Literature Survey

LEACH (Low-Energy Adaptive Clustering Hierarchy)

Low-Energy Adaptive Clustering Hierarchy (LEACH) remains one of the most widely studied clustering-based routing protocols in Wireless Sensor Networks (WSNs) due to its simplicity and energy efficiency. Originally proposed by Heinzelman et al. [1], LEACH introduced a distributed algorithm that randomly selects cluster heads (CHs) to evenly distribute energy consumption among sensor nodes.

LEACH operates in two phases: the setup phase, where CHs are selected, and the steady-state phase, where data is transmitted. The probability of a node becoming a CH is given by:

where is the desired percentage of CHs, is the current round, and s the node. Despite its effectiveness in improving network longevity, LEACH does not account for the residual energy of sensor nodes, which may result in early energy depletion of CHs. Recent studies such as [2] have introduced modifications to LEACH, incorporating residual energy in the CH selection process to further improve energy efficiency and network lifespan.

In 2022, Zhang et al. [3] proposed an enhanced version of LEACH, termed LEACH-RE, where the CH selection probability is dynamically adjusted based on the remaining energy of nodes. The modified selection criterion is expressed as:

where is the residual energy of node , and is the average energy of all nodes. This enhancement has demonstrated significant improvements in network longevity compared to traditional LEACH.

Ant Colony Optimization-based Clustering (ACO-C)

Ant Colony Optimization (ACO) has been widely adopted for clustering in WSNs due to its ability to solve combinatorial optimization problems inspired by the foraging behavior of ants. In the context of WSNs, ACO-based Clustering (ACO-C) optimizes cluster head selection and routing by leveraging pheromone trails that represent the desirability of selecting certain nodes as CHs.

ACO-C algorithms, as explored in recent works [4], update the pheromone value between nodes and based on the distance and the residual energy of node , given by:

where is the pheromone evaporation rate, and is the pheromone deposit based on the quality of the solution. ACO-C not only ensures efficient cluster formation but also minimizes the overall energy consumption of WSNs by favoring nodes with higher residual energy during CH selection.

Recent advancements in ACO-C, such as the work by Liu et al. [5], have integrated residual energy awareness into the pheromone update mechanism, further enhancing the energy efficiency of WSNs. The energy-efficient CH selection mechanism is given by:

This approach significantly reduces the likelihood of low-energy nodes being selected as CHs, thus improving network longevity.

Dynamic Segmentation

Dynamic segmentation in WSNs refers to the process of partitioning sensor nodes into segments or clusters based on dynamic factors, such as residual energy, node density, and communication range. Dynamic segmentation addresses the limitations of static clustering approaches by adapting the segmentation strategy to the changing energy levels and network conditions.

In 2023, Gupta et al. [6] proposed a dynamic segmentation approach based on residual energy, where the clustering mechanism adapts according to the energy levels of the nodes. The segmentation criterion is formulated as:

where represents the segmentation probability for node , is the node's remaining energy, is the node density, and is the communication range. The segmentation process dynamically selects CHs from nodes with higher energy reserves, ensuring even distribution of energy consumption across the network.

The study by Singh et al. [7] introduced a dynamic segmentation mechanism combined with reinforcement learning (RL), where the RL agent dynamically adjusts the clustering strategy based on real-time energy consumption patterns. This approach significantly prolongs network lifetime compared to traditional static segmentation methods.

Intrusion Detection in WSNs

Intrusion detection in WSNs plays a critical role in ensuring network security, as WSNs are often deployed in sensitive environments where data integrity and network reliability are paramount. Intrusion detection systems (IDS) in WSNs are designed to identify malicious behavior, such as unauthorized access, data tampering, and denial-of-service attacks.

In recent years, machine learning-based IDSs have gained prominence due to their ability to detect complex attack patterns. A common approach is anomaly-based detection, where a model is trained on normal network behavior and any deviations from this behavior are flagged as potential intrusions. The detection accuracy of such systems can be improved using optimization techniques like the Levenberg–Marquardt algorithm, which refines the model's distance metric.

The study by Akyildiz et al. [8] introduced an anomaly detection framework using a Levenberg–Marquardt Neural Network (LMNN), where the distance metric is optimized to minimize the energy consumption while improving detection accuracy. The LMNN's objective function is expressed as:

where is the indicator function, is the distance between nodes and , and is the threshold distance for detecting anomalies.

In 2024, Ali et al. [9] proposed an IDS framework that integrates LMNN with reinforcement learning for real-time intrusion detection in energy-constrained WSNs. The system dynamically adjusts detection thresholds based on network conditions, reducing false positives and enhancing detection accuracy.

References

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