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Improve WSN Lifetime Based on K-Means, Genetic Clusters, and Data Compression

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Abstract

Environmental monitoring and industrial process automation are dependent on wireless sensor networks (WSNs). The limited power supply of WSNs' sensor nodes makes energy efficiency difficult. The key goals are selecting cluster heads (CH), distributing nodes, transmitting data, and compressing data. Genetic algorithms improve CH selection. This method incorporates residual energy, base station (BS) distance, and communication overhead. Network lifetime and energy efficiency are maximised by the selection of genetic algorithms. The sensor nodes are distributed using K-means clustering to share load and energy consumption among clusters in a balanced way. Our study's multi-hop data transmission mechanism sends compressed data packets to the base station. Multi-hop communication reduces sensor device energy use. Intermediary nodes for data forwarding significantly reduce network energy usage. To save energy, we suggest implementing a compressed data packet transmission technique. Compression methods minimize data packet size while keeping data precision, improving sensor network energy efficiency. This sustains the network's longevity. Our proposed method has been extensively simulated for energy usage, network longevity, and data delivery ratio. The results show 100% optimization over LEACH, LEACH-C, FIGWO, PSO, ABC-SD, CGTABC2 & ACO, ED-LEACH, I-LEACH, CBDAS, GHND, R-LEACH, MH-LEACH, D-LEACH, 98% for ADMH-LEACH. In the 1657 round, the proposed MOCDA-LEACH protocol reduced energy consumption by 18% compared to LEACH. Although the specific PDR values are not shown graphically, the improvements in the package delivery ratio were achieved through data compression, multi-hop communication, and the optimized CH elections using GA. These improvements led to significantly lower energy consumption and a useful life of the network extended by more than 82%, demonstrating the suitability of the WSN applications limited by energy. This study optimizes sensor efficiency in wireless networks by conserving energy in the LEACH protocol. It helps design resilient and efficient WSNs, enabling sensor-driven applications in energy-constrained environments.

1. Introduction

A WSN is a decentralized network of environmental sensors. WSNs have been extensively employed in a variety of domains, including healthcare, environmental monitoring, military operations, disaster forecasting, and smart residences, as a consequence of their adaptability. AWSN is a collection of sensor devices that are situated within a specific geographic area. The energy efficacy of each sensor is compromised by its predetermined data buffer size and restricted battery capacity. Consequently, a variety of strategies are implemented to enhance the energy efficiency of WSN [1].

Four fundamental ratio modules are present: data reduction, sleep/awake schemes, and battery charging. The ratio module analyzes the four states of each sensor node: idle, sleep, transmit, and receive. Inactivity of sensors often leads to depletion of nodes [2]. The ratio module optimizes settings to decrease energy consumption. The ratio module governs four states, resulting in increased energy consumption. Data reduction serves as a solution by minimizing packet sizes to conserve energy and decrease traffic and latency. Imbalanced energy consumption reduces network lifespan. Multiple research studies have investigated the utilization of measurement systems to collect data aimed at minimizing non-uniform energy consumption. The MS facilitates the transmission of sensor node data packets across the WSN. No-data-forwarding and hybrid approaches represent the primary focus of this discipline [3, 4, and 5]. The no-data-forwarding technology employs a mobile sink (MS) to collect data packets without a direct connection among sensor nodes, thereby reducing energy consumption in the network; however, the extended routing of MSs leads to increased network delays. The hybrid approach employs cluster heads to collect data packets and establish connections with sensor nodes. Data packets are exclusively collected from CHs by the MS [6]. The primary objective is to balance the amount of time spent gathering data and the energy used for node communication. The majority of methods choose and group locations known as CHs (collection points), after which they develop a tour schedule that allows the mobile unit to visit each CH independently. Nonetheless, there is a tight relationship between geography and pathway design. The trip path is determined by the locations and the maximum journey length. While completely using the maximum touring length may increase network lifetime, addressing the two challenges independently may lead to wasteful use of it. Figure 1 illustrates how path efficacy may be reduced by splitting the processes of selecting collected points (CHs), creating the path, and performing local optimisation.

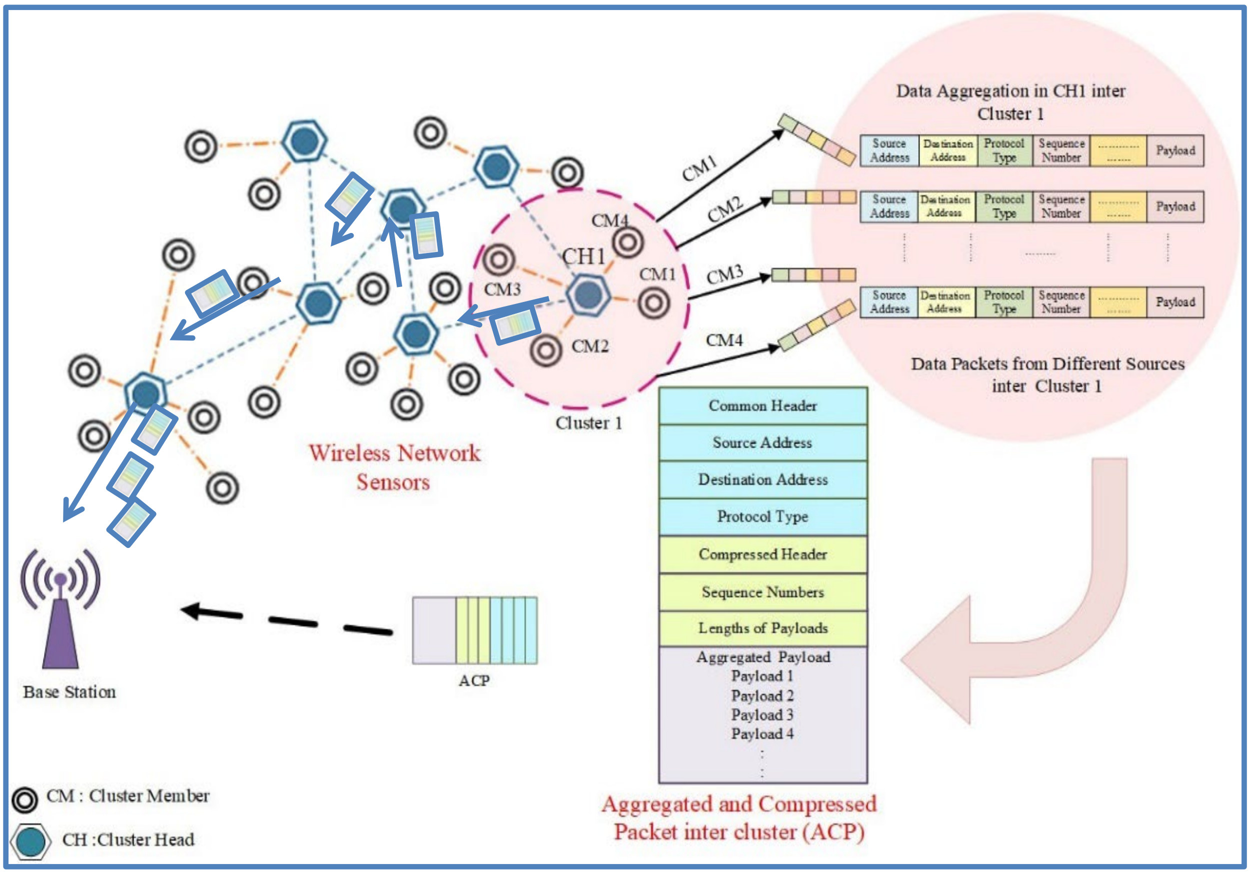


Fig. 1 *Mechanism for aggregating and compressing data packets*

In order to increase network longevity, we investigate the potential for addressing collection point selection and path planning challenges in a cohesive manner. By collecting data packets via an MS instead of direct connection between sensor nodes, the no-data-forwarding method lowers network energy consumption. However, MSs' long journey causes a large amount of delay in the network [7]. The hybrid method collects data packets and connects to sensor nodes using data collection points, or CHs. The MS only exchanges information with CHs in order to collect data packets. The primary objective is to attain a balanced relationship between energy consumption in node communication and the latency of data collection. Many methods select and categorize locations, commonly known as collecting points or CHs, and subsequently develop a tour itinerary that allows the mobile unit to visit each CH independently. Nonetheless, there is a direct relationship between the path pattern and site selection. The destinations chosen determine the journey path, and the selection process is impacted by the longest trip length [8]. Although using the maximum touring length might ultimately increase the network's longevity, addressing the two problems independently could have the unintended consequence of causing the maximum touring length to be used less effectively. If the path design and collection points (CHs) selection procedures are separated and local optimisation is done, Figure 1 shows how the path's overall effectiveness may be decreased [9]. We have presented a comprehensive data collection approach that integrates data collecting from especially locations (CHs) with concurrent heuristic scheduling of the touring schedule. The first step is to create a genetic algorithm aimed at determining the optimal cluster heads (CHs). The selection process evaluates the residual energy levels of each sensor, the distance between sensors and cluster heads, along with additional pertinent factors. This approach is then used to find the most efficient and succinct path for MS movement, replacing the path taken by the most optimum particle detected with a re-estimated shortest path, hence increasing the efficacy of the Particle Swarm Optimisation (PSO) algorithm.

1.1 Problem Statement

Low-power sensor nodes, radio communication channels, and base stations are all features of WSNs. It is crucial to have a new routing technique with the best CHs selection probability. Selecting the appropriate CHs and cluster configurations, as well as developing an energy-efficient routing strategy, are challenges faced by many scholars [10]. According to publications [11–12], Compared to direct transmission and minimum-transmission-energy (MTE) approaches, the LEACH protocol performed better in the clustering problem. LEACH-based data aggregation on CHs improves longevity and reduces network traffic [11]. One major limitation of LEACH is its unequal and unpredictable CH selection. For high-node clusters, rough CHs increase energy consumption while decreasing energy utilization for node clusters. Consequently, network performance is impacted by the distribution. To address the limitations of the LEACH protocol, the (Centralized LEACH-C) protocol was put out in [13]. By taking node position and energy into account, this technique improves CH selection. LEACH-C lasts longer than LEACH. Long-distance communication or larger networks might not be able to use it. LEACH-GA should be more likely to choose the best CH than LEACH and LEACH-C. Network performance is better for LEACH-GA than LEACH and LEACH-C [14]. GADA-LEACH [15] performs better than earlier LEACH variants that used relay nodes to connect CHs to the BS. CH option makes this better. LEACH protocol cluster choices have been improved. Cluster node construction optimizes strength in LEACH. The closest CHs are used to send data to the sink.

1.2 Paper Goals

An energy-efficient WSN sensor efficiency method is presented in this work. One of the main WSN concerns, sensor node power limitations, is addressed in this paper.

- CH selection is optimized using a genetic algorithm. Communication overhead, BS distance, and residual energy are utilized. Network lifetime and energy efficiency are increased by CH optimization.
- The paper optimizes the distribution of sensor nodes by clustering K-means clustering. Effective matching of energy consumption and load between clusters is necessary for sensor nodes.
- Optimization of Data Transmission: Network energy is conserved by intermediary nodes that forward data, and the study's BS receives compressed data packets via multi-hop communication.
- Data Compression Optimization: According to the study, compressed data packet transmission can lower data transport energy use. Data packets are compressed with good data fidelity usage during data transport. Data packets are compressed with good data fidelity.
- Performance Evaluation and Validation: The study simulates extensively to evaluate the proposed approach. The study compares energy usage, network lifetime, and data delivery ratio to traditional methods to demonstrate the claimed methods' efficacy.

This paper provides energy-saving techniques for WSN sensor efficiency optimization. The article helps build resilient, energy-efficient WSNs by addressing energy efficiency issues holistically. The goal is to seamlessly incorporate sensor-driven applications across energy-limited domains to ensure WSNs' long-term sustainability.

1.3 The Main Contributions

Sensor networks benefit greatly from the combination of GA for effective CH selection, K-means clustering, LZW compressing data for collecting data inside CH, delta modulation encoding the data compressed into packets, and multi-hop communication. Let us review each of these contributions immediately:

1. Sensor Grouping Using K-means Clustering:
    a. K-means clustering primarily contributes by geographically clustering sensors according to their geographic closeness, allowing the network to effectively handle and interpret sensor input inside each cluster.
2. A successful clustering approach ensures minimal resemblance across groups and a high amount of intra-group similarity.
3. The strategy's and its implementation's use of a similarity metric establishes the group's quality.
    a. K-means reduces transmission costs by allowing sensors in a group to communicate on a single channel rather than sending data to a BS.
    b. By increasing data aggregation in each cluster, it gets rid of redundant data and makes the most of network resources by sending the collected data to the sensor's CH.
4. Effective Genetic Algorithm for CH Selection:
    a. Network CH selection is optimized via genetic algorithms. CH selection is necessary for energy-efficient sensor networks.
    b. The evolutionary algorithm improves selection by considering sensor energy, connectivity, and base station proximity.
    c. Effective CH selection extends network lifetime by balancing sensor energy consumption.
5. Data Aggregation Using LZW Data Compression Within CH:
    a. The CH data size is decreased by LZW data compression because the algorithm effectively substitutes shorter codes for repetitive data patterns.
    b. Data compression inside CH lowers communication overhead and energy consumption by requiring less data to be transferred.
    c. When sensor data, which is frequently found in sensor networks, has patterns or redundancy, LZW data compression is very advantageous.
6. Multi-hop Communication:
    a. To send data effectively over greater distances, WSNs require multi-hop communication.
    b. Sensors may send data over long distances or in vast networks via intermediary nodes (multi-hop).
    c. Enhancing network coverage and enabling even remote sensors to participate in data gathering are two benefits of multi-hop communication.

This is how the rest of the paper is set up: In the second part of the paper, we check out the research on clustering, cluster-based routing, energy efficiency, optimization methods for CH selection, compression algorithms, and K-means clustering in WSN routing techniques. Section 3 of the model dives into the proposed systems and networks, highlighting the new algorithm we have developed. You can find all the details about how the proposed protocol works in the fourth section. The fifth section covers the findings from the models and the observations for various parameters. We check how well things are working by looking at the results and comparing them to what is already out there. The work wraps up in the sixth part.

2. Literature Review

Energy-efficient WSNs are needed since sensor nodes have limited energy. Many researches have examined WSN energy efficiency. Research has examined many methods, including Energy Conservation Strategies [7]. IEEE suggested sleep scheduling, duty cycling, and transmission power management for 2021 WSN energy reductions. Industrial WSNs' Industry 4.0 advantages were noted by another researcher [16]. Data-driven and quality-of-service-based architecture was advocated for industrial energy efficiency. A top-down examination analyzed IoT WSN energy efficiency. Environmental IoT and energy-saving implementation [17]. Many researches have examined WSN energy efficiency. Smith et al. examined WSN energy efficiency [18]. This context examined energy-saving and optimization options. [19] Li et al. studied WSN energy efficiency. Developed energy-efficient power management, data aggregation, and routing algorithms for these networks. WSN data routing and aggregation need cluster heads. For CH selection, popular genetic algorithms maximize cluster formation. [20], [21Multi-objective clustering with a focus on WSNs was developed. This software enhances data aggregation, network coverage, and energy efficiency in WSNs. An evolutionary algorithm-based clustering approach for heterogeneous WSNs was developed by R. Samadi and J. Seitz. It is energy efficient [22]. Evolutionary algorithms improve solution quality and aggregate composition via coupling, morphing, selection, uses, challenges, and metaheuristic solutions for WSNs [23].

S. Khriji, D. El Houssaini, et al. [24] investigated energy-efficient WSN techniques to extend the lifespan of the network and conserve energy. The study examined energy-efficient WSN solutions to save electricity and extend network life. We study node energy optimization, communication, and network organization. Each strategy has merits and downsides. Large wireless sensor networks save energy with gorilla-inspired multi-objective optimization. A new chimpanzee troop collaboration method saves energy in large-scale WSNs [25]. Algorithms evaluate energy, connectivity, and network coverage. Gorilla troop network energy usage increases with communication and cooperation. Dispersion of gorilla troops enhances wild sensor node location and energy use. Environment and resources enhance network lifespan and energy consumption. [26] Phasmatodea population expansion and surrogates improve WSNs. The surrogate model accelerates algorithmic evolution. Researchers recommend Phasmatodea population evolution-based stick insect optimization. Through surrogates, the method is theoretically optimized. Surrogate models estimate candidate solution fitness and develop favorable search space areas, boosting algorithm performance. Surrogate models accelerate convergence and solution space exploration. Surrogates improve WSNs' efficiency and quality. A hybrid optimization method utilizing a genetic algorithm and tabu search for coverage set scheduling optimizes the lifespan of WSNs [27]. Researchers enhance coverage set scheduling to prolong WSN life. The study recommended evolutionary algorithms and tabu search scheduling. Optimize coverage set scheduling to expand WSNs. Coverage and lifespan approach for evolving sensor networks developed by Tam et al. The authors assess sensor network coverage and longevity. An evolutionary-TLBO hybrid algorithm was introduced. Energy utilization, network longevity, sensor monitoring area, and coverage are optimized. Second-level genetics improved WSN cluster head selection and routing [28]. It optimizes with two-level genetic algorithms. First, CHs are chosen. Cluster heads gather and share network data. First-level leaders optimize second-level inter-cluster routing. Genetic algorithm-selected cluster heads may improve WSNs [29]. Heterogeneous WSNs make cluster head selection challenging due to sensor node energy and capability. The initiative boosts networks and enhances network performance. Node energy and load are reduced via WSN K-means clustering. MacQueen K-means organized WSN multivariate data in 1967. Energy-saving operations were studied. K-means clustering for load balancing and node distribution [30]. B. Solaiman improved WSN energy by hybrid k-means PSO clustering [31]. Optimizing WSN clusters saves power. K-means clustering and PSO optimization boost energy efficiency and WSN cluster creation. S. El Khediri et al. enhanced WSN node localization with K-means clustering [32]. WSN sensor nodes are positioned correctly. Improved K-means clustering finds WSNs. Soft-k-means clustering by B. Zhu et al. balances wireless sensor network energy. K-means increases node energy allocation, increasing network life [33]. Gouissem et al. provide a method for energy-efficient grid-based k-means clustering in large WSNs [34]. Grid-based WSN aggregation saves power. Grid-based solutions improve tremendous WSN energy efficiency. WSN distributed k-means clustering by J. Zhou et al. [35]. Scalable WSNs conserve energy, and decentralized clustering and local information flow between nodes improve energy efficiency and scalability. A. Mahboub and M. Ariouf [36] developed an energy-efficient hybrid k-means method for clustered WSNs. Energize WSN clustering less. Histrionics and k-means conserve energy and networks. et al. [37] suggested hybrid clustering for WSN optimization. The k-means and heuristics method clusters WSNs best. Combining methods boosts cluster formation and WSN energy usage.

3. Model for Energy Dissipation in Network Radio Systems

This part goes over the network energy model and the basic ideas that support what we're bringing to the table.

3.1 Network Model

The recommended approach is tested using a WSN with 100 nodes scattered over (M × M) m^2. Consider this network as follows:

- • Nodes and BS are anticipated. To be stationary when they are initially installed in the environment.
- The BS can be found in a variety of the monitoring field, including the center, corners, and outside.
- There are no limits on the BS's memory, computing power, or energy consumption.
- Every node's identification is known to the BS.
- Each node can transmit data to the BS.
- All nodes are uniform.
- The symbol CH represents a cluster
- Nodes must gather and relay information from their surroundings to the CH.
- Every node is assigned a unique identification.
- Data gathering, compression, and Its transmission to the BS is the responsibility of the CH.

3.2 System of Radio Communication

This paper proposes the MOCDA-LEACH Protocol (Multi-hop Optimum Cluster Head Compression Data Aggregation - LEACH Protocol) for a network model based on specific assumptions. Each sensor includes a GPS or other location device. Sensor nodes remain in place after deployment, BSCs have a lot of resources, and neighboring sensors provide data correlation. The radio model in Fig. 2 and the symmetry of the communication channel means that sending a message from s. The transmitter-receiver distance determined the channel model used: d^2 power loss in open space or d^4 power loss in multipath fading. A k-bit message sent d meters away requires the radio to expend:

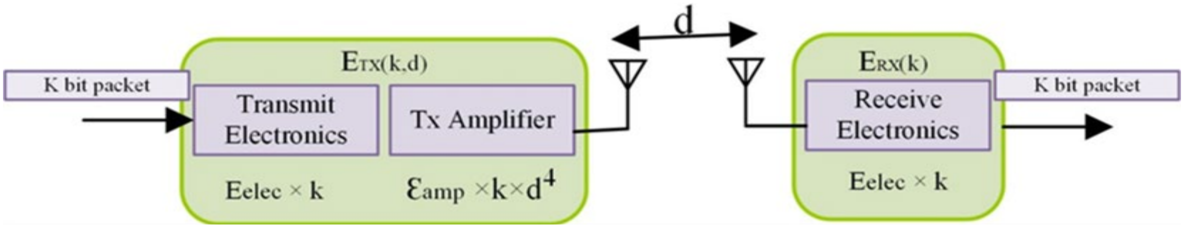


Fig. 2 *Radio model*

The proposed MOCDA-LEACH protocol is analysed using the radio model reported in [1], which is illustrated in Fig. 2. An expression for the energy sent and received via k-bits may be found in equations (1, 2, and 3). Where:

$$E_{TX}(k,d) = E_{TX-elec}(K) + E_{TX-amp}(k,d) \tag{1}$$

$$E_{TX}(k,d) = \begin{cases} k \times E_{elec} + k \times \varepsilon fs \times d^2 & d < d_0 \\ k \times E_{elec} + k \times E_{TX-amp} \times d^4 & d \geq d_0 \end{cases} \tag{2}$$

$$E_{RX} = K \times E_{elec} \tag{3}$$

Where:

E_{TX} (k, d): Total transferred energy considering packet size and transmitter-receiver distance.
$E_{TX\text{-elec}(K)}$: Packet-size transmitter electron energy.
E_{TX} (k, d): Total transferred energy considering packet size and transmitter-receiver distance.
$E_{TX\text{-elec}(K)}$: Transmitter electron energy for packet size.
$E_{TX\text{-amp}}$(k, d): Amplification energy based on packet size and transmitter-receiver distance.
E_{RX}: Energy received.

$$d_o = \sqrt{\varepsilon fs / E_{Tx-amp}} \tag{4}$$

$$d = \sqrt{(x2 - x1)^2 + (y2 - y1)^2} \tag{5}$$

When determining the electronic energy (Eelec) of a signal, the threshold distance is one of the most significant elements to take into consideration. This energy is influenced by a wide variety of elements, including digital coding, the broadcasting methods that are utilized, filtering, and modulation. Additionally, the amplifier power ($\varepsilon fs\ d^2$ or $ETx\text{-amp}\ d^4$) is determined by the distance between the source and the receiver, in addition to the number of bits error that is allowed. Consider an area of dimensions M × M with a uniform distribution of N nodes. The CH utilizes energy by receiving and integrating messages from other nodes, subsequently transmitting the resulting signal to the BS for L clusters, each containing mi member nodes (i = 1, 2,..., L). The energy expended by the CH node in the ith cluster can be determined using equations within a single frame. In the given equation, the variable k represents the number of bits in each data packet, assumptive of perfect data aggregation in Equations (6) and (7), and Di-to BS denotes the distance between the ith CH node and the BS. Once per frame, each member node must send the info it has found to the appropriate CH.

$$E_{CH}(i,k,d) = \begin{cases} k \times E_{elec} \times m_i + k \times E_{DA}(m_i + 1) + k \times E_{elec} + k \times \varepsilon fs \times d_{i-to\ BS}^2 & if\ d_{i-to\ BS} < d_0 \\ k \times E_{elec} \times m_i + k \times E_{DA}(m_i + 1) + k \times E_{elec} + k \times E_{TX-amp} \times d_{i-to\ BS}^4 & if\ d_{i-to\ BS} \geq d_0 \end{cases} \tag{6}$$

$$E_{mem-i}(l,k,d) = \begin{cases} k \times E_{elec} + \varepsilon fs \times k \times d_{i-to\,CH}^{2} & if\ d_{1-to\,CH} < d_0 \\ k \times E_{elec} + E_{TX-amp} \times k \times d_{i-to\,CH}^{4} & if\ d_{1-to\,CH} \geq d_0 \end{cases} \tag{7}$$

E_{DA}: The amount of energy lost for aggregated data
$E_{CH}(i, k, d)$: The energy dissipated by each CH node
$E_{mem-i}(l, k, d)$: The amount of energy lost by each member node

4. Proposed Work

In order to improve network longevity and scalability, researchers have examined the concept of clustering sensor nodes. As seen in Fig. 3, each cluster typically has a designated leader, or CH. While the hierarchical protocol initially saw widespread usage in wired networks, it underwent revisions tailored to WSNs in an effort to extend the life of the networks while also decreasing their power consumption.

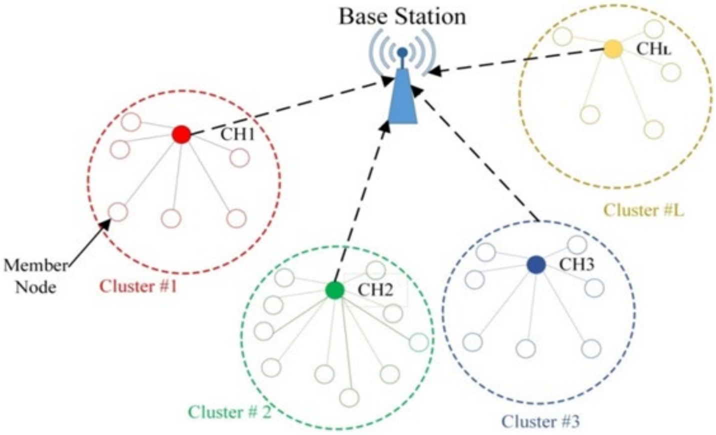


Fig. 3 *Hierarchical clustering structure*

They came up with the LEACH protocol in 2000 and Srividhya et al. 2021. It was the first adaptable protocol for CH selection in WSNs. Traditional cluster selection methods are used along with self-organization and a random distribution with a round component [11]. The primary objective of the LEACH protocol is to minimize power consumption. Clusters are selected through a two-stage process: setup and stable state. During the planning process, all nodes are distributed randomly, and the base station transmits messages to all cluster heads. The K-means method is employed in section 4.1 to demonstrate how the proposed approach forms clusters within the target sensor network. The clustering method outlined in this study divides the entire dataset into k groups, with k representing the number of groups [38]. A message from the base station is transmitted to all control nodes of the LEACH protocol, or cluster heads. Equation (8) indicates that cluster heads (CHs) are selected based on a cutoff value T(n), which considers their probability of becoming a CH (p), the current round (r), and the number of non-CHs remaining from the previous 1/p rounds.

$$T_{(n)} = \begin{cases} \dfrac{p}{1 - p\left(r \bmod \dfrac{1}{p}\right)} & \forall_n \epsilon\, G \\ 0 & if\ n \notin G \end{cases} \tag{8}$$

The network assigns a random integer between 0 and 1 to each node. If the number of nodes created is less than T(n), any of them can take over as the cluster's control node. Any additional node can join the cluster as a member or not join at all. When everything is stable, CHs start sending data by inviting CMs to their clusters. Thirdly, data is sent from CHs to the sink node by nodes that are not CHs. When choosing a CH, neither the node's position nor its remaining energy is considered. As shown in 4.2, MOCDA-LEACH employs a GA to ascertain the optimal cluster head probability during the preparation phase. Prior to setup and steady-state, there is this initial round. Like the LEACH protocol, the network nodes choose possible CHs. Every node's location, ID, and CH are sent to the BS. Popt is computed by the BS using the Genetic Algorithm. Launching Popt to every node is the first step in the setup and steady-state stages. Section 4 explains the MOCDA-LEACH technique. With the use of MOCDA-LEACH, the optimal value for the cluster head, Popt, is determined. The energy consumption for the CH nodes can be calculated using Equations 1, 2, 3, 6, and 7. After the evolutionary algorithm has chosen the most suitable CHs, once they have become CHs, they notify the other sensors by sending control signals. After that, the rest of the sensors congregate close to the CH. Once everything is set up, the clustering and steady-state stages may start. Throughout the steady phase, sensor nodes in the cluster maintain contact with the CH. Data from all of the nodes in the CH are averaged or added together. The aggregation of CH data by LEACH has reduced power consumption and data transmission by WSNs. Data compression or collection at intermediate cluster nodes prior to transmission to the CH and BS can significantly reduce data transfer. Basic operations like adding and averaging may be part of the data aggregation process, depending on the data and its intended use. Solving more complicated procedures, or determining the top and lower limits. Among the energy-saving features of our proposed protocol is data aggregation, which reduces transmissions from sensor nodes, and the lossless compression method LZW (Lempel-Ziv-Welch), suitable for data integrity. Section 4.3 provides evidence of this. Finally, as mentioned briefly in section 4.4, the compressed aggregated data is transmitted to BS using multi-hop connections. See the evolutionary algorithm, K-means clustering, and multi-hop communication flow diagram in Fig. 3, which shows the MOCDA-LEACH protocol's system architecture.

5. Methodology

Here, we highlight the uniqueness and intricacy of our proposed procedure. In order to increase the WSN lifespan, we employ clustering, multi-hop communication, compression, and optimal CH selection.

5.1 The K-Means Algorithm

The target sensor network is clustered using the K-means algorithm. Concerning unsupervised grouping, this is relevant. In this study, we show how to group datasets into k subsets, where k is the total number of groups [2]. For the purpose of categorizing objects, the Euclidean distance metric is employed. Using an iterative technique, each data point in the dataset is assigned to a single cluster. None of them are similar. Following this, the K-means grouping algorithm performs the operations shown in Figure 4.

```
Algorithm K-Means Clustering
Procedure Create K-means Clustering (Model, Area)
    n = Model.n
    x = Area.x
    y = Area.y
    X = rand(1, n) * x
    Y = rand(1, n) * y
    [idx, ~] = kmeans([X', Y'], k)
    clusterCenters = zeros(k, 2)
    for i = 1:k do
        clusterIdx = find(idx == i)
        clusterCenter = mean([X(clusterIdx)', Y(clusterIdx)'], 1)
        clusterCenters(i, :) = clusterCenter
    end for
    for i = 1:n do
        clusterIdx = idx(i)
        radius = min(x, y) / 5
        angle = rand() * 2* pi
        displacement = radius * [cos(angle), sin(angle)]
        X(i) = clusterCenters(clusterIdx, 1) + displacement(1)
        Y(i) = clusterCenters(clusterIdx, 2) + displacement(2)
    end for
end Procedure
```

Fig. 4 *For the MOCDA-LEACH protocol, the Psoudio K-means network*

A collection K is partitioned into a predetermined number of groups using the K-means grouping algorithm. The data points that make up a cluster might be similar to one another and yet unique. The K-means method iteratively assigns each data point to the centroid of the nearest cluster. Each data point is then assigned to the cluster center that is physically nearest to it once the centroid's position is recalculated. After a specific amount of iterations or when the centroids cease moving about, the aforementioned procedure is applied. Every data point is assigned one K-cluster. K-means clustering requires several components. The correct number of clusters (K) and their locations must be determined before a clustering research can be conducted [39]. Choose the first centers at random or use K-means. The use of distance measurements like the Euclidean distance is context dependent. Keep the network architecture and node groupings in mind while distributing nodes using K-means clustering. Distance between nodes and other network metrics allow for K-means clustering.

5.2 Optimal CH Using Genetic Algorithm

GA determined the Popt, the ideal probability of cluster heads. Once setup is complete and the BS distributes Popt values to every node, the steady-state phase starts. View Figure 5. We use a genetic algorithm to choose the leaders of each cluster. When selecting leaders for each cluster, each node's remaining energy, the distance between its heads and members, the overall number of clusters, and the distances between clusters and the base station are all factors that the GA considers. See below. The CH status should be set to 1 if the node is the cluster head and to 0 otherwise. Consider the node at the given x and y coordinates.

1. Distance between Base Station and node: $d_{i-to\ BS}= \sqrt{(x2+\ y2)}$
2. Determine fitness using a variety of criteria:
    a. Fitness of Consumer Energy (F_{CE}) (chromosome)=
    b. The distance to Base Station Fitness ($F_{di\text{-}to\ BS}$) = 1 / $d_{i\text{-}to\ BS}$
    c. Nodes' Fitness Number (F_N)= number Nodes / (number Nodes + 1)
    d. Each Cluster fitness's number of nodes ($F_{Cluster}$)= 1 /(number Nodes+ 1)
    e. The formula for Fitness in Network Area (F_{Area}) = (network area / (max (x, y)^2))
3. Determine the total frame and chromosomal fitness:
   Chromosome Fitness = Fitness of Consumer Energy × The distance to Base Station Fitness × Nodes' Fitness Number × Cluster fitness's number of nodes × Fitness in Network Area
4. Fitness = $F_{CE} + F_{di\text{-}to\text{-}BS} + F_N + F_{Cluster} + F_{Area}$
5.

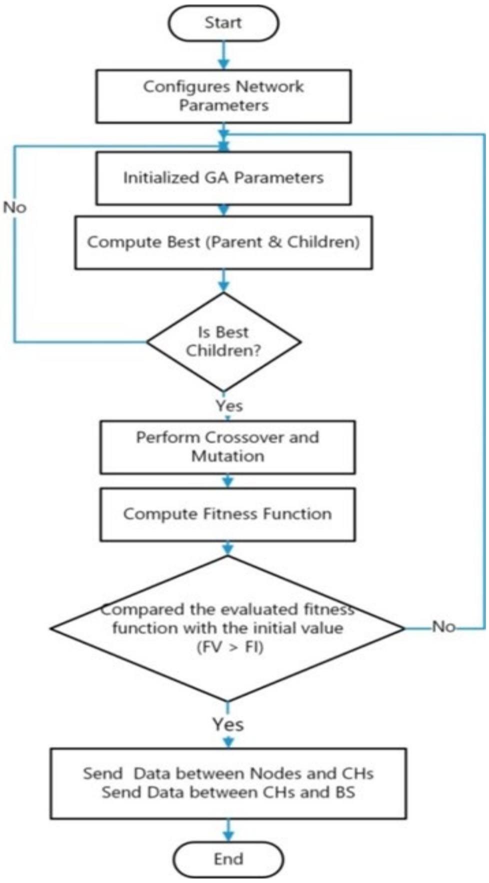


Fig. 5 *The flow chart shows the CH selection algorithm in the MOCDA-LEACHprotocol*

Fitness is calculated using this formula. The fitness function considers network longevity, energy consumption, and load balance while evaluating chromosomal configuration. It evaluates cluster head numbers, placements, base station distances, cluster proportions, and load balancing across clusters. The fitness function evaluates these characteristics to assess system effectiveness.

5.3 LZW Compression Algorithm

The well-liked lossless data compression technique Lempel-Ziv-Welch (LZW) reduces data size without sacrificing information. It was started in 1977 by Abraham Lempel, Terry Welch, and Jacob Ziv. In the suggested protocol, the code uses the widely used lossless LZW compression method. By using shorter codes to encode recurring patterns, one method to compress data without losing any information is LZW, which is based on dictionaries. LZW compression may achieve high compression ratios and works well with many different types of data, especially those that contain lengthy string of characters or patterns with repeated elements. Compression ratio is affected by data type. To keep the first dictionary from growing too big, the process resets it frequently. The compressed data was then delta-encoded. Data size is reduced using delta encoding as opposed to absolute values.

5.4 Communications That Include Multiple Hops

Through relay nodes, The sensor nodes that are part of the multi-hop WSN connection send data to the BS. This manner, the network and communications can cover more ground. Many parts work together to allow multi-hop WSNs to send compressed packets back to the main station.

- Information Received from Sensor Nodes: CHs receive environmental data transmitted by network sensors.
- Gathering Data: Gathering information from nearby sensor nodes and then transmitting it on is known as multi-hop communication. Enable data compression prior to transmission. Data was sent via LZW. CHs. Data aggregation reduced transmission and duplication.
- Routing Protocol: It identifies the best BS data packet pathways. Hop count, energy, connection quality, and network structure must be considered by the routing protocol. Work with LEACH. Sensor node cluster chiefs are elected via LEACH. CHs give BSs cluster-info. LEACH node energy is balanced via CH rotation.
- Relay Node Data Forwarding and Aggregation: Intermediate relay nodes forward neighbors' data packets to the BS. In each step before transmission, relay nodes might gather data. This continues until BS data packets arrive.
- Data Reception at Base Station: Sensor nodes may transmit data over extensive distances, even in constrained connection ranges, to facilitate comprehensive monitoring and surveillance. Network coverage, expansion, and energy efficiency are improved by WSN multi-hop communication, which includes compression, aggregation, and effective routing. Relay node data is gathered and examined by the BS. Analysis and decision-making of all sensor node data.

6. Simulation and Results

The protocols were simulated in MATLAB to evaluate the recommended technique. Table 1 lists simulation model parameters. The BS is in the middle of 100 randomly distributed nodes. Energy usage, active and idle nodes, and base station packets are utilized to evaluate the proposed solutions. The K-means method forms clusters after a network deployment with K clusters. Setup: N = 100 nodes, area = 100 x100 m^2, Eo =0.5J, and packet size = 4000 bits. Figure 6 indicates K = 15 had the longest network lifespan. As network contact develops, node energy demand rises. Relationships boost a node's connectivity, making this event commonplace. Thus, the node receives more packets, using more power. The multi-hop communication of the proposed network is illustrated in Figure 7. The green line connects CHs to transmit compressed and aggregated data, while the blue lines show sensors that sent data to CHs. Over long distances, multi-hop communication could be more energy efficient. Energy is conserved for nodes that transmit and receive data by means of intermediate relays. If you want to measure how well a network is doing, you need the BS.

Communication reliability, network coverage, and energy efficiency may be affected by the BS. Examine network response to BS position changes. Simulations reveal that the corner (20,20) and outside the monitoring zone (50,150) BS performs better than the middle (50,50). Over BS(50,50) and BS(50,150), BS (20,20) has the longest network lifespan. The optimal unstable condition is BS(50,50), where half the nodes die. Fig. 8 illustrates network lifetime locations.

Table 1 *Parameter of the simulation model*

Parameters	The Values
The size of the network	100 × 100 m^2
Quantity of nodes	100 ,200
The size of the packet	2000,4000 bits
Initial energy, E_0	0.2, 0.3, 0.5, 1 J/node
Energy transmission, E_{TX}	50 nJ/bit
Reception Energy, E_{RX}	50 nJ/bit
Short-range energy amplification, εfs	10pJ/bit/m^2
Long-range energy amplification, E_{mp}	0.0013 pJ/bit/m^2
Energy data aggregate, E_{da}	0.0013 pJ/bit/m^2
Maximum number of Iteration	5
Number of populations	10
Number of the cluster (K)	15

Fig. 9 illustrates the first, half, and final nodes dead (FND, HND, and LND) to demonstrate MOCDA-LEACH's network efficacy under different BS locations.

Fig. 10 illustrates MOCDA-LEACH energy use during BS position modifications. Excellent conditions are at BS (20,20). Energy variance is the differential in sensor node energy levels in WSN effectiveness. It measures how equitably each network node receives energy. Energy fluctuation is crucial since it impacts network performance, stability, and longevity. Fig. 11 shows a Gaussian energy variance curve, suggesting that sensor node energy levels follow a Gaussian (or average) distribution curve. The above factors affect network behaviour and performance. As seen in Fig. 11. Gaussian distributions have a centre peak and symmetrical decline on both sides; this refers to balanced energy distribution. Energy is more uniformly distributed in WSNs since most nodes' energy levels are around the peak. And enhances network stability and durability. Nodes around the mean deplete energy less often, prolonging network lifespan. Network performance is maintained by this stability. Compared to networks with highly skewed distributions, networks with a Gaussian-like energy distribution may be easier to manage and require fewer methods. There is less computational overhead and a simpler protocol architecture.

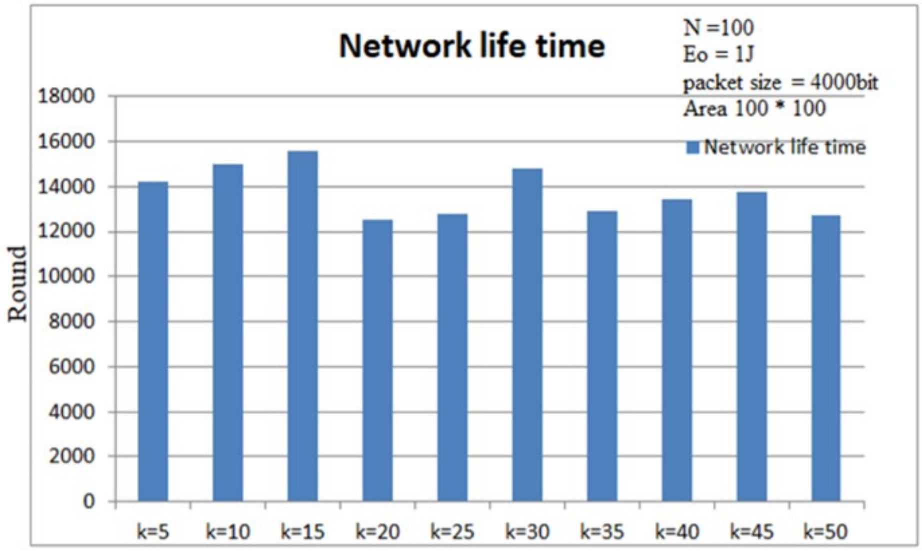


Fig. 6 *Network lifetime with various number of K*

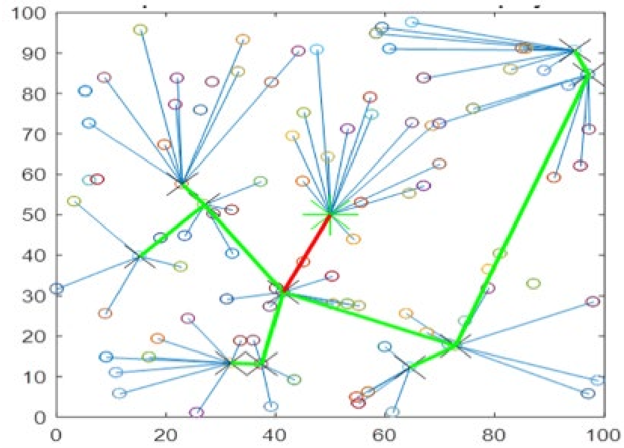


Fig. 7 *The multihop communication in the proposed network*

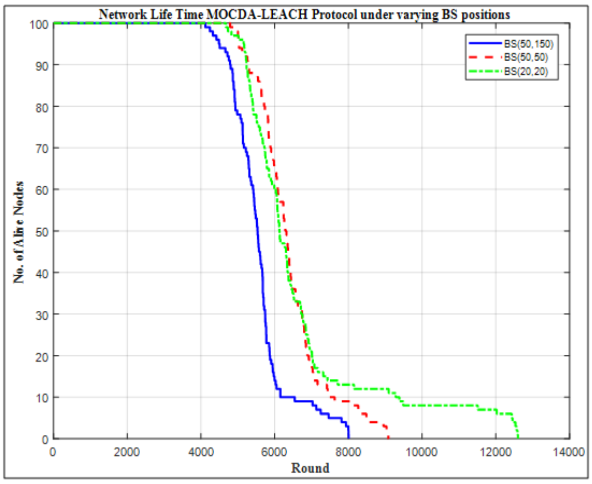
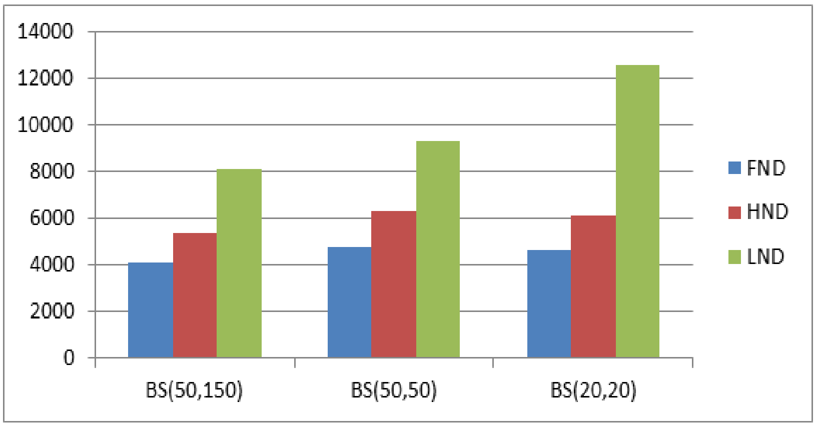


Fig. 8 *MOCDA-LEACH protocol network lifetime under different BS positions*

Gaussian-like distributions help fine-tune parameters for energy-efficient network optimization techniques. Energy efficiency improves with balanced energy distribution in sleep scheduling and duty cycling. One factor that could affect a WSN's performance is the amount of group heads (CHs) used in each round (Fig. 12).



	BS(50,150)	BS(50,50)	BS(20,20)
FND	4121	4793	4678
HND	5409	6290	6090
LND	8114	9291	12600

Fig. 9 *Eo=0.5J and variegated BS on the MOCDA-LEACH protocol's network performance*

CH numbers affect data gathering, energy efficiency, connection resilience, and network lifetime. CHs directly affect network power usage. The ideal CH count balances overhead and energy distribution. Evolution picks the top cluster heads to give you the most CH each round. After round 4400, when dead nodes increased, the number of CHs elected every five rounds only reduced from (10-7) to (8-5). In Figure 12, the rate of CH election using GA is relative to the number of nodes remaining alive, and thus we ensure the network remains and operates in a balanced manner throughout the monitoring environment area. In contrast, in the LEACH protocol, one of the drawbacks was the lack of balance in CH election, and thus the death of some or most of the nodes in a specific part of the monitoring field, while the remaining nodes remain in other parts. Election is done using GA every five rounds, not every round. Optimal CH numbers increase communication and decrease overhead, improving power balance and network availability. Number of CHs affects network function distribution. Nodes are evenly distributed throughout CHs to balance load. CHs affect network coverage.

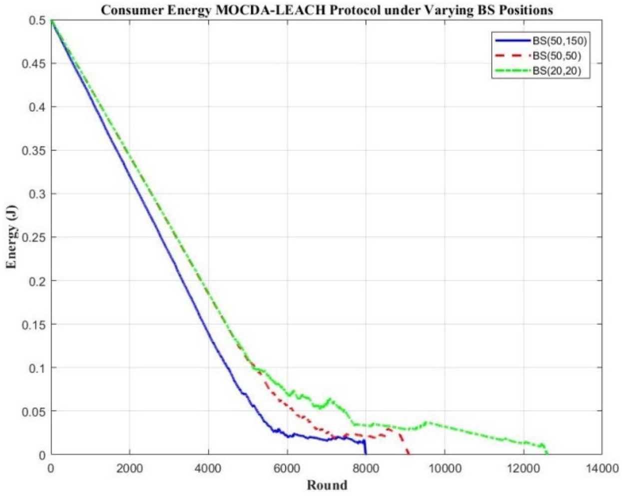


Fig. 10 *Analysis of energy consumption in the MOCDA-LEACH protocol with varying BS positions, Eo=0.5J*

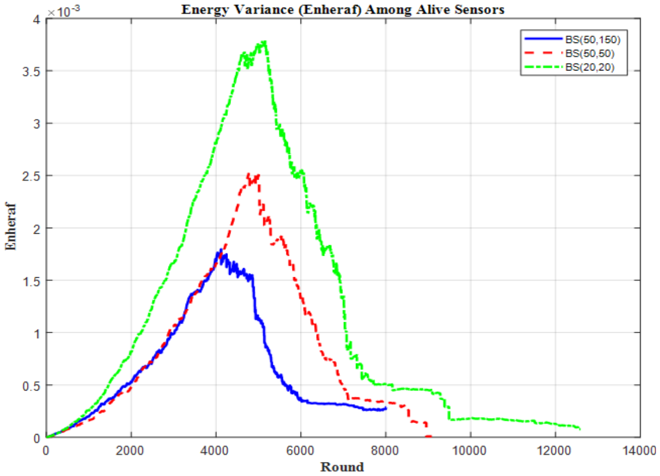


Fig. 11 *Analysis of energy variations in the MOCDA-LEACH protocol based on various BS locations*

The sensing area is covered by perfect CH dispersion, which also minimises blind spots and enhances data collecting. Fig. 13. Display the MOCDA-LEACH protocol's performance in relation to other routeing protocols. all showed 100% improvement with the suggested approach, according to the results. The improvement is 98% for ADMH-LEACH and 82% for MHOCH-LEACH, respectively.

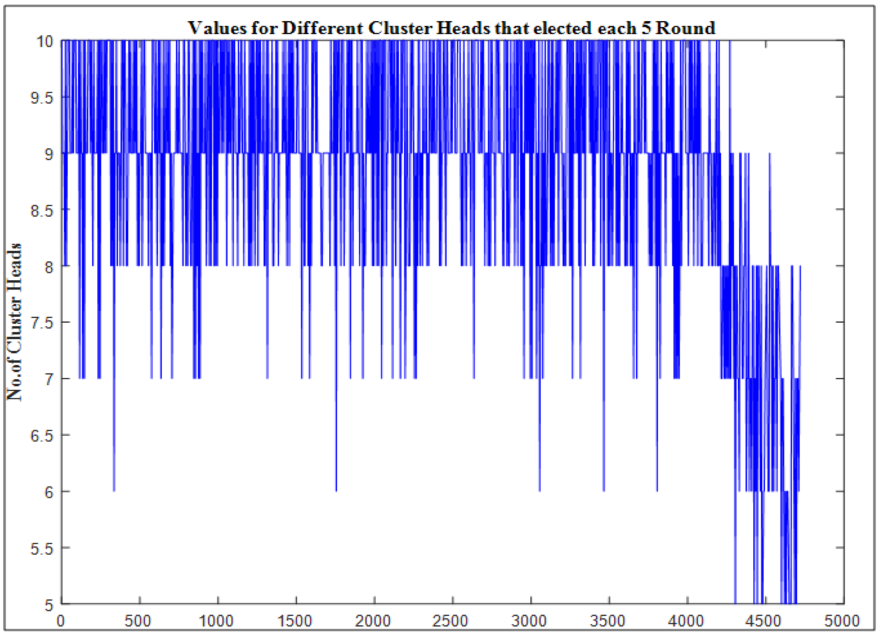
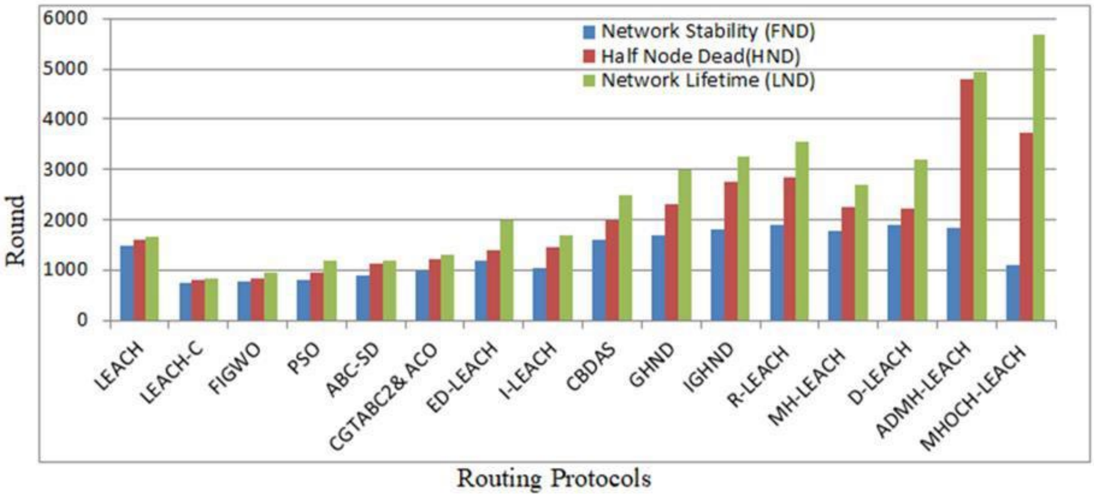


Fig. 12 *The count of CH representatives elected during each of the five rounds*

In Figure 13, the improvement percentage was computed as follows: The original value = 100 devices; (The total number of devices in the network), devices that remained active under the MOCDA-LEACH protocol after 1657 round = 82 devices; (value after increase),Devices that remain active according to the LEACH protocol after 1657 round = 0 devices; (value before increase),The amount of increase = 82-0,Increase amount = 82, percentage increase = (82 ÷ 100) × 100, percentage increase = 82%. In the same way, the proposed protocol is compared with the rest of the protocols mentioned.



Routing protocols	Network Stability (FND)	Half Node Dead(HND)	Network Lifetime (LND)	Percentage of Improvement
LEACH[11]	1485	1600	1657	100%
LEACH-C[40]	750	800	850	100%
FIGWO[41]	780	830	960	100%
PSO[42]	800	950	1180	100%
ABC-SD[43]	900	1140	1200	100%
CGTABC2& ACO[44]	1000	1222	1300	100%
ED-LEAC[45]	1188	1400	2000	100%
I-LEACH[46]	353	1350	2229	100%
CBDAS[47]	1600	2000	2500	100%
GHND[48]	1700	2300	3000	100%
IGHND[49]	1800	2750	3250	100%
R-LEACH [50]	1900	2850	3550	100%
MH-LEACH [51]	1788	2260	2700	100%
D-LEACH[51]	1900	2220	3200	100%
ADMH-LEACH[51]	1850	4800	4950	98%
MHOCH-LEACH [52]	1112	3742	5677	82%

Fig. 13 *Comparative analysis of the performance of the MOCDA-LEACH protocol against multiple routing protocols*

Fig. 13 presents a comparison of the performance of various routing protocols, evaluated against critical metrics including network stability (FND), dead node medium (HND), and the last node dead (LND), along with the corresponding percentage of improvement.

- LEACH and its variations, such as LEACH-C and FIGWO, constantly show stable performance in all metrics, maintaining a 100% improvement percentage. The protocols exhibit an effective balance between network stability and operational lifespan, with LEACH attaining a useful life of 1657 for the network (LND).
- The protocol PSO shows a remarkable increase in performance, particularly in the useful life of the network, which reaches 1180, but still aligns with a 100% improvement percentage.
- ABC-SD and CGTABC2 and ACO also maintain high values, with CGTABC2 and ACO that shows slightly better results in stability and useful life of the network, with the LND that reaches 1300.
- The protocol ED-LEAC demonstrates strong stability, with FND of 1188 and LND that reach 2000, maintaining a 100% improvement.
- I-LEACH, despite an FND much lower than 353, achieves significant improvements both in HND and LND, and the latter reaches 2229. It maintains the improvement of 100%, but shows greater variability.
- CBDAS, GHND and IGHND stand out with high values for both HND and LND, which show strong scalability in the useful life of the network. In particular, IGHND achieves a 3250 LND, still with a 100% improvement.
- The protocol R-leach is consistent, with FND in 1900 and LNA reaching 3550, maintaining a constant improvement.

- MH-LEACH, D-LEACH and ADMH-LEACH, the protocols show strong performance but with slight variations in the results. ADMH-LEACH. It falls to a 98% improvement, and MH-LEACH shows values consisting of all metrics.
- Finally, MHOCH-LEACH, the current work shows a drop in improvement at 82%, with a 5677 LND, indicating the possibility of greater optimization for the protocol.

7. Conclusion and Future Work

In order for WSNs to overcome power constraints, this work devised an overall LEACH protocol efficiency optimization approach. Data transmission, compression, node dispersion, and CH selection have all been discussed. For workload and power, K-denotes clustering of nodes that are uniformly distributed throughout clusters. We used a genetic technique to maximize CH selection using residual energy, BS distance, and contact load to Improve network reliability efficiency and selection. Forwarding data between intermediate nodes reduces power consumption in a multi-hop connection, decreasing Network energy usage. Another idea was to transmit compressed packets to save power and keep the data accurate. When compared to case orientation procedures, the simulations' findings demonstrated a notable improvement in energy efficiency. Utilizing compressed data packet transmission, multi-hop communication, K-means aggregation, and evolutionary algorithms to select the optimal cluster head enhances network longevity, promotes energy balance, and improves overall energy efficiency. This paper provides WSN sensor efficiency optimization techniques for power-limited networks to be robust and efficient. Compared to existing routing protocols such as LEACH, LEACH-C, PSO and ADMH-LEACH, our approach in most cases shows 100% increase in energy efficiency, network life and data provision and 98% improvement compared to ADMH-LEACH, confirming significant advantages of the optimization strategy. In Round 1657, the proposed MOCDA-LEACH protocol reduced energy consumption by 18% compared to LEACH. Due to the least transmissions and the use of compressed data packages. Although the specific PDR values are not drawn, the improvements in the packet delivery ratio were achieved by using data compression, multiple communications and optimized copy elections every 5 rounds using a genetic algorithm. These techniques minimized redundant transmissions, avoided the random selection of CH and improved data delivery efficiency, which leads to lower energy consumption and a longest useful life compared to traditional LEACH. This study makes WSNs more real. The durable and flexible sensor network architecture makes use of multi-hop communication, LZW data compression, a genetic approach for CH selection, and K-means clustering. This integrated technology increases data transmission while reducing waste of energy and resources, enhancing network efficiency, lifetime, and performance. These technologies create a flexible and reliable sensor network architecture for many applications. Researchers are studying energy efficiency improvements to allow WSN deployment and enhance the Internet of Things and industrial applications. Despite the many potential uses for WSNs, addressing their energy efficiency concerns is crucial for their long-term viability. Scientists and engineers are coming up with novel methods to employ WSNs in various contexts, conserve energy, and prolong network life.

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Conflict of Interest

Authors affirm that there are no conflicts of interest pertaining to the publication of this paper.

Author Contribution

The authors acknowledge their respective contributions to the paper as detailed below: ***Study conception and design:*** *Noor Raad Saadallah and Salah Abdulghani Alabady; Data collection: Noor Raad Saadallah;* ***Analysis and interpretation of results:*** *Noor Raad Saadallah and Salah Abdulghani Alabady;* ***Draft manuscript preparation:*** *Noor Raad Saadallah. All authors conducted a review of the results and provided their approval for the final version of the manuscript.*

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