station (BS). Despite its simplicity, the random selection of CHs can result in increased energy consumption and premature node death. Heinzelman et al. **[**7**]** introduced the LEACH-centralized (LEACH-C) protocol, which calculates the average energy level of cluster members (CMs) at the base station (BS) and excludes nodes with below-average energy from being selected as cluster heads (CHs). While centralized clusters formed by LEACH-C are more efficient than those in LEACH, the protocol lacks scalability and robustness for larger networks. Mumtaz et al. **[**8**]** proposed energy-aware routing using the improved LEACH protocol (E-LEACH), which estimates the number of CHs based on a parameter equal to the square root of the total number of sensors using a minimum spanning mechanism. This method increases the network's lifespan by optimizing energy during initialization. However, the random selection of CHs still leads to higher energy consumption and earlier node dead nodes. Sharma et al. [9] introduced the Distance-based Cluster Head (DBCH) method, which selects CHs based on both energy levels and the distance from nodes to the BS. Despite these improvements, CHs still have many tasks that deplete their energy. To mitigate this, the use of a vice cluster head (VCH) or a secondary cluster head (SCH) is suggested to share the workload and minimize energy consumption. Sert et al. [10] proposed a two-tier distributed fuzzy protocol (TTDFP) for energy-efficient data aggregation in multiloop WSNs. This protocol considers node connectivity, remaining energy, and distance to the BS for CH selection, and average link remaining energy and proportional distance for route selection, utilizing fuzzy logic (FL) to manage uncertainties. Sert et al**. [**11**]** introduced a multi-objective fuzzy clustering algorithm (MOFCA) that is energy-efficient and distributionindependent. MOFCA calculates the CH competition radius by evaluating remaining energy levels, distance to the BS, and node density, using FL to address uncertainties. Sert and Adnan **[**12**]** proposed a modified energy-efficient clonal selection algorithm (CLONALG-M) for rule-based clustering algorithms, incorporating fuzzy validity measures into the mutation and solution production steps of the original CLONALG technique. Wang et al. [13] developed a compressive sensing-based (CS-based) clustering technique to handle load balancing in WSNs. Lin et al. [14] introduced the game theory-based energyefficient clustering-routing protocol (GEEC) to address the load-balancing problem in WSNs using CHs. Cheng et al. **[**15**]** article introduces an optimal combined weighting (OCW) and improved ant colony optimization (IACO) algorithm aimed at optimizing the LEACH protocol. Initially, cluster head nodes undergo dynamic replacement across the network to reduce energy consumption. To enhance the selection of cluster head nodes, the OCW method adjusts weights dynamically based on the node's residual energy, density, and distance to the sink node in various regions.

4. Comparison Table :

	Cluster Head selection criteria	Number of clusters	Cluster level	Medium access
TDDFP [10]	A base station and remaining node energy for selecting CH. Average link remaining energy and proportional distance for selecting a route. This paper examines remaining energy, distance to base station, and density to calculate CH competition	Dynamic	One level	Distributed
MOFCA [11]	For CH selection density is used. FL is used to solve uncertainties.	Dynamic	One level	Centralized
CLONALG-m [12]	Extended the energy-efficient clonal selection algorithm for rule-based clustering algorithms.	Dynamic	One level	Distributed
OCW-IACO [15]	Nodes were updated via a dynamic replacement mechanism	Dynamic	One level	Distributed.

Simulation Result :

Based on the above analysis, a comprehensive simulation using an open-source platform has been done. At first three clusters have been made using the K-means clustering method. Given below is an image showing cluster members and cluster center.

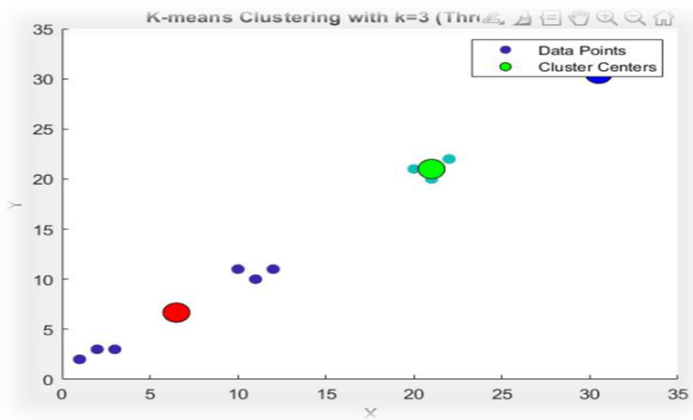
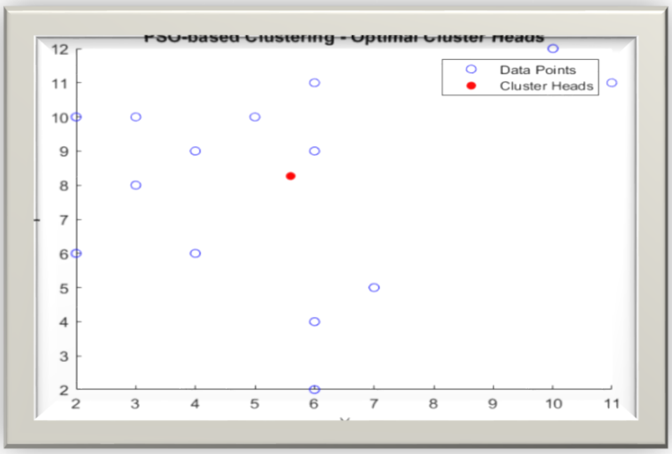


Figure 1 Cluster formation for K-means clustering (k=3).

Another cluster formation is done, particle swarm optimization has been applied to find the cluster centers. The result is shown in the figure 2 below.

Figure 2 PSO-based clustering to obtain optimal cluster head.



Now the fuzzy inference system is used for selection of primary cluster head (PCH) and secondary cluster head (SCH). The complete system has been simulated in a MATLAB environment. The detail of primary cluster head selection and secondary cluster head selection is discussed here. For primary cluster head selection, three parameters are used as an antecedent

1. Energy of the sensor node
2. distance to center heads
3. distance to base station

And ‘chance of PCH selection’s is the consequent

The rule base used for the PCH selection is

a) IF Residual Energy is High AND Distance is Near AND Node Density is Medium THEN PCH Selection Probability is High.
b) IF Residual Energy is High AND Distance is Far AND Node Density is Sparse THEN PCH Selection Probability is Medium.
c) IF Residual Energy is Medium AND Distance is Near AND Node Density is Dense THEN PCH Selection Probability is Medium.
d) IF Residual Energy is Low AND Distance is Near AND Node Density is Sparse THEN PCH Selection Probability is Low.
e) IF Residual Energy is Medium AND Distance is Medium AND Node Density is Medium THEN PCH Selection Probability is Medium.
f) IF Residual Energy is Low AND Distance is Far AND Node Density is Dense THEN PCH Selection Probability is Low.
g) IF Residual Energy is High AND Distance is Medium AND Node Density is Sparse THEN PCH Selection Probability is High.
h) IF Residual Energy is Medium AND Distance is Far AND Node Density is Dense THEN PCH Selection Probability is Low.

A fuzzy inference system for the PCH selection is shown below.

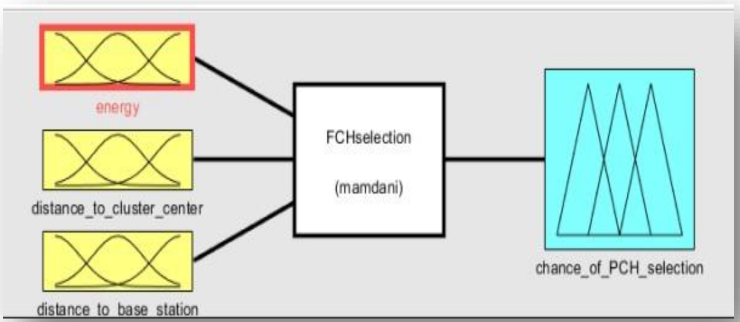


Figure 3 Fuzzy inference engine for PCH selection.

For SCH selection energy and distance to cluster head A the antecedent and output are the chances of SCH selection. The rule base used for the secondary cluster head selection is

a) IF Residual Energy is High AND Distance to Cluster Head is Near THEN Chance of SCH Selection is High.
b) IF Residual Energy is High AND Distance to Cluster Head is Far THEN Chance of SCH Selection is Medium.
c) IF Residual Energy is Medium AND Distance to Cluster Head is Near THEN Chance of SCH Selection is Medium.
d) IF Residual Energy is Medium AND Distance to Cluster Head is Far THEN Chance of SCH Selection is Low.
e) IF Residual Energy is Low AND Distance to Cluster Head is Near THEN Chance of SCH Selection is Low.
f) IF Residual Energy is Low AND Distance to Cluster Head is Far THEN Chance of SCH Selection is Very Low.
g) IF Residual Energy is Medium AND Distance to Cluster Head is Medium THEN Chance of SCH Selection is Medium.
h) IF Residual Energy is High AND Distance to Cluster Head is Medium THEN Chance of SCH Selection is High.

The fuzzy inference system for the secondary cluster head selection is shown in Figure 4.

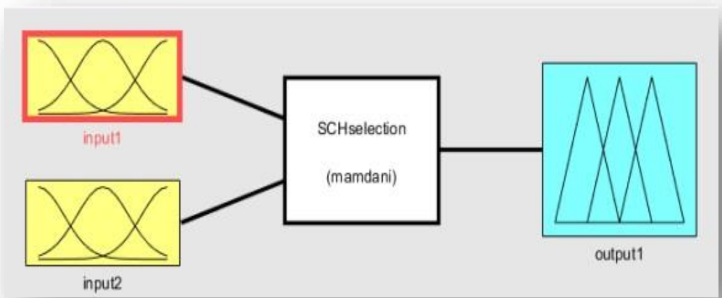


Figure 4 Fuzzy inference engine for SCH selection.

The developed engine has been tested by giving the input as per the antecedent and the result obtained is shown in the figure 5. As shown in the figure 5, When the

Energy is high (1), distance to center head is low (0) and the distance to base station is low (0), then the output obtained from the Fuzzy based PCH selection is 0.6644. After applying a threshold of 0.5, we obtain a high chance of that node to be a primary cluster head. Similarly, for the SCH selection, energy of the node is high(1) and distance to center head is low (0), the computation shows 0.8844 value at the output. This high value is closer to unity and it suggest the considered node has high chance of secondary cluster head selection.

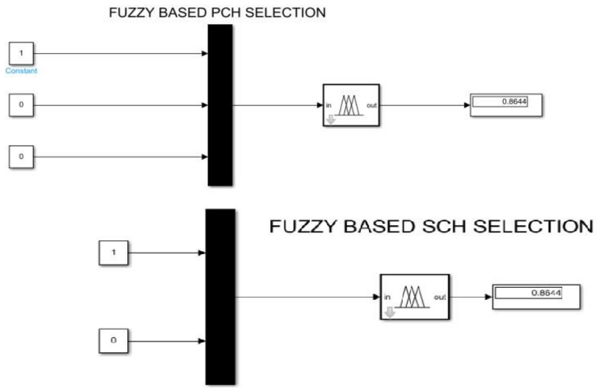


Figure 5 Simulation results of the developed inference engines.

6. Conclusion :

This review paper has thoroughly examined the LEACH protocol and its variants, highlighting the importance of energy efficiency, network lifespan, and data aggregation in Wireless Sensor Networks (WSNs). By introducing a novel fuzzy logic-based approach for the optimal selection of primary and secondary cluster heads, the study demonstrates a significant improvement in overall performance, as evidenced by the MATLAB simulation results. Future work can further enhance the system by exploring additional parameters of the LEACH protocol, such as node mobility, fault tolerance, and security, to refine the fuzzy logic inference system and improve WSN adaptability and robustness in diverse environments.

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