

## A MACHINE LEARNING BASED CLUSTER HEAD SELECTION METHOD FOR DATA TRANSMISSION AND ENERGY EFFICIENCY IN UNDERWATER WIRELESS SENSOR NETWORKS

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### ABSTRACT

Underwater wireless sensor networks (WSNs) have become more important due to their various applications. To maintain network connectivity and transmission efficiency, routing protocols are crucial for UWSN. Efficient energy consumption and reliable data transmission are critical challenges in Underwater Wireless Sensor Networks (UWSNs) due to harsh underwater environment and limited energy resources. In an existing data transmission method, a routing protocol called multi-hop is used, which leads to high energy consumption. In the proposed method, all the sensor nodes are organized into different clusters, a random sensor node is selected as a cluster head who gathers and sends data among the cluster. Selection of cluster-head can be done by using Machine Learning based Cluster Head Selection Method (ML-CHSM). This cluster-head selection method reduces energy usage and increases durability of the network. The machine learning-based cluster head selection method aims to optimize energy consumption, and improve network's operational lifetime, data transmission reliability. In this paper, the usage of machine learning techniques is proposed to increase energy level and optimize transmission of data in UWSNs. Through simulations, the effectiveness of overall efficiency and data transmission reliability is shown in UWSNs.



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### I. INTRODUCTION

Underwater wireless sensor networks represent a specialized category of wireless sensor networks designed to operate in aquatic environments such as oceans, seas, lakes, and rivers. Regulation of underwater communication has been increased now-a-days. Due to its emerging applications, a lot of scientists and researchers are interested in the underwater environment. These networks enable the monitoring and collection of data from underwater areas, facilitating applications in scientific research, environmental monitoring, defense, and industrial activities [1]. Many challenges are associated with finite energy resources and harsh underwater environment. Due to many challenges energy efficiency has become an important aspect in designing and operating of underwater wireless sensor networks [2]. There are many restrictions and characteristics for underwater like temperature, salinity, pressure at whereas depths which lead to vital communication [3]. Short distance communication carried out trials on electromagnetic waves first, but large sized antennas were required for propagating low bits. This was not preferred for long-distance communication [4]. Later optical waves were used in aquatic communication which resulted in refraction and reflection problems. Extensive research has shown that, in aquatic environments, acoustic communication is significantly more effective than using radio or optic waves [5]. The energy limitations associated with underwater acoustic sensors pose significant challenges to their service lifetime [6]. Underwater wireless sensor networks often rely on acoustic communication, and the energy consumption during communication affects the overall operational duration of these sensor nodes.

In UWSNs, the data collected from different sensor nodes is transmitted to the central node for processing [7]. The processed data is

then shared with external networks [8]. While minimal sensor networks allow for direct, single hop communication between sensor nodes and the central hub due to their proximity, the extensive coverage areas typical in most UWSN applications necessitate the deployment of thousands of nodes. Consequently, multi-hop communication becomes essential, because many sensor nodes are located far away from the central node, preventing direct communication [9]. Communication in a network is categorized as “one hop” for direct communication and “many hops” for indirect communication. In a multi-hop communication scenario, sensor nodes not only generate and share their own data but also serve as conduits, facilitating connections for other sensor nodes to the base station.

Alongside content production and distribution, these nodes are responsible for creating and disseminating advertisements. Routing is a critical function at the network layer which involves selecting the best route between any two nodes [10]. Efficient routing protocols are essential for extending operational lifetime of sensors in UWSNs [11]. The choice of routing protocol can significantly impact the efficiency of energy usage in the network. Ongoing research continues to explore and develop novel routing techniques to tackle the distinct challenges of underwater communication and contribute to improved energy efficiency. The best path between source node and destination node can be determined by routing protocols. Finding the optimal route has become a challenge due to network specs, performance metrics vary and channel parameters.

## 1.1 UNDERWATER ENVIRONMENT MAJOR PROPAGATION FACTORS

The following are the major factors which affect underwater communication.

### 1.1.1 Path loss

Path loss in underwater communication is a significant challenge because of the environment’s unique properties. Many factors which contribute to path loss are mentioned below [12].

### 1.1.2 Attenuation

Attenuation in underwater communication primarily results from absorption of acoustic energy. The degree of attenuation is directly proportional to distance and frequency. Scattering and reverberation occurred on rough ocean surfaces and bottoms. The water depth is a crucial factor determining the extent of attenuation in underwater communication.

### 1.1.3 Geometric spreading

Geometric spreading is also known as spherical spreading. This is a fundamental concept in wireless communication that describes how a signal’s power is distributed as it travels through space.

### 1.1.4 Scattering Loss

The ocean surface can scatter sound waves due to its roughness leading to irregular reflections. Surface scattering introduces additional complexity in signal paths affecting the predictability of acoustic communication and contributing to signal loss.

### 1.1.5 Noise

Noise refers to unwanted disturbances that affect the integrity and quality of acoustic signals transmitted through water. Noise can be caused by both natural and anthropogenic factors. Common sources of noise in underwater communication include natural ambient noise, anthropogenic noise, biological noise, self-noise from transducers, thermal noise, multipath interference, and signal attenuation noise.

### 1.1.6 Doppler Spread

Doppler spread is the range of frequencies. It represents the spread in the received signal’s frequency spectrum due to the varying distances between the transmitter and receiver. Doppler shift refers to the change in frequency. It is caused by the compression or expansion of wave fronts due to the motion.

## II. RELATED WORK

Numerous journal articles have highlighted the advantages of wireless sensor networks (WSNs) and various energy saving methods for them. WSNs comprise individual hardware nodes designed for data collection, information processing, and wireless transmission Jiasen Zhang [13] et al.2023 proposes a hierarchical framework to maximize energy efficiency in UWSNs. The paper addresses the challenges posed by distinct properties of underwater environment, such as high attenuation, finite bandwidth, and elevated deployment costs. By organizing sensor nodes into multiple levels of hierarchy, the proposed framework minimizes energy consumption by optimizing data transmission strategies and routing protocols. Zhang’s work contributes significantly to the development of efficient communication solutions for UWSNs, offering valuable insights for researchers and practitioners in the field. Rawaa Ali [14] et al. 2023 presents a comprehensive overview of transmission protocols and characteristics specific to underwater wireless sensor networks (UWSNs). The survey delves into the unique challenges faced by UWSNs, such as signal magnitude, finite bandwidth, and high propagation delay, and examines how various protocols address these challenges at different layers of the communication stack. Ali explores transmission techniques, routing protocols, and energy efficient strategies tailored to the underwater environment. Zhao et al. introduced an enhanced cluster head selection algorithm based on a DAAM [15] (Distributed Address Assignment Mechanism).

This method inspects nodes remaining energy and their coordinates to adjust threshold in equation 1. Consequently, it helps to inform stable clusters and reduce energy usage in the WSN. Additionally, the algorithm incorporates a competing mechanism for cluster head selection, which enhances load balancing within the network. Zhixin Liu et al. 2022, represents an algorithm named EEGNBR, a localization free routing algorithm introduced to achieve better performance when compared with some related routing protocols. This algorithm is based on the guiding network which is established using the query mechanism [16]. A node is chosen as a cluster head randomly selecting a number. This node becomes the cluster head if its value is less than  $T(n)$ . After receiving the transmission message, other nodes join the cluster. Randomization of this protocol is its advantage. Load balancing is provided because different nodes take on the role of cluster leaders. A few limitations of LEACH are that the CH is chosen at random, which means that classification of CHs in the field is not guaranteed. This can cause CHs to be more concentrated in one place. The CHs chosen at random may frequently result in shorter lifespans and inconsistent energy usage [17].

## II.1 CLUSTER HEAD SELECTION METHODS

Several methods are used to select cluster heads in clustering algorithms, each with its advantages, limitations, and suitability for different scenarios. Some common cluster head selection methods include the following. [18].

### II.1.1 Centroid-Based Selection

In centroid-based methods, cluster head is chosen as centroid of cluster. This approach is commonly used in centroid-based clustering algorithms like K-means, where the cluster centroid naturally serves as the cluster head [19].

### II.1.2 Density-Based Selection

Density-based methods select cluster heads based on density of data points within clusters. Cluster heads may be chosen as points with high local density or as representatives of dense regions within clusters. Density-based methods are effective for handling clusters of irregular shapes and varying densities [20].

### II.1.3 Graph-Based Selection

Graph-based methods select cluster heads based on graph representations of the data, where data points are represented as nodes, and relationships between points are represented as edges. Cluster heads may be chosen as nodes with high centrality or influence within the graph. These are effective for capturing complex relations and connectivity patterns in data [21].

## III. MACHINE LEARNING BASED CLUSTER HEAD SELECTION METHOD (ML CHSM)

In clustering, a cluster head refers to a representative point or entity within a cluster that acts as a central node or leader for that cluster. Cluster heads play a crucial role in various clustering algorithms and applications, as they help organize and manage the clusters. The responsibilities and characteristics of cluster heads may vary depending on the specific clustering algorithm and application context.

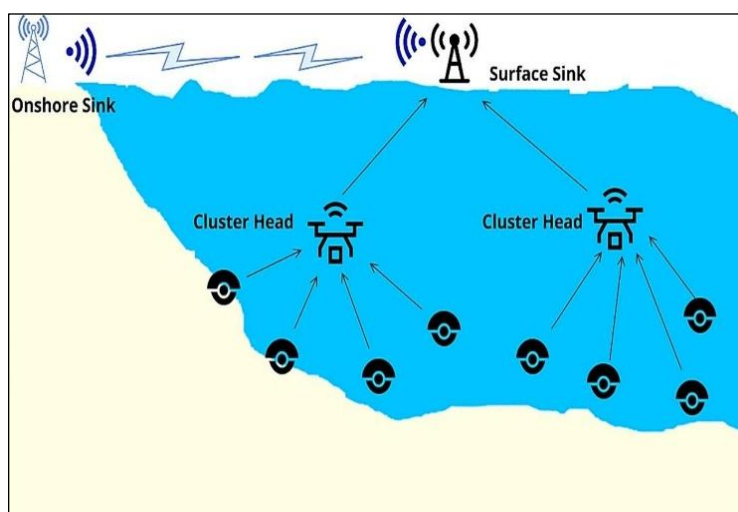


Figure 1: Cluster Head Selection.  
Source: Authors, (2026).

## III.1 IMPORTANCE OF SELECTING APPROPRIATE CLUSTER HEADS

Selecting appropriate cluster heads is essential for the effectiveness and efficiency of clustering.

### III.1.1 Cluster Representation

Cluster heads should accurately represent the underlying cluster they belong to, reflecting the common characteristics of the cluster's data points. Choosing representative cluster heads enhances the interpretability of the clustering results.

### III.1.2 Cluster Management

Cluster heads facilitate communication and coordination within clusters in distributed clustering systems. They may serve as decision-making nodes or aggregation points for cluster-related tasks, such as data fusion, routing, or resource allocation.

### III.1.3 Scalability and Efficiency

In large-scale clustering scenarios, selecting efficient cluster heads can reduce computational complexity and communication overhead. Well-chosen cluster heads enable faster convergence and more scalable clustering solutions.

### III.1.4 Robustness

Appropriate cluster head selection improves the robustness of clustering algorithms by reducing sensitivity to noise, outliers, and initialization variations. Robust cluster heads enhance the stability and reliability of the clustering results.

## III.2 CLUSTER HEAD SELECTION USING K-MEANS

This algorithm aims to enhance network simulations using machine learning. k-means algorithm is used for formation of cluster and CH selection. Simulation can be done by segmenting into rounds. The first round in simulation is setup phase, and next round is steady phase. In the initial phase of each round k-means clustering technique is used for grouping. To ensure dynamic and balanced cluster formation, density and active nodes are considered. Node which is nearer to the centroid is selected as the CH. The CH must be at equal distance from all nodes and convenient to cluster. This results in less energy consumption and reduces the average distance for data transmission. In steady phase, data transmission is done between nodes and CH, later received data is forwarded to sink node. Nodes in network end their life and die out when energy loses completely, then simulation is concluded.

### III.2.1 Energy Consumption for Transmitting Data (E<sub>transmit</sub>)

The energy used by a node while data transmission to its Cluster Head (CH). It considers energy at transmission (ETX) and the energy spent due to path loss, which depends on the distance between node and its CH.

$$E_{\text{transmit}} = \text{Bits} \times (\text{ETX} + (E_{\text{fs}} \times \text{d}_{\text{tch}}^2)) \quad (1)$$

Where  $\text{d}_{\text{tch}}$ , is the distance from its CH, Bits are the number of bits to be transferred.

### III.2.2 Energy consumption for receiving Data (E<sub>recept</sub>)

The energy is consumed by a CH when data is received from its member nodes. It includes the energy used for reception (ERX) and the energy required for data aggregation (EDA).

$$E_{\text{recept}} = \text{Bits} \times (\text{ERX} + \text{EDA}) \quad (2)$$

### III.2.3 Energy Consumption for Cluster Formation (Density\_Parameter)

The density parameter used in determining number of clusters to be formed based on network density. It's a Heuristic parameter to balance the number of clusters in the network.

$$E_{\text{transmitSink}} = \text{Bits} \times ((\text{ETX} + \text{EDA}) + (E_{\text{amp}} \times \text{nodes}(i) \times \text{Dts})) \quad (3)$$

Where  $\text{Dts}$ , is the distance from base station.

### III.2.4 Count of clusters (CoC)

$$\text{CoC} = \text{round}((\text{round}(\text{alive\_nodes}/100) \times \text{density parameter})) \quad (4)$$

### III.2.5 Distance Calculation Between a Data Point and a Centroid

$$d(x_i, c_j) = \sqrt{\sum_{k=1}^n (x_{ik} - c_{jk})^2} \quad (5)$$

Where  $x_i$  is the data point,  $c_j$  is the centroid,  $n$  is the number of dimensions.

### III.2.6 Centroid Updation

$$c_j = \frac{1}{|S_j|} \sum_{x_i \in S_j} x_i \quad (6)$$

Where  $S_j$  is the set of data points assigned to cluster  $j$ .

### III.3 CLUSTER HEAD SELECTION ALGORITHM STEPS

K-means cluster head selection algorithm is an extension of traditional K-means clustering algorithm, specifically focused on selecting representative cluster heads to summarize each cluster. Here's how it works:

#### III.3.1 Initialization

By using k means method choose centroids. These centroids will serve as the initial cluster heads.

#### III.3.2 Assignment

Assign each node to its nearest CH based on Euclidean distance. Each node belongs to the cluster represented by its nearest cluster head.

Mathematical Formulation and Implementation Details.

- $X$  as the dataset with  $n$  data points and  $d$  dimensions.
- $K$  as the number of clusters.
- $C_k$  as the cluster head for cluster  $k$ , where  $k=1,2, K$ .

The mathematical formulation for updating the cluster heads in each iteration can be represented as follows:

For each data point  $x_i$  in  $X$ :

Calculate  $\text{dis}(x_i, C_k)$  for all  $k=1,2, K$

Assign  $x_i$  to the cluster represented by the nearest cluster head.

$$\text{argminkdis}(x_i, C_k) \quad (7)$$

#### III.3.3 Update Cluster Heads

Calculate CHs by computing the mean of each node assigned in a cluster. The new cluster heads represent the centroids of their respective clusters.

For each cluster  $k=1,2, K$

$$C_k = \frac{1}{|S_k|} \sum_{x_i \in S_k} x_i \quad (8)$$

where  $|S_k|$  represents the number of data points assigned to cluster  $k$ .

#### III.3.4 Repeat

Iterate steps 2,3 until convergence, where cluster heads don't change between iterations, or number of iterations limit is reached.

#### III.3.5 Output

The final cluster heads represent the selected cluster heads for each cluster, summarizing the characteristics of the data points within each cluster.

## IV. RESULTS AND DISCUSSIONS

The proposed method is simulated on MATLAB. MATLAB is the best suit for implementing machine learning techniques. Implementation on this platform is also simple and fast. The visualization of outputs is better understandable.

### IV.1 VISUALIZING THE NETWORK

To get a better understanding of network setup, the initial configuration of the network is visualized. Locations of all nodes within network area and the position of Base Station are plotted as shown in figure 2.

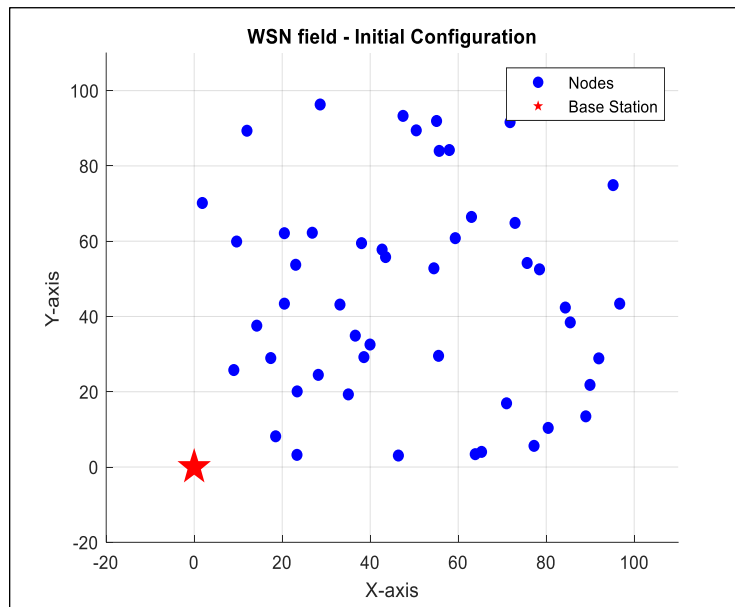


Figure 2: WSN Field Initial Configuration.

Source: Authors, (2026).

With the network set up, monitoring of network's status is done over time. This helps to understand how the network evolves and adapts as the simulation progresses. The clustering technique is applied to the nodes using k-means clustering technique, the figure 3 is a graphical simulation of clusters and centroids.

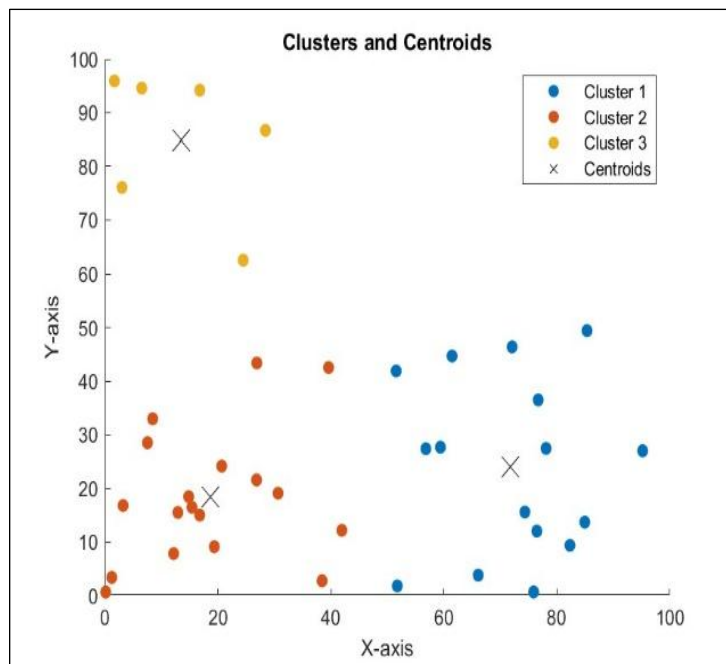


Figure 3: Cluster and Centroids.

Source: Authors, (2026).

#### IV.2 FINDING ALL POSSIBLE PATHS

In this phase, all potential routes for node communication are explored and visualized with the Base Station (BS) in the Wireless Sensor Network (WSN). Imagine mapping out every conceivable path a message could take from a node to the central hub, revealing the network's.

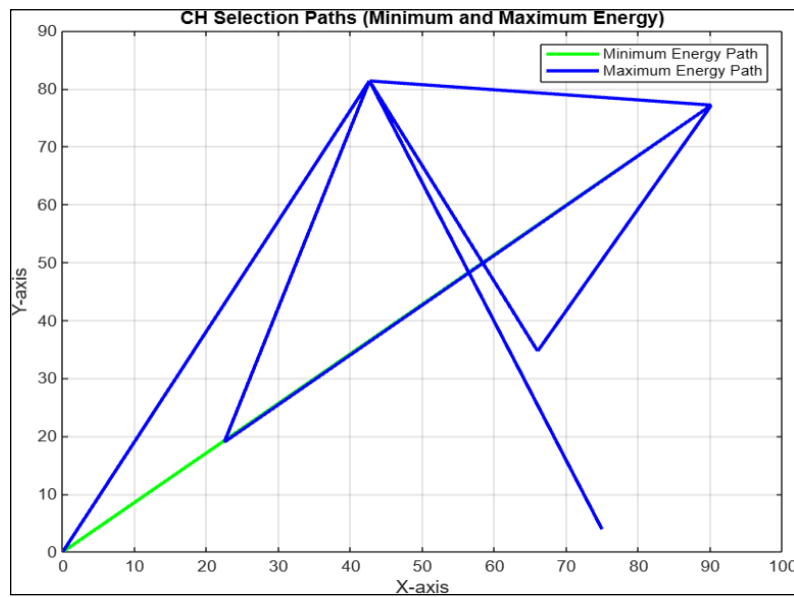


Figure 4: CH Selection Paths (Min & Max).  
Source: Authors, (2026).

### IV.3 CLUSTER ASSIGNMENT

After clustering, the index vector is used to assign each node to its corresponding cluster. The algorithm then proceeds to select a Cluster Head (CH) within each cluster based on proximity to the cluster centroid. Understanding all possible paths in network is essential for designing robust communication protocols and ensuring reliable data transmission. By visualizing the network's connectivity, potential points of failure can be identified and take proactive measures to address them.

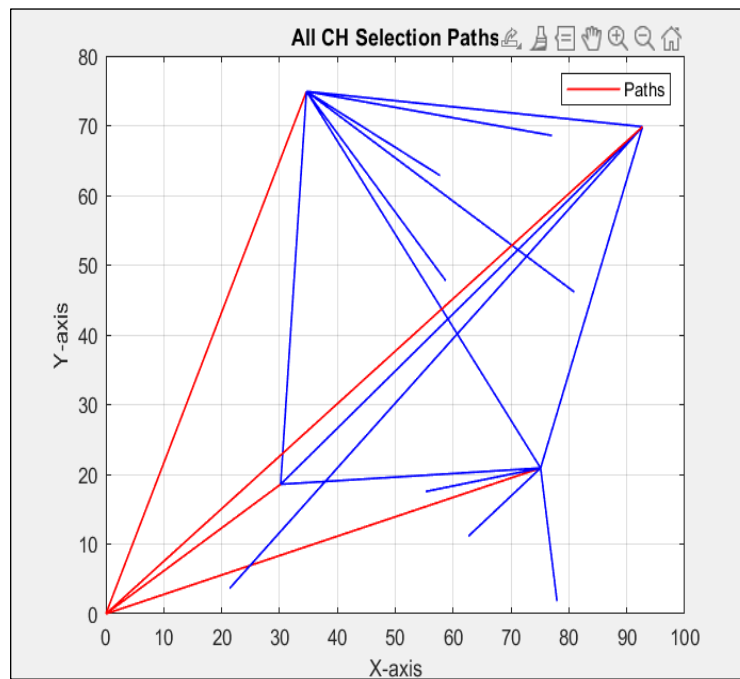


Figure 5: All CH Paths.  
Source: Authors, (2026).

Analyzing node survival is essential for evaluating the reliability and effectiveness of the network. It allows to identify potential weaknesses or vulnerabilities in the network design or protocols.

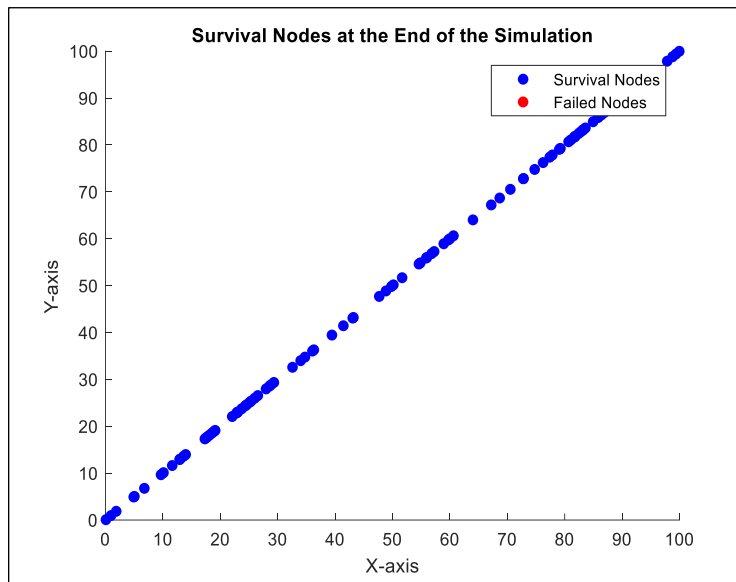


Figure 6: Network Survival Nodes.

Source: Authors, (2026).

#### IV.4 SELECTION OF MINIMUM ENERGY PATH

Selecting the best path is crucial for optimizing energy usage and ensuring efficient data delivery in wireless sensor networks. By identifying the path with the lowest energy consumption, resource utilization is minimized and prolong network lifespan while maintaining reliable communication.

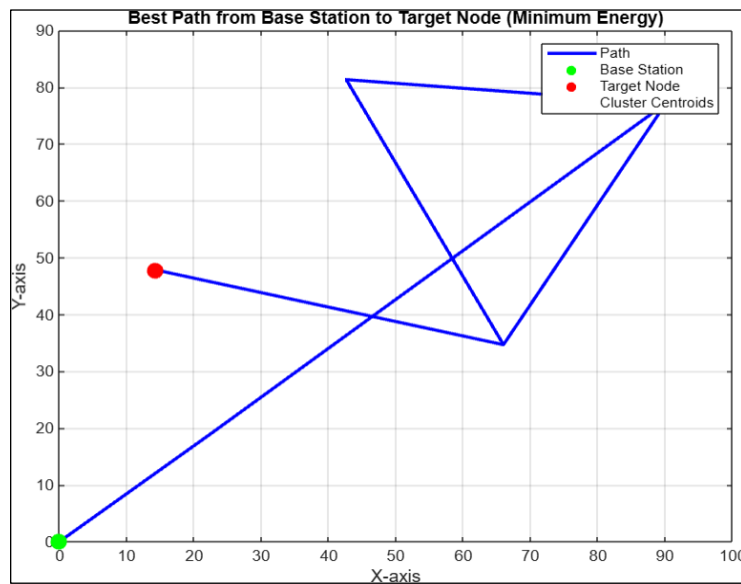


Figure 7. Best Path from Base Station to Target Node.

Source: Authors, (2026).

Table 1: Simulation Reports.

|                                       |              |
|---------------------------------------|--------------|
| Total Transmitted Data                | 0.037500 J   |
| Total Received Data                   | 0.041250 J   |
| Total Aggregated Data                 | 0.041250 J   |
| Total Energy Consumed                 | 0.120000 J   |
| Min Energy Required for Data Transfer | 9.0990e-13 J |
| Min energy consumed for data transfer | 9.5989e-13 J |
| Packet Delivery Ratio (PDR)           | 91.57%       |

Source: Authors, (2026).

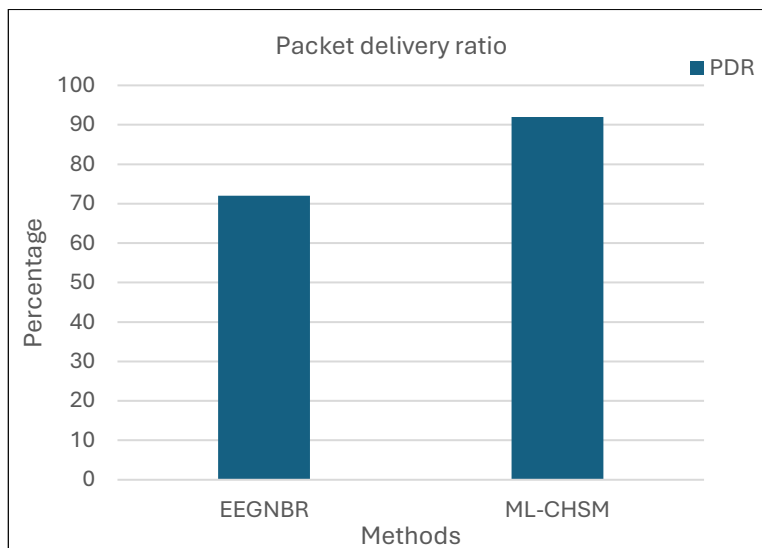


Figure 8: Packet Delivery Ratio.  
Source: Authors, (2026).

## V. CONCLUSIONS

Cluster head-based routing uses a hierarchical structure that allows for data aggregation, reducing the overall communication overhead within the network. This method enables better energy management by rotating the cluster head role, preventing excessive energy drain on a single node. Additionally, hierarchical organization supports scalability, making it suitable for larger networks. The proposed cluster head selection approach further enhances the network's strength by choosing the optimal clusters. This reduces the risk of cluster head failures and increases the network's fault tolerance. The cluster head selection approach in a cluster head-based routing system provides greater benefits in terms of energy efficiency, scalability, and robustness. This makes it a more suitable choice for WSNs, especially in large-scale or energy-critical deployments.

## VI. AUTHOR'S CONTRIBUTION

**Conceptualization:** B. Grace Jemimah, D. Rajesh.

**Methodology:** B. Grace Jemimah, D. Rajesh.

**Investigation:** B. Grace Jemimah, D. Rajesh.

**Discussion of results:** B. Grace Jemimah, D. Rajesh.

**Writing – Original Draft:** B. Grace Jemimah, D. Rajesh.

**Writing – Review and Editing:** B. Grace Jemimah, D. Rajesh.

**Resources:** B. Grace Jemimah, D. Rajesh.

**Supervision:** B. Grace Jemimah, D. Rajesh.

**Approval of the final text:** B. Grace Jemimah, D. Rajesh.

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