Methodology

In this work, we introduced an innovative approach to energy optimization in Wireless Sensor Networks (WSNs) by integrating Ant Colony Optimization-based Clustering (ACO-C), dynamic segmentation, the LEACH protocol, and anomaly detection using machine learning. Our contributions focus on enhancing energy efficiency while improving network reliability, achieved through the novel combination of these techniques and their tailored application in WSNs

1. Network Setup and Assumptions

1.1 Network Assumptions:

* We assume the WSN consists of sensor nodes randomly deployed over a 2D area, each with an initial energy These nodes have limited computational resources, and we optimized the network performance by addressing these constraints.
* A Base Station (BS) is positioned either inside or outside the network area and is responsible for collecting aggregated data from the cluster heads (CHs). Our contributions include an efficient multi-hop communication strategy for minimizing energy expenditure during data transmission.

1.2 Energy Model:

* The energy consumption model we utilized for transmitting a -bit message over distance leverages a simplified energy dissipation equation, incorporating both free-space and multi-path models:

* This energy model, combined with our dynamic communication protocol, contributed to reducing the overall energy consumption and prolonging the network lifetime.

2. Ant Colony Optimization for Clustering (ACO-C)

Our significant contribution lies in the use of Ant Colony Optimization (ACO) to optimize the selection of cluster heads (CHs), reducing intra-cluster communication energy and balancing energy consumption across nodes.

2.1 Problem Formulation:

* We formulated the problem of finding the optimal set of CHs to minimize communication energy and balance node energy consumption. Our approach led to significant improvements in energy efficiency through an optimized clustering process.

2.2 ACO Algorithm Steps:

* Initialization: We initialized the pheromone levels for each node and CH selection, setting the foundation for the ACO optimization process.
* Ant Path Construction: Our contribution includes designing an ant path construction process where each ant selects CHs probabilistically based on pheromone and heuristic information, optimizing the energy costs.
* Pheromone Update: We implemented a novel pheromone update mechanism that reinforces better solutions, significantly improving the clustering performance.
* Cluster Formation: Nodes are dynamically assigned to CHs based on distance and residual energy, forming highly energy-efficient clusters.

3. Dynamic Segmentation for Load Balancing

Dynamic segmentation was introduced in our approach to ensure that nodes are not overburdened, especially those with low residual energy. This mechanism contributed to prolonging network lifetime by balancing the energy load.

3.1 Dynamic Energy-Based Clustering:

* We developed a residual energy-based clustering approach, where nodes with higher energy are preferentially selected as CHs. This contribution directly reduced the likelihood of premature node failures.

* We also implemented an energy update strategy to keep track of energy consumption over time and make dynamic adjustments to cluster assignments.

4. LEACH Protocol for Energy-Efficient Communication

Our work incorporates the LEACH (Low-Energy Adaptive Clustering Hierarchy) protocol to further optimize energy-efficient communication within clusters. This contribution reduced direct transmissions to the BS and enhanced the overall network efficiency.

4.1 LEACH Communication Process:

* We utilized LEACH to perform data aggregation at CHs, reducing redundant information and minimizing communication overhead. Our contributions in multi-hop routing further reduced long-distance transmissions, conserving energy.

4.2 Cluster Head Rotation:

* To balance the load and prevent low-energy nodes from being overburdened, we introduced a periodic CH rotation mechanism based on residual energy levels:

This approach extended the network lifetime by ensuring equitable energy distribution across nodes.

5. Anomaly Detection Using Machine Learning

We contributed to improving network reliability by integrating advanced machine learning-based anomaly detection techniques, which allowed for the identification of compromised or faulty nodes in the network.

5.1 Isolation Forest: We adapted Isolation Forest to identify anomalies based on energy consumption and communication behavior, leading to more accurate detection of outliers.

5.2 One-Class SVM: Our use of One-Class SVM allowed for the detection of anomalous nodes based on features like transmission frequency, energy consumption, and packet loss, contributing to enhanced network security.

5.3 Levenberg–Marquardt Neural Network (LMNN): We introduced LMNN to further optimize the detection process, reducing false positives and enhancing the overall reliability of the network.

6. Performance Metrics

We evaluated our proposed methodology using several key performance metrics:

* Network Lifetime: We significantly extended the network lifetime by optimizing energy consumption across the network.
* Energy Efficiency: Our model showed considerable improvements in total energy consumption per communication round.
* Anomaly Detection Accuracy: The true positive rate (TPR) and false positive rate (FPR) for detecting compromised nodes were improved due to our anomaly detection framework.
* Load Balancing: The variance in energy consumption across nodes was minimized, indicating effective load balancing achieved through dynamic segmentation.