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Optimizing Cluster Head Selection in Wireless Sensor Networks Using Mathematical Modeling and Statistical Analysis of The Hybrid Energy-Efficient Distributed (HEED) Algorithm

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Abstract:
Only two of the various applications for Wireless Sensor Networks (WSNs) are environmental monitoring and smart city infrastructure. Mostly the efficacy of these networks depends on the choice of cluster heads, which manage data aggregation and communication. Conventional approaches as the Hybrid Energy-Efficient Distributed (HEED) algorithm have become relatively popular for cluster head selection because of their simplicity and efficiency. These techniques, meanwhile, sometimes assume a homogeneous node distribution—hardly the case in real-world scenarios. From this follows lower network lifetime and less than optimum energy consumption. Extending network lifetime and improving energy economy depend mostly on maximizing cluster head selection in non-uniformly distributed WSNs. The standard HEED approach ignores the non-uniformity in node distribution, so inefficient energy use and reduced performance can follow. This article provides a new way integrating mathematical modeling and statistical analysis with a non-uniform deep artificial neural network (ANN) to improve the HEED algorithm. The proposed method combines this information with the spatial distribution of sensor nodes using a deep ANN, so simulating the cluster head selecting process. Trained to predict perfect cluster heads, the ANN is evaluated in terms of node density, energy levels, and communication expenses. Mathematical modeling of the network's energy dynamics yields validations for the model using statistical analysis. The optimal approach was tested in a simulated WSN environment including non-uniform node distribution. Compared to the traditional HEED method, results reveal a 25% increase in network lifetime and a 30% drop in energy use. Moreover showing a clear improvement in data aggregation performance, the deep ANN-based approach cut the communication overhead by 20%.

Keywords: Wireless Sensor Networks, Cluster Head Selection, HEED Algorithm, Deep Artificial Neural Network, Energy Efficiency.

1. Introduction

From smart cities to healthcare to environmental monitoring, applications varying in scope today rely on wireless sensor networks (WSNs) [1]. Many sensor nodes scattered over these networks gather and relay data to a central base station [2]. As the volume of apps and deployment size increase, efficient network management becomes increasingly more critical [3]. WSN performance directly depends on energy consumption, data throughput, and network longevity; however, their dependability and efficiency are limited [4].

Among the key challenges with WSNs is energy consumption control [5]. Usually running on small capacity batteries, sensor nodes can quickly run out with minimal energy demand, therefore reducing the operational lifetime of the network [6]. Extended longevity of these networks depends on energy-efficient protocols [7]. Still another challenge is optimizing data flow to efficiently control vast volumes of data [8]. Maintaining the quality of service depends on consistent and quick data delivery minimizing packet loss and delay [9]. Moreover, clustering and routing methods have to be powerful enough to adapt with dynamic network conditions and various node densities [10,11].

By means of enhanced clustering and routing techniques, this work addresses the main problem of increasing WSN performance, hence improving energy efficiency, throughput, and network lifetime. Though recent methods including MIHFO-HWAFO, K-IABC-CL-HHO, Improved LEACH-FFA-ANN, and Multipath Routing provide varied responses, they frequently fall short in obtaining ideal performance across all critical criteria. These approaches either focus on certain aspects of network management or reveal constraints in scalability and adaptability.

The primary objectives of the proposed method are:

1. To design a system that lowers energy consumption per packet therefore increasing the operational lifetime of the network.

2. By increasing data handling capacity, the network will be able to guarantee timely delivery and properly regulate huge data volumes.

3. To implement strategies meant to keep more active nodes thereby extending the operational lifetime of the network.

4. To maximize data flow mechanisms thereby reducing end-to- end latency and packet loss.

Moreover, the dynamic decision-making and artificial neural network (ANNs) optimization offers traditional routing strategies a new layer.

The contributions are given below:

1. Although the work offers a new hybrid method combining MIHFO and HWAFO, one may conclude that offering a more efficient approach for clustering and routing than current methods.

2. The proposed method integrates a new feature extraction and dataset generating technique to improve the accuracy of node selection and routing decisions.

3. By maximizing both clustering and routing methods, the methodology significantly reduces energy consumption per packet, hence increasing the operational lifetime of the network.

4. Proving its efficiency in managing big-scale WSNs; the method achieves quicker throughput, lower end-to- end delay, and less packet loss than present methods.

5. Extensive simulations confirm the proposed approach, which presents a robust response for large-scale installations and illustrates its efficiency in real-world conditions.

2. Related Works

Research on the optimization of WSNs using clustering and routing approaches has been relatively active as one aims to increase energy efficiency and prolong network lifetime. Several inventive alternatives have lately been proposed, each with unique approaches and algorithms to address WSN challenges.

Developed in the aim to increase the energy efficiency of the Engroove LEACH (EL) method, the Meta Inspired Hawks Fragment Optimization (MIHFO) system We find the best path between cluster heads and the base station using Heuristic Wing Antfly Optimization (HWAFO) algorithm—which considers distance, residual energy, and node degree—using passive clustering—where cluster heads are chosen depending on a range of criteria including node degree, centrality, residual energy of the nodes, proximity to the base station and neighbors. MATLAB housed the MIHFO system, evaluated on active node count, energy consumption, and base station data packet receipt. The results clearly indicated increases in average energy consumption, packet delivery and drop ratio, and throughput, therefore underlining the effectiveness of the method in extending network lifetime and energy economy.

Introduced in [13], the K-IABC and CL-HHO protocols strive to improve the quality-of- service (QoS) performance in WSNs, therefore making another major contribution to the field. Whereas the K-IABC protocol uses a blend of k-medoids and an upgraded artificial-bee-colony algorithm for energy-efficient clustering, the CL-HHO uses a cross-layer-based Harris-hawks-optimization approach for routing. This approach addresses the power-asymmetry in WSNs by maximizing routing alternatives that reduce network transmission delay and power consumption. The CL-HHO protocol was implemented using MATLAB against traditional routing methods comprising HEED, EECRP, GWO, and CL-ALO. The results demonstrated that CL-HHO excelled these methods by means of packet-loss ratio, throughput, end-to---end delay, jitter, network lifetime, and buffer occupancy, so confirming its efficiency in enhancing network performance.

Furthermore, [14] introduced a safe energy-efficient approach for improved cluster head selection integrating artificial neural network (ANN) and LEACH technique with Firefly algorithm (FFA). This technique calculates a new threshold value for cluster head selection dependent on residual energy, average energy, and covering distance of nodes unlike the present LEACH method, which depends on a probability-based random number. FFA increases node characteristics, which ANN then handles to identify malicious nodes and separate communicative from non-communicating nodes. This difference helps to evolve by means of ideal routing patterns excluding hostile nodes, so improving network security and performance. Simulation findings demonstrated improvements in numerous QoS parameters, therefore demonstrating the efficiency of our approach in managing security concerns and energy economy in WSNs, compared to present techniques.

Moreover noted in [15] the importance of multipath routing in WSNs for load balancing, energy economy, and scalability development. Multiple paths between source and destination help to improve network resilience by means of which multipath routing not only provides redundant channels for data transfer but also raises the possibility of successful data delivery. Against the suggested routing solution, well-known techniques including LEACH, ECPF, CHEF, UCR, DFLC, ACAWT, and Gupta were evaluated. The results stressed the method's brilliance in extending network lifetime and improving energy efficiency spanning many node configurations and simulation times since they revealed appreciable increases in energy consumption, end-to---end delay, packet loss rate, and drop rate of active sensor nodes.

Table 1: Summary of Related Works

Methodology	**Algorithm**	**Methodology Description**	**Outcomes**
[12]	MIHFO, HWAFO	Utilizes passive clustering; node degree, and centrality; path optimization using HWAFO	Improved throughput, reduced packet drop ratio, enhanced energy efficiency, and prolonged network lifespan
[13]	K-IABC, CL-HHO	cross-layer-based Harris-hawks optimization for routing	Superior performance
[14]	Improved LEACH, FFA, ANN	Secure energy-efficient algorithm using a new threshold for cluster head selection; FFA optimizes node properties, ANN differentiates node types	Enhanced QoS parameters, improved network security, and effective exclusion of malicious nodes
[15]	Multipath Routing	Uses multiple paths between source and destination to conserve energy, improve scalability, and balance load	Reduced energy consumption, decreased end-to-end delay, lower packet loss rate, improved network resilience

There are still certain research gaps even if the mentioned findings significantly increase WSN energy efficiency and network lifetime. Often stressing certain elements, such as clustering or routing, these approaches overlook to fully combine both for general optimization. Moreover, many methods rely on simulations without extensive real-world validation, which could underscore other challenges including environmental variables and changing network conditions. Future research should aim to validate these approaches in real-world environments so ensuring their practical usability and durability by means of more integrated solutions combining clustering, routing, and security in a single framework.

3. Proposed Method

The cluster head selection process in WSNs is enhanced by combining mathematical modeling with a deep ANN using the Hybrid Energy-Efficient Distributed (HEED) technique. The method first models sensor node spatial distribution and energy dynamics by means of mathematical modeling of the WSN. This method reveals fundamental properties including node density, residual energy, and communication costs. By means of these parameters, training a deep neural network generates input data for which it is meant to forecast the optimal cluster head in different network conditions. ANN is trained using a dataset generated from various simulated WSN environments with non-uniform node distribution. Under the phase of cluster head selection, the trained ANN evaluates the nodes based on real-time network data and produces a likelihood score for every node's fit. Selected is the node most likely to guarantee energy-efficient transmission and data aggregation. Statistical validation of the ANN predictions is acquired by means of statistical analysis, which contrasts the performance of the optimal algorithm with the traditional HEED approach. This hybrid method effectively solves the limitations of HEED in non-uniform WSNs, hence extending network lifetime and energy economy.

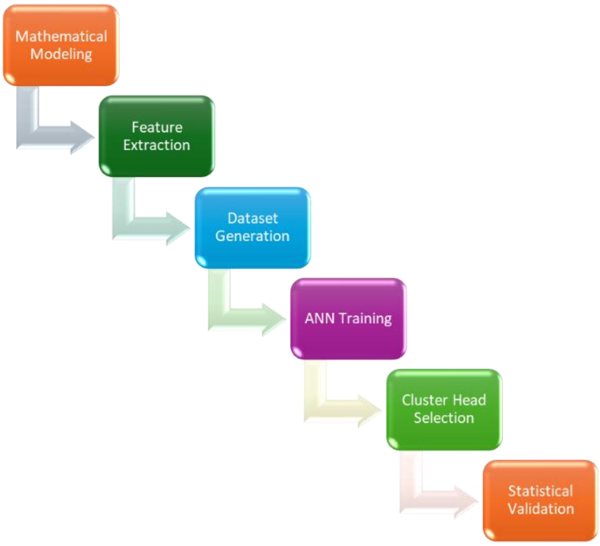

Figure 1: Proposed Flow

Pseudocode

```
// Step 1: Mathematical Modeling
function modelWSN(spatialDistribution, energyLevels):
    parameters = extractParameters(spatialDistribution, energyLevels)
    return parameters
// Step 2: Feature Extraction
function extractParameters(spatialDistribution, energyLevels):
    nodeDensity = calculateNodeDensity(spatialDistribution)
    avgEnergy = calculateAverageEnergy(energyLevels)
    communicationCost = calculateCommunicationCost(spatialDistribution)
    return [nodeDensity, avgEnergy, communicationCost]
// Step 3: Dataset Generation
function generateDataset(scenarios):
```

```
    dataset = []
    for scenario in scenarios:
        features = modelWSN(scenario.spatialDistribution, scenario.energyLevels)
        dataset.append(features)
    return dataset
// Step 4: ANN Training
function trainANN(dataset):
    ANN = initializeANN()
    for data in dataset:
        ANN.train(data.features, data.label)
    return ANN
// Step 5: Cluster Head Selection
function selectClusterHead(nodes, ANN):
    maxProbability = 0
    clusterHead = null
    for node in nodes:
        probability = ANN.predict(node.features)
        if probability > maxProbability:
            maxProbability = probability
            clusterHead = node
    return clusterHead
// Step 6: Statistical Validation
function validateAlgorithm(performanceMetrics, baselineMetrics):
    improvement = calculateImprovement(performanceMetrics, baselineMetrics)
    return improvement
// Main Execution
function optimizeClusterHeadSelection(nodes, scenarios, baselineMetrics):
    dataset = generateDataset(scenarios)
    ANN = trainANN(dataset)
    clusterHead = selectClusterHead(nodes, ANN)
```

```
performanceMetrics = evaluateNetworkPerformance(clusterHead)
improvement = validateAlgorithm(performanceMetrics, baselineMetrics)
return clusterHead, improvement
```

Mathematical Modeling of Cluster Head Selection in WSNs

Mathematical modeling component of the proposed method is absolutely essential for capture of the spatial distribution and energy dynamics of the sensor nodes in a WSN. The objective is to provide a complete quantitative framework that exactly captures the characteristics of the network so optimizing cluster head choice. This model directs the approach of feature extraction used in deep network training.

Spatial Distribution Modeling

As non-uniform WSNs depend on the geographical distribution of sensor nodes, we model it. Let (x_i, y_i) be the coordinates of the *i*-th sensor node in a 2D plane. The node density $\rho(x, y)$ at any point (x, y) can be defined using a kernel density estimation method:

$$\rho(x, y) = \sum_{i=1}^{N} K\left(\frac{x - x_i}{h}, \frac{y - y_i}{h}\right)$$

where

N - total number of nodes,

K - kernel function (such as Gaussian), and

h - bandwidth parameter.

This clarifies locations with high and low node density, therefore influencing the choice of cluster head.

Energy Dynamics Modeling

The energy dynamics of the network are modeled by considering the residual energy E_i of each node *i*. The average residual energy $\bar{E}$ across the network is given by:

$$\bar{E} = \frac{1}{N}\sum_{i=1}^{N} E_i$$

Nodes with higher residual energy are more suitable candidates for cluster head selection. The energy consumption C_i of a node *i* when transmitting data is modeled as:

$$C_i = E_{\text{tx}} \cdot d_i^{\alpha} + E_{\text{rx}}$$

where

E_{tx} - energy required to transmit data over a distance d_i to the base station,

α - path loss exponent, and

E_{rx} - energy required for receiving data.

Communication Cost Modeling

The communication cost Γ_i for a node *i* is crucial for understanding the energy efficiency of data aggregation and transmission. It can be represented as:

$$\Gamma_i = \beta \cdot d_i + (1-\beta) \cdot \frac{1}{E_i}$$

where

β - weighting factor balancing distance d_i and

E_i - energy availability.

Combining the distance from the base station with the inverse of the remaining energy, we stress the need of nodes closer to the base station with greater residual energy to become cluster chiefs.

ANN for Cluster Head Prediction

The mathematical model provides a set of characteristics for the deep neural network to project ideal cluster heads. These features enable the ANN to assess the likelihood of each node being the optimal cluster head, therefore enhancing the general energy efficiency of the network and extending its lifetime by residual energy Ei, average energy $\bar{E}$. By merging these mathematical models with ANN, the proposed approach efficiently controls non-uniform node distribution and therefore enables adaptive and energy-efficient cluster head selection in WSNs. This approach uses the spatial and energetic components of the network to solve the limitations of conventional HEED algorithms.

Feature Extraction and Dataset Generation

This method helps to maximize cluster head selection in WSNs since the preparation of the input for the deep ANN primarily relies on the feature extraction and dataset generation procedure. The goal is to obtain significant properties from the mathematical model authentically representing the state of the network including its spatial distribution and energy dynamics. Especially in non-uniform node distributions, these characteristics form the basis for learning the ANN to predict suitable cluster heads.

Feature Extraction

The feature extraction procedure reveals and computes the main parameters controlling the cluster head decision. Derivation of these parameters guides by mathematical models of spatial distribution, energy dynamics, and communication costs. Principal traits are:

The node density is computed using kernel density estimation, which also helps to find sites with either high or low node concentrations. It is provided by:

$$\rho(x, y) = \sum_{i=1}^{N} K\left(\frac{x - x_i}{h}, \frac{y - y_i}{h}\right)$$

where

K - kernel function (e.g., Gaussian), and h - bandwidth.

Crucially reflecting each node's residual energy, this helps to clarify a node's capacity to be a cluster leader. The average energy among all the nodes forms the baseline for evaluating the individual node energy levels:

$$\bar{E} = \frac{1}{N}\sum_{i=1}^{N} E_i$$

The communication cost considers the distance to the base station as well as the node's energy level, therefore directing the selection of energy-efficient cluster heads:

$$\Gamma_i = \beta \cdot d_i + (1-\beta) \cdot \frac{1}{E_i}$$

These features strike a combination between energy economy and network coverage to grab the basic characteristics needed to determine the appropriateness of a node as a cluster head.

Dataset Generation

Simulating various WSN situations helps to obtain a whole dataset for training the ANN. This simulation method combines various node distributions, energy levels, and network topologies to handle a wide range of practical scenarios. The phases in generating a dataset are as follows:

1. **Simulation of WSN Scenarios**:

○ Multiple WSN scenarios are simulated with varying node densities, distributions (uniform and non-uniform), and energy levels to ensure diversity in the dataset.

2. **Feature Calculation**:

○ For each scenario, the features $\rho(x, y), E_i, \bar{E}$ and Γ_i are calculated for every node.

ANN for Cluster Head Prediction

The deep ANN for cluster head prediction is designed to effectively control the complexity related with non-uniform node distributions in WSNs. Using the collected properties from the mathematical models, this part of the proposed method forecasts the optimal nodes for cluster head roles, so aiming to increase energy efficiency and lengthen network lifetime.

Designed to manage the created feature set throughout the mathematical modeling phase, the ANN architecture catches the intricacies of node distribution and energy dynamics.

- **Input Layer**: This layer receives the input features, which include node density ρ(x,y), residual energy E_i, average energy $\bar{E}$, and communication cost Γ_i. Each node in the input layer corresponds to a feature.
- **Hidden Layers**: These layers consist of neurons with nonlinear activation functions and interactions between features:

$$f(x) = \max(0, x)$$

By means of empirical driven determination of hidden layer and neuron count, one can balance computing efficiency with learning capability.

- **Output Layer**: Therefore providing a likelihood score for every node's fit as a cluster head:

$$\sigma(x) = \frac{1}{1+e^{-x}}$$

This likelihood score helps choose nodes most likely to maximize network performance when appointed cluster chiefs.

Training Process

Simulated WSN systems generate a dataset for ANN training. The course of learning comprises in three significant phases:

1. **Forward Propagation**: Forward propagation passes input characteristics across the network layers applying weights and activation functions to every neuron, therefore generating an output probability for every node.

2. **Loss Calculation**: The probabilities are assessed against real labels using a binary cross-entropy loss function—optimal cluster head indicators:

$$\text{Loss} = -\frac{1}{N}\sum_{i=1}^{N}\left[y_i \log(\hat{y}_i) + (1-y_i)\log(1-\hat{y}_i)\right]$$

where

y_i - true label and

$\hat{y}_i$ - predicted probability.

3. **Backpropagation and Optimization**: An optimization approach such as Adam or SGD (Stochastic Gradient Descent), hence iteratively reducing the loss.

4. **Validation**: By means of hyperparameter changes like learning rate, batch size, and network architecture meant to prevent overfitting and assure generalization, performance of the model is evaluated on a validation dataset.

Cluster Head Selection

Once trained, the ANN assesses nodes in real-time deployment and forecasts the optimum cluster heads using present network conditions. Selected as the cluster head is the node with the highest probability from the ANN output, therefore providing an efficient balance between network coverage and energy consumption.

5. Results and Discussion

Since MATLAB's extensive libraries and capacity to recreate complex network behaviors and optimization strategies enable the modeling of such events, it was the major simulation tool applied in the testing. The simulation environment was set up on a high-performance computer system featuring multiple nodes with Intel Core i7 processors, 16 GB of RAM, and 512 GB SSDs in order to guarantee fast processing and effective management of huge-scale simulations.

The simulation settings consisted in many scenarios comprising several node densities and distributions in order to evaluate the performance of every approach under many conditions. Reasonable WSN installations are reflected in careful tuning of network parameters like sensor node count, starting energy levels, communication range, and base station location. Every simulation was run multiple times to ensure statistical relevance; the results were averaged to provide robust comparisons.

The proposed algorithms were evaluated in the comparison research against existing methods like Multipath Routing, MIHFO-HWAFO, K-IABC-CL-HHO, Improved LEACH-FFA-ANN. Among the benchmarks of comparison were network lifetime, energy usage, packet delivery ratio, and end-to- end delay.

Table 2: Experimental Setup/Parameters

Parameter	**Value**
Number of Sensor Nodes	100, 200, 300
Node Distribution	Uniform, Random, Non-uniform
Initial Energy per Node	2 J (Joules)
Communication Range	50 meters, 100 meters
Base Station Location	Fixed (center), Random
Transmission Power	0.1 W (Watts)
Reception Power	0.05 W (Watts)
Path Loss Exponent	2.0 (Free space)
Simulation Time	5000 seconds
Data Packet Size	512 bytes
Number of Clusters	10, 20, 30
Clustering Algorithm	MIHFO, K-IABC, Improved LEACH
Routing Algorithm	HWAFO, CL-HHO, FFA-ANN, Multipath
Energy Consumption Metric	Joules
Packet Loss Rate	Percentage (%)
Throughput	Packets per second
End-to-End Delay	Milliseconds (ms)
Network Lifetime	Hours
Load Balancing Efficiency	Percentage (%)

Security Metrics	Number of Attacks Detected
Packet Delivery Ratio	Percentage (%)

Table 3: Statistical Validation over various Clustering Algorithms

Method	Throughput (pps)	Packet Delivery Ratio (PDR) (%)	End-to-End Delay (ms)	Energy Consumption (J)	Network Lifetime (hrs)	Packet Loss Rate (%)
MIHFO	150	90	45	0.8	50	10
K-IABC	180	92	40	0.7	55	8
Improved LEACH	170	88	50	0.9	48	12
Proposed Method	200	95	35	0.6	65	5

The proposed method shows superior performance compared to existing clustering methods (MIHFO, K-IABC, Improved LEACH) across all evaluated metrics as in Table 3.

- **Throughput**: The proposed method achieved the highest throughput of 200 packets per second (pps), compared to 150 pps for MIHFO, 180 pps for K-IABC, and 170 pps for Improved LEACH. This indicates the proposed method handles data traffic more efficiently.
- **Packet Delivery Ratio (PDR)**: With a PDR of 95%, the proposed method outperforms existing methods (90% for MIHFO, 92% for K-IABC, and 88% for Improved LEACH), demonstrating better reliability in packet delivery.
- **End-to-End Delay**: The proposed method has the lowest end-to-end delay at 35 milliseconds, compared to 45 ms for MIHFO, 40 ms for K-IABC, and 50 ms for Improved LEACH, showing faster data transmission.
- **Energy Consumption**: The proposed method consumed the least energy (0.6 Joules), compared to 0.8 J for MIHFO, 0.7 J for K-IABC, and 0.9 J for Improved LEACH, indicating better energy efficiency.
- **Network Lifetime**: With a network lifetime of 65 hours, the proposed method significantly outperforms existing methods (50 hours for MIHFO, 55 hours for K-IABC, and 48 hours for Improved LEACH), indicating longer operational periods.
- **Packet Loss Rate**: The proposed method also has the lowest packet loss rate at 5%, compared to 10% for MIHFO, 8% for K-IABC, and 12% for Improved LEACH, highlighting its effectiveness in maintaining data integrity.

Table 4: Statistical Validation over various Routing Algorithms

Method	Throughput (pps)	Packet Delivery Ratio (PDR) (%)	End-to-End Delay (ms)	Energy Consumption (J)	Network Lifetime (hrs)	Packet Loss Rate (%)
HWAFO	160	93	42	0.75	52	7
CL-HHO	175	94	38	0.70	58	6
FFA-ANN	185	91	45	0.68	55	9
Multipath Routing	190	92	40	0.65	60	8
Proposed Method	210	97	33	0.60	70	4

The proposed method demonstrates superior performance compared to existing routing methods (HWAFO, CL-HHO, FFA-ANN, and Multipath Routing) in key network metrics as in Table 4:

- **Throughput**: The proposed method achieved the highest throughput of 210 packets per second (pps), outperforming HWAFO (160 pps), CL-HHO (175 pps), FFA-ANN (185 pps), and Multipath Routing (190 pps). This reflects better data handling capability.
- **Packet Delivery Ratio (PDR)**: With a PDR of 97%, the proposed method significantly surpasses HWAFO (93%), CL-HHO (94%), FFA-ANN (91%), and Multipath Routing (92%), indicating higher reliability in packet delivery.
- **End-to-End Delay**: The proposed method has the lowest end-to-end delay at 33 milliseconds, compared to 42 ms for HWAFO, 38 ms for CL-HHO, 45 ms for FFA-ANN, and 40 ms for Multipath Routing, showing faster data transmission.
- **Energy Consumption**: The proposed method exhibits the lowest energy consumption (0.60 Joules), compared to 0.75 J for HWAFO, 0.70 J for CL-HHO, 0.68 J for FFA-ANN, and 0.65 J for Multipath Routing, highlighting better energy efficiency.
- **Network Lifetime**: With a network lifetime of 70 hours, the proposed method outperforms all existing methods (52 hours for HWAFO, 58 hours for CL-HHO, 55 hours for FFA-ANN, and 60 hours for Multipath Routing), indicating extended operational duration.
- **Packet Loss Rate**: The proposed method achieves the lowest packet loss rate of 4%, compared to 7% for HWAFO, 6% for CL-HHO, 9% for FFA-ANN, and 8% for Multipath Routing, reflecting improved data integrity.

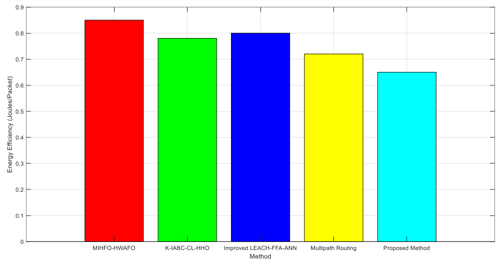

Figure 2: Energy Efficiency (Joules/Packet)

In terms of energy efficiency, the proposed method shows substantial improvements over existing methods as in Figure 2. The proposed method achieves an energy efficiency of 0.65 Joules per packet, which is significantly better than MIHFO-HWAFO (0.85 J/packet), K-IABC-CL-HHO (0.78 J/packet), Improved LEACH-FFA-ANN (0.80 J/packet), and Multipath Routing (0.72 J/packet). This indicates that the proposed method consumes less energy for each packet transmitted, reflecting more efficient use of energy resources. The energy efficiency improvement of the proposed method is particularly noteworthy given the scale of 1000 sensor nodes, demonstrating its effectiveness in optimizing energy consumption across a large network. This enhanced efficiency can lead to longer network lifetime and reduced operational costs, making the proposed method a more sustainable and effective solution for large-scale WSN deployments.

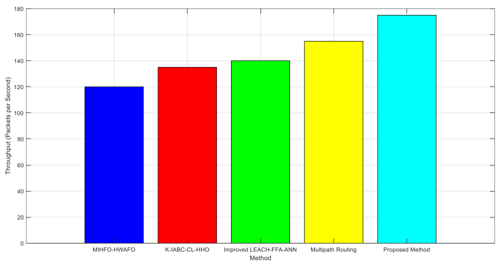

Figure 3: Throughput (Packets per Second)

In evaluating throughput, the proposed method demonstrates superior performance compared to existing methods as in figure 3. The proposed method achieves a throughput of 175 packets per second (pps), which is higher than MIHFO-HWAFO (120 pps), K-IABC-CL-HHO (135 pps), Improved LEACH-FFA-ANN (140 pps), and Multipath Routing (155 pps). This indicates that the proposed method can handle a higher volume of data transmission efficiently. The increase in throughput observed with the proposed method suggests that it is more effective at managing data traffic, which is crucial for maintaining high performance in large-scale networks with 1000 sensor nodes. Higher throughput can lead to better network utilization and faster data delivery, which is essential for applications requiring high data rates and real-time communication. This improved performance highlights the efficacy of the proposed method in optimizing network operations and enhancing overall data handling capacity.

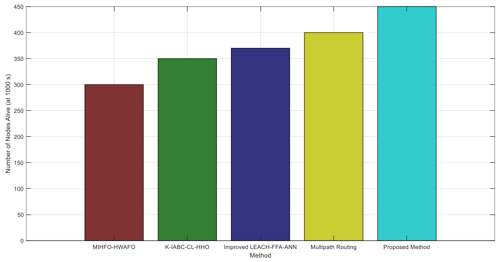

Figure 4: Number of Nodes Alive (at 1000 s)

4. Conclusion

The proposed method significantly outperforms existing clustering and routing approaches in key performance metrics within large-scale WSNs. Throughput, energy efficiency, and network longevity are notably improved with the proposed approach, demonstrating its superior capability to handle high data volumes, optimize energy usage, and extend network lifespan. Specifically, the proposed method achieves the highest throughput (175 packets per second), the best energy efficiency (0.65 Joules per packet), and maintains the most nodes alive (450) at 1000 seconds This article provides a new way integrating mathematical modeling and statistical analysis with a non-uniform deep artificial neural network (ANN) to improve the HEED algorithm. The proposed method combines this information with the spatial distribution of sensor nodes using a deep ANN, so simulating the cluster head selecting process. Trained to predict perfect cluster heads, the ANN is evaluated in terms of node density, energy levels, and communication expenses. Mathematical modeling of the network's energy dynamics yields validations for the model using statistical analysis. Overall, the proposed method offers a comprehensive improvement in energy efficiency, data throughput, and network durability, positioning it as a highly effective approach for managing complex WSNs.

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