Clustering Multilevel Energy Nodes in Wireless Sensor Network for Multiple Goals

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Abstract: - By acting as a last-mile link for real-time communication systems, the adoption of clustered wireless sensor systems has improved communication entities' efficiency and core goals. However, the energy restrictions of sensor nodes limit their activity and total longevity, restricting this development. Thus, extending the lifetime and improving the stability of clustered sensor networks requires an energy-efficient solution immediately. Extending node lives by heterogeneity introduction and communication activity regulation in wireless sensor network (WSN) is a feasible approach. Along with improving network longevity and stability, this clever energy-efficient strategy also solves issues with heterogeneity and node deployment scenarios. It improves network stability and longevity by controlling internal overhead associated with communication between and within clusters, communication load inside the network regardless of boundary conditions, and the likelihood of cluster formation. The Clustering of Multilevel Energy Nodes (CMEN) in Wireless Sensor Network for Multiple Goals (CMENWSNMG), which is the intelligent clustering approach that has been suggested, provides a complete answer to these problems. Crucially, this methodology demonstrates enhanced performance across various performance metrics, levels of heterogeneity, and deployment scenarios. Simulation results illustrate the remarkable efficacy of this suggested strategy, surpassing widely acknowledged published systems.

Keywords: *node degree, sink, multihop, node index*

1. Introduction

The sensory system is a vital component of intelligent communication systems, facilitating remote event monitoring. However, the limited energy resources of sensor nodes pose challenges for exploring the full potential of Wireless Sensor Networks (WSNs). Researchers propose solutions such as modified aggregation, routing, and hybrid communication schemes at the transport layer. Nevertheless, updates to the network layer appear to be the most effective choice. Alternatively, introducing mobility to the sink node during data collection, especially in a hierarchical network, is a viable yet energy-intensive option. The incorporation of heterogeneity into a homogeneous network improves sensor network performance, referred to as "heterogeneous WSN." This approach aligns more closely with real-life system devices, with categories including networks with nodes of varied computing power, links, and energy capabilities. WSNs or HWSNs find applications in weather forecasting, agriculture for plant health monitoring, disaster management for efficient rescue operations, human health conditioning, and industry. The efficiency of data communication within the WSN significantly influences energy expenses and network sustainability. Therefore, a well-designed energy-efficient protocol combines a suitable data communication approach, energy management strategy, and node placement technique [1-5]. The clustered approach emerges as an effective communication method compared to other routing schemes, enhancing energy efficiency and minimizing internal control packets. Additionally, load balancing, achieved through an energy-saving communication approach and regular rotation of node responsibilities based on predetermined criteria towards cluster members (CM) or cluster heads (CH), contributes significantly to energy efficiency. Cluster-based routing protocols are essential for reducing the load on distant nodes, enhancing network connectivity, and supporting scalability. This improvement in energy efficiency prolongs the stability and overall lifetime of the network. There are various categories of clustering methods, including balanced, unequal, centralized, distributed, flat model, hierarchical, or multi-level clustering, each consisting of base station, CH, and CM elements. The BS node acts as the primary control element, overseeing the entire network activity through the CH node. CM nodes are typically utilized for event sensing, CH updating, or reporting to the sink node, depending on the protocol policy. Different data collection strategies, such as timely controlled (driven), event-based, and query-based approaches, offer flexibility based on specific requirements. CH nodes collect data periodically or at set times for the BS, based on event occurrences, or initiated by the BS [6-8]. The adopted CMEN algorithm significantly improves energy efficiency and network performance. By considering criteria such as initial energy, residual energy, relative distance, varied epoch, and node reusability, the algorithm optimizes the selection of cluster heads for communication within the network. This approach enhances stability, extends the network's lifetime, and ensures balanced load distribution through the rotation of cluster head roles based on epoch periods. Moreover, by leveraging records of node reusability and intra-distance between nodes and the sink, the implemented algorithm effectively reduces energy expenses for diverse nodes, contributing to overall energy conservation. The simulation results demonstrate that the embraced Clustering of Multilevel Energy Nodes (CMEN) in Wireless Sensor Network for Multiple Goals outperforms a well-known protocol by 1.97 times over 20000 cluster rounds, highlighting its superiority in energy efficiency and network stability.

2. Literature Survey

The growing demand for energy-efficient designs in remote event monitoring underscores the significance of cluster-based routing as a viable solution to achieve both energy efficiency and prolonged performance parameters. The implementation of cluster-based routing not only improves network connectivity, management, and reliability but also represents a notable advancement in scalability. This routing method can be categorized based on node type, arrangement, and the type of communication employed (whether single-hop or multi-hop). Clustered Wireless Sensor Networks (WSNs) can exhibit static or dynamic characteristics. To enhance energy efficiency by reducing the energy consumption of relaying collected data, various options are available. These options include clustering based on random Cluster Head (CH) selection, residual energy-based selection, ratio-based selection, or average node energy. The methods for CH selection vary and may involve the Deployment and DFS algorithm, subgraph connectivity, auto-correlation, fuzzy parameters, or aspects of particle swarm optimization. Achieving effective clustering entails dividing the network layout into smaller subsections or zones. This approach not only makes network management more efficient but also reduces internal overheads, contributing to overall system optimization. The attainment of load balancing within a cluster is facilitated through the amalgamation of a chain structure within the cluster and the incorporation of the spanning tree protocol between the Cluster Head (CH) and sink nodes. Embedding anthropological principles into the process of CH selection, employing recurrent procedures, results in a meticulously balanced clustering approach. This approach encompasses the application of a modified fusion rate for communication, thereby contributing to an overall enhancement in the system's longevity [5-10]. Sustained stability and an extended system lifetime are realized by steering clear of CH nodes characterized by minimal energy and short distances. Elevating network performance involves establishing a circular arrangement featuring virtual circle nodes, each distinguished by varying residual energy and relative distance. Researchers suggest using heterogeneity-aware clustering to increase network stability and pairing energy-efficient clustering with stability to improve overall performance. To increase the lifetime of the clustering protocol, a network must be intelligently deployed, giving preference to high-energy nodes in sparse regions. By dividing the network into manageable clusters according to their respective capabilities, this well-organized deployment can maximize stability. The result, though, could be an imbalance of energy. Such deficiencies can be addressed by regional clustering, which compensates for internal overheads and recurrent Cluster Head (CH) selection based on energy supplied by isolated nodes. By node type, grouping technique, and communication type (single-hop or multi-hop), cluster-based routes can be classified.

Static and dynamic WSN clustering classifications are available, and some published articles describe energy-saving strategies. While some presumptions need to be verified, effective clustering requires a critical approach to cluster hierarchies employing adaptive approaches. Random CH selection, residual energy selection, average node energy selection, residual to network energy ratio selection, and the use of multifeatured heterogeneous clustering are among the clustering techniques [9-13]. The implementation of heterogeneity-aware clustering emerges as a pivotal factor in significantly bolstering the stability of deployed networks. Through the integration of stability and an energy-efficient clustering approach, multiple performance metrics experience favorable outcomes. Implementing a strategic deployment strategy, such as situating high-energy nodes in remote fields as opposed to densely populated ones, enhances the overall longevity of the network. Nevertheless, it is crucial to exercise caution, as partitioning the network into smaller clusters based on capabilities has the potential to create an imbalance in energy utilization. The application of regional clustering in Wireless Sensor Networks (WSN), focusing on energy considerations and incorporating isolated nodes, aims to address shortcomings in the clustering process. These issues include internal overheads and the repetitive selection of Cluster Heads (CH). To tackle these challenges, an energy-efficient protocol called the Energy-Aware Routing Protocol in WSN has been developed. This protocol selects CH by evaluating the ratio of a node's residual energy to the average residual energy of its neighboring nodes. Specifically designed for heterogeneity, the clustering protocol utilizes the Spanning Tree Protocol between CH families and sink nodes through direct communication. This approach helps reduce energy consumption, thereby extending the network's lifespan. The method is conducive to scalability and enhances the performance parameters of the application at hand. Given the energy constraints of sensor nodes limiting their lifespan, there is a necessity for specialized handling to improve the overall energy efficiency of the network. In a scalable network, employing a multi-hop approach minimizes the energy costs incurred by individual nodes along the communication path. Nevertheless, the identification of the most suitable routing path remains a challenging task. Hence, we introduce a mechanism for cluster routing that emphasizes a well-balanced and energy-efficient approach. The optimal communication path is determined by selecting the shortest or lowest-energy route, with options such as Dijkstra, link states, and destination sequence routing (DSR) available for finding the shortest path. However, the selection of cluster heads (CH) incurs internal overhead costs. One notable example of an energy-efficient clustering and routing method is the multi-object-based SMO, which concentrates on load balancing at gateways to increase the overall lifespan of the network. Its performance outperforms both PSO and GWO algorithms, indicating a higher capacity to maintain network operations over an extended period. The system is made more sophisticated by the creative way that GWO and whale optimization algorithms are integrated for clustering and dynamic Cluster Head (CH) selection. This combination contributes to an even more resilient and flexible solution by strengthening the algorithm's capabilities and expanding its exploitation and exploration reach. There are two phases in each of the two rounds and the clustering process goes through formation and stabilisation. Nodes are methodically arranged into distinct clusters during these rounds, each under the direction of a designated CH. As data aggregators, these CHs play a crucial role in sending sensed data to the recipient by gathering data from sensor nodes inside their clusters. Different methods are used to make this data aggregation easier, which increases the effectiveness of the clustering procedures. One important feature of these methods is the energy savings that are obtained by assigning CHs strategically. In this case, the KMeans algorithm finds a fixed number of clusters (k) with centroids and computes the Euclidean distance between every node and every cluster, which increases the clustering process's overall efficacy. Along with integrating Bacterial Feeding Optimisation (BFO) with an optimized fitness function intended to simulate the delicate balance between data throughput and energy consumption, a novel Natural Inspired Cross-Layer Clustering (NICC) methodology has been explored.

The BFO approach is used to discover the best sensor nodes strategically by using cross-layer parameter-based fitness values to address routing and clustering challenges. Experiment results in various Wireless Sensor Network (WSN) situations clearly show that the NICC protocol outperforms both classic and new clustering approaches. ACO, BA, GA, PSO, WOA, MFO, and other cutting-edge metaheuristic algorithms have been suggested in the literature to solve optimization problems in engineering applications. The combination of COA with a dimension learning-based hunting strategy is one notable way to sustain diversity and improve the balance between exploitation and exploration. This integration performs admirably when it comes to optimizing energy constraints in Wireless Sensor Networks (WSNs).Furthermore, CSA is used to select the best Cluster

Heads (CHs) in heterogeneous WSNs to increase network longevity and energy efficiency. When compared to traditional algorithms like PSO, GA, and LEACH, this application of CSA yields better results [14-17]. Because of insufficient investigation in the initial phases, the traditional GWO algorithm typically yields sub-optimal or locally optimal solutions. The purpose of this improved version of the GWO is to enhance optimization accuracy explicitly. This improvement guarantees a better balance between exploration and exploitation throughout the optimization process, in addition to quickening the GWO algorithm's convergence. Many attempts have been made to address the issues with the traditional GWO, specifically those related to convergence speed, accuracy, and stability. To improve energy efficiency, the research provides a Cluster Head (CH) selection approach that uses an enhanced Grey Wolf Optimizer (GWO) algorithm. To make CH selection easier, the suggested EECHIGWO methodology includes variables including average intra-cluster distance, balancing factor, sink distance, and residual energy. A fitness function design based on residual energy and the Euclidean distance to the Base Station (BS) is incorporated into the protocol. Premature Sensor Node (SN) failures are prevented, and balanced energy consumption is promoted by ensuring deterministic CH selection. The protocol's effectiveness is confirmed by simulation results, which show fewer dead nodes, increased network stability, lower energy usage, higher throughput, and longer network lifetime. A comparative investigation reveals notable enhancements over the current energy-efficient routing protocols for Wireless Sensor Networks (WSNs), with FIGWO, LEACH-PRO, and HMGWO protocols being outperformed in terms of network stability. Future studies on the effectiveness of the suggested method in heterogeneous WSNs with more nodes and higher densities are suggested by the research. One of the most important methods for maximizing the effectiveness of data transmission is clustering. The K-medoid methodology was used in the current study as a sophisticated way to classify similar data into cohesive groups. The process of categorizing nodes is accomplished by using their average energy usage as a defining factor. Through the utilization of the K-medoids method, which is an improved version of the widely recognized K-means algorithm, the suggested work guarantees a strong and efficient clustering procedure. This technique groups nodes with similar patterns of energy use, which improves the network's general organization and makes it easier to find commonalities between data points [18-20]. Location-insensitive nodes are typically used to form clusters based on a probability value. The connectivity between nodes in adjacent clusters is controlled by hop count and energy considerations. During runtime, nodes can be categorized into three groups based on their activity, energy, and communication strategies. While researchers strive for greater variability, current techniques are unable to fully account for all features when selecting CHs. A restricted range of performance metrics, such as the network's residual energy, life period, and stability period, are provided by published protocols. We present the CMEN in Wireless Sensor Network for Multiple Goals to address these issues and improve every possible performance metric. Putting up a comprehensive plan to support the resilience and durability of a sensor network requires taking care of several important factors. First, the focus is on coming up with an energy-saving strategy to prolong the life of sensor nodes. Simultaneously, efforts are focused on investigating techniques that lead to an overall improvement in network stability. The introduction of heterogeneity into wireless sensor networks (WSN) emerges as a pivotal aspect, to boost performance by refining communication control and extending node lifetimes. The creation of a sophisticated, energy-efficient approach emphasizes the importance of stability and endurance, alleviating concerns about node placement. Managing internal communication overheads entails putting suggestions in place to reduce load and increase efficiency. Load balancing solutions are employed within the network, which includes the rotation of node duties based on certain parameters. For Heterogeneous Wireless Sensor Networks (WSN), a uniquely customized Clustering of Multilevel Energy Nodes (CMEN) in Wireless Sensor Networks for Multiple Goals has been methodically devised, undergoing extensive validation across different situations and performance metrics. This protocol integrates crucial elements such as node degree, sink, receive signal strength, multihop, and node index, thereby refining the clustering process. Its effectiveness is rigorously affirmed through simulations and comparative analyses against existing design schemes. The central focus revolves around crafting an energy-efficient protocol that considers node characteristics, with an emphasis on optimizing cluster size for streamlined communication. Comprehensive investigations and optimizations are conducted across various performance parameters, encompassing stability period, lifetime, throughput, and remaining energy. The incorporation of node heterogeneity, spanning energy levels and capabilities, is conjoined with an evaluation of node reusability in the cluster head selection process.

The investigation into multi-level clustering is initiated to unlock potential advantages in optimizing the overall performance of the network. Innovative approaches to the selection of cluster heads (CH) are explored, considering factors such as initial energy, relative distance, and node reusability. The analysis goes on to assess the effect of different deployment conditions and levels of heterogeneity on the performance of the recommended method. To ensure a continual improvement and optimization trajectory, the protocol design is constantly refined in response to changing technologies and research discoveries. The overarching goal is to create a sensor network that is both durable and efficient, displaying excellence in stability, longevity, and energy efficiency.

2.1. Energy utilization model

This presentation outlines the communication of data between two sensor nodes, focusing on specific communicational attributes. The propagation model is divided into two classes: direct and multipath, determined by a threshold communication distance. The sender node typically expends more energy during the transmission of collected data, attributable to expected energy consumption at the modulator, energy depletion in the environment, and energy dissipation at the transmitting amplifying section at the antenna. In contrast, the receiver incurs energy consumption only in the radio electronics, and this occurs beyond the threshold distance 'd_0'. In the context of data communication, when the communication distance 'd' is less than the crossover or threshold distance in direct communication, energy expenses can be calculated based on the multipath or multi-hop propagation model. Close by, data communication is initiated for a data packet of length L (in bits), employing radio link features similar to those found in existing literature. The energy model details various communicational attributes, including 'E_{TX}' for the energy cost of transmitting a data packet, 'E_{RX}' for the energy consumed by the receiver, 'E_{elec}' for the energy consumed by radio electronics, 'E_{mp}' for the energy cost of the multipath model, and 'E_{fs}' for the energy required in free space propagation. Furthermore, 'E_{DA}' represents the energy expenses during data aggregation in the summer, while 'E_{Relay}' signifies the energy involved in relaying a data packet of length L. The subsequent section concentrates on calculating various attributes used in the energy model, starting with the determination of 'd_0' as outlined here.

The energy expended by the transmitter for a packet of length 'L' over a distance 'd' [9].

$$d_0 = \text{sqroot}\ (E_{fs}/E_{mp}) \qquad (1)$$

$$E_{TX}\ (L, d) = L \cdot E_{elec} + L \cdot E_{fs} \cdot d^2 \quad \text{if } d \leq d_0 \qquad (2)$$

$$E_{TX}\ (L, d) = L \cdot E_{elec} + L \cdot E^{mp} \cdot d^4 \quad \text{if } d > d_0 \qquad (3)$$

Energy computation at the receiving node involves...

$$E_{RX}\ (L, d) = L.\ E_{elec} + L \cdot E_{DA} \qquad (4)$$

If the receiving node acts as a relay in data communication, energy expenditures can be determined using the following equation for one-hop communication:

$$E_{Relay}\ (L, d) = E_{RX}\ (L) + E_{TX}\ (L, d) \qquad (5)$$

2.2. Network Structure

Now, we present network models that combine different energy nodes with varying population percentages, accompanied by specific assumptions:

I-All nodes are deployed proprietorially (randomly and evenly) distributed.

II-Once deployed, nodes remain stationary and consistently retain data.

III-Inactivity is defined as when nodes are incapable of operation.

IV-Nodes exhibit insensitivity and sensitivity to location.

The introduced network model aligns with existing literature and is formulated based on diverse node populations. Specifically, we incorporate three and four types of nodes: normal, advanced, super, and ultra-nodes. The total node count is denoted as N, with advanced nodes having a population value 'a' each equipped with higher energy (denoted as A_e, a fractional value) compared to normal nodes. The standard node is characterized by an initial energy N_e and a percentage population factor nn. Higher-type nodes, referred to as Supernodes, have a population value of s and an energy value S_e time greater than the normal node energy. Meanwhile, the ultra-node, identified by a percentage population factor u, features energy U_E times higher than the normal node energy. For a normal node, the energy value is N_e, calculated based on the population factor nn and the total number of nodes N [9]. The energy contribution from each node is outlined as follows:

2.2.1. Three type node model

The energy calculation for a standard node is determined by:

$E_{NN} = nn.\ N_e.\ N$; Where $nn = (1-a-s)$ (6)

The energy of an Advanced node,

$E_{AN} = a.\ (1+A_e).\ N_e.\ N$ (7)

The energy provided by a Supernode:

$E_{SN} = s.\ (1+S_e).\ N_e.\ N$ (8)

Hence, the total energy of the network model is computed as follows:

$E_{Network} = E_{NN} + E_{AN} + E_{SN}$ (9)

Details of the energy contributed by individual nodes to the overall network energy are presented as follows:

$E_{Network} = (N_e\,(nn + a\,(1+A_e) + s(1+S_e)))\ N$ (10)

When the energy increases twofold, the total available energy within the network is described as follows: The energy distribution for a network with three types of nodes is as follows:

$E_{Network} = (nn.\ N_e\,(1+3a+5s)).\ N$ (11)

Thus, a comprehensive equation for a multilevel heterogeneous network can be expressed as follows:

$E_{Network} = N_e\ (1+2a+\ldots\ldots\ldots+(2^{m-1})t)\ N$;$m=3.........x$ (12)

Here, x represents any integer value, and t denotes the percentage population factor at the corresponding level.

3. Methodology

The envisioned design's main goal is to capitalize on the heterogeneity of 3- and 4-level nodes while validating the introduced protocol. Concurrently, we want to evaluate energy efficiency improvements and examine numerous performance criteria. Our focus is on managing energy consumption during data relay to the sink node and examining diverse performance metrics. To achieve this, we actively rotate the role of Cluster Head (CH) and adjust the epoch value in CH selection based on the remaining network energy. The fine-tuning of the epoch ensures uniform expiration intervals for all nodes in the network. The selection of CHs is rooted in the Node Quality Index (NQI) and specific criteria of the value function. This proposal employs a regression-based formula to choose potential Cluster Heads (CHs) by selecting nodes with a higher NQI value than the network's average NQI (filtering criteria). To ensure adherence to boundary conditions and avoid placement at the network's edge, selected CHs must meet specific criteria. Our protocol design involves dividing the network into four equal zones relative to the base station (BS). Each zone's average NQI or Node Importance (NI) value serves as a threshold for filtering criteria, guiding the selection of the most suitable CH for each role. The BS calculates the NQI value of individual nodes, and an initially chosen "temporary CH" is a high-value NI node. The final CH is determined by selecting the node with the best NQI value among those in each zone. The ultimate CH serves as a relay element, providing support to the temporary CH in data communication. It's worth noting that, in this scheme, we make a concerted effort to minimize assigning the CH role to nodes located near the network boundary [9].

4. Proposed Protocol

By deliberately selecting nodes for the CH role and executing appropriate load balancing, the draft protocol and its implementation improve the energy efficiency of the tested network model. CH selection now takes into account aspects such as energy expenditure, relative position, and reusability value. This method ensures a balanced distribution of network load, resulting in higher node degrees at each head level. As a result, rather than being left to chance, the cluster size is systematically regulated, resulting in better management of residual energy in the network through the regulation of energy expenses. It is vital to note that sensor nodes in the transmitting state consume much more energy than other operations. To mitigate this, we aim to minimize energy expenditure by employing multi-hop communication with distant nodes. On the deck, the burden on the Cluster Head (CH) is mitigated by deploying a temporary CH within each zone (determined by the node index value) and a primary CH selected based on the highest node index value across the network. Each temporary CH node in a zone forwards the collected data to the primary CH, facilitating subsequent communication with the Base Station (BS). In instances where a node's communication distance with the BS is greater, it redirects the collected data to a nearby node based on the node index value. Alternatively, the data can be directly transmitted to the BS, employing the same strategy used by Cluster Members (CM) in relaying data to either the CH or the primary CH. We evaluated several features of wireless sensor nodes concerning clustering in our stated research, emphasizing the importance of relay nodes selected to cost the least energy when conveying sensed events. The chosen Cluster Head (CH) must have an NQI value greater than the average NQI value, effectively screening out other nodes. These CHs are intentionally placed distant from the network boundary and assigned to CH responsibilities. In the early rounds, there may be occasions where a significant proportion of nodes have a higher NQI value than the optimal cluster head value. As a result, we use the LEACH technique during the first 100 cluster rounds to overcome this issue. During this phase, our primary focus is on a query-based technique suitable for agricultural applications [9]. The supporting parameters of the clustering process are calculated in a manner consistent with the aforementioned considerations.

4.1. Result

In this section, we aim to elucidate the specifics of simulation parameters and performance criteria. The implemented protocol undergoes rigorous testing and validation using a predefined set of standard parameters. The particulars are outlined below: The practical constraints for the subsequent parameters lie within the range of 0 to 99999. Specifics regarding performance parameters employed in the validation process are detailed as follows:

I-Stability: This metric gauges the number of cluster rounds that transpire before the first operational node succumbs within the network.

II-Number of alive or viable nodes per cluster round: This represents the count of nodes that can endure the varied energy fluctuations in the network during operation. The expectation is that this count remains considerably high or depletes at a sluggish pace, indicative of the requested protocol's effective load-handling characteristics.

III-Number of dead Nodes/Depleted Nodes Count per cluster round/ Quantity of inactive nodes: In contrast to the previous parameter, this aspect influences the overall survival time of the network. A lower count or a higher depletion rate contributes to a reduction in the network's lifetime.

IV-Throughput: This refers to the reception of data packets by the receiver from deployed sensors during each cluster round. It serves as a key measure of the reliability and effectiveness of the designed protocol.

V-Network Lifetime or Lifetime: This denotes the duration extending across multiple cluster rounds until the last active node ceases to operate, marking the conclusion of its participation in the network.

VI-Remaining Energy in the Network per cluster round: This metric indicates the energy that remains available in the network after the completion of each cluster round. Its presentation denotes the success of load balancing performed across the deployed network using the specified protocol.

Testing the suggested implementation against predetermined simulation parameters—represented by the dataset in Table 1—is the experimental verification process. The network configuration consists of 200 nodes that are arranged at random in a 200 x 200 arrangement. A percentage population factor, represented like a = 0.1 and s = 0.2, or can be 0.2 and 0.1 is applied in the context of the 3-level network model about all 200 nodes. The energy value increases by a factor of 1.2 as more node types are added. Nodes' energy order is defined as ultra, super, advanced, and normal, which corresponds to different energy levels.

Table 1: Simulation Parameters used in the implementation and testing

Symbol	Details of parameter	Values
M X M	Network area	200m X 200m
N	Total number of nodes	200
N_e	The initial energy of normal nodes	0.5–1.5J
L	Data packet length	4000bits
E_{elec}	Radio energy	50 nJ/bit
E_{fs}	Free path energy	10 pJ/bit/m^2
E_{mp}	Multipath energy	0.0013 pJ/bit/m^4
E_{DA}	Data Aggregation energy	5 nJ/bit/signal
d_0	Threshold or crossover distance	87-87.7 m
BS	Base station	100m X100m

4.2. Discussion

The suggested implementation is presently being validated at different phases. We first analyze the performance under the condition that nodes are deployed in a random and uniform format with controlled epochs. The results of the implementation and testing are presented in the form of Figures 1 to 3 and recorded in the form of Table 2. Following that, we attempt to comprehend what is offered in the location awareness scenario to test the performance of our design protocol. The result is provided here in the form of Table 3, with the intricate repeated nature of the figure eliminated for simplicity. Finally, we try to have the scenario for varied heterogeneity level implementation to test the design for a multilevel approach in the form of Table 4 to present three, four, and five-level heterogeneity. With the help of the centrally located Base Station (BS), a source with significant processing and energy capacity. For location insensitivity, we are utilizing the received signal strength indicator (RSSI) of nodes for applications. The Low Energy Adaptive Clustering Hierarchy Protocol (LEACH) architecture concept of clustering was first established by the authors in [1-2]. So we are comparing our implementation with this. Details of the leach present an approach based on random number generation in CH selection. A premature node depletion may occur if the resulting cluster is arbitrarily large, further taxing the CH. Uneven load distribution across nodes might occasionally result from the selected Cluster Head coming from the surrounding network area. Because of this imbalance, the network's stability and lifespan may be shortened by needless energy use. As a result, both the energy stores and the throughput quickly exhaust. In particular, the Low Energy Adaptive Clustering Hierarchy is unable to fully utilize heterogeneous Wireless Sensor Networks (WSN). LEACH is incapable of differentiating between nodes' capabilities since it views all of them as having equal capabilities. In contrast to this Stable Election Protocol found to be the initiator for various energy level nodes or heterogenous networks, which provide better performance than LEACH, suggests heterogeneity by adding sophisticated nodes in the form of advanced nodes into homogeneous WSNs.The suggested approach selects the CH mostly based on initial or starting energy. Furthermore, in this specific design, advanced nodes are typically penalized by the SEP scheme. Although there are times when the Low Energy Adaptive Clustering Hierarchy (LEACH) protocol is less stable than the SEP, this is not always the case.

In SEP, a lack of systematic Cluster Head (CH) selection might damage node health in each cluster round, especially concerning the network's residual energy and throughput as a whole[3]. On the other hand, as the author illustrates [5], the Design Energy Efficient Clustering (DEEC) protocol emphasizes network energy awareness and attempts to solve energy balancing across the network. The epoch in this architecture fluctuates according to the node's energy level. On the other hand, increased energy consumption could arise from CH's direct communication with the Base Station (BS) and the related data transmission activities, especially when the data transmission condition of operation is in effect. Consequently, this may jeopardize the stability of the network and result in an uneven distribution of energy throughout the network. As such, it prolongs the life of the network. It performs better than LEACH and SEP. Unlike our previous upgrades, this proposal carefully chooses an appropriate Cluster Head (CH) to optimize energy use while improving several performance parameters. Notable characteristics have been taken into account, including the node's location, energy availability, and making sure the chosen CH is positioned away from the network boundary. The CH is freed from having to communicate data with the Base Station (BS) in each zone. In the first stage, the suggested approach outperforms LEACH, SEP, and DEEC in terms of stability and lifetime since the CH nodes inside zones submit collected data to the principal CH for relaying data packets to the BS. As a result, the cluster that is created has a more balanced configuration than those that were created using earlier clustering techniques. A node's reusability is assessed before selecting it for the Cluster Head (CH) position. Since nodes in the suggested framework are not location-sensitive sometimes, energy consumption is much less than with the previous location-aware nodes method. The data communication approach is in line with Contrib 1, which lowers the node death rate in comparison to the prior design. In addition to increasing network connectivity, this slowdown lowers energy depletion by a proportionate amount. Through partitioning networks, clusters are bounded to finite sizes instead of infinite ones. This cluster size and limits of network zone constraint extend the total survival time of the network. As a result, the final suggested design outperforms the current procedure in terms of throughput, residual energy, longevity, and stability period. This response is presented in the form of the number of node deaths, energy left, and throughput from the network over the cluster rounds with the planned protocol displayed in the listed figure based on the supported cluster cycle or rounds satisfactorily. Finally, we will display the readings obtained for various deployment strategies and heterogeneity levels in Tables 2 to 4. Performance parameters recorded with simulation by using table 1 parameters for three type nodes, at the same time for four and five type nodes:

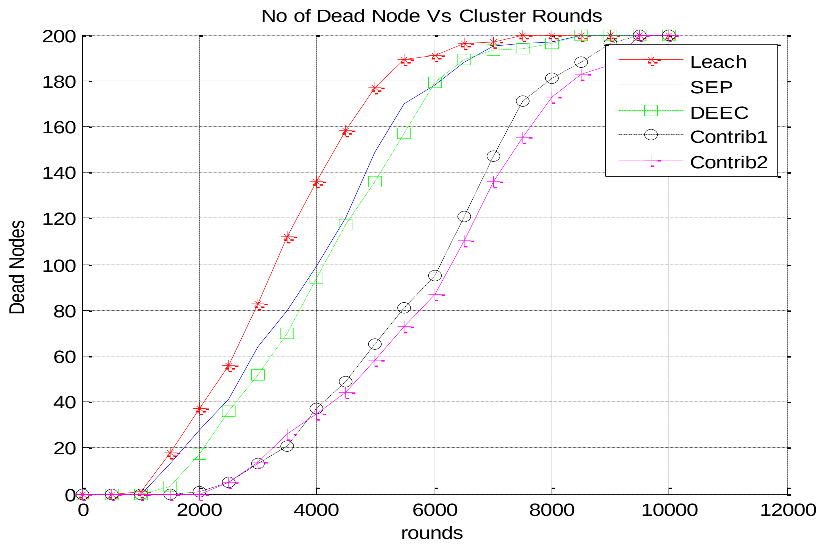

Figure 1 Relationship between the quantity of inactive nodes and the number of cluster rounds.

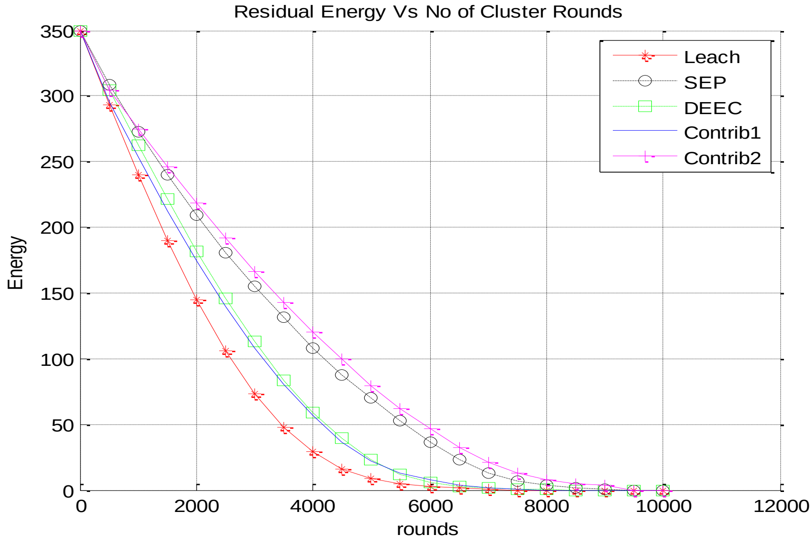

Figure 2 Correlation between the remaining energy in the network and the number of cluster rounds

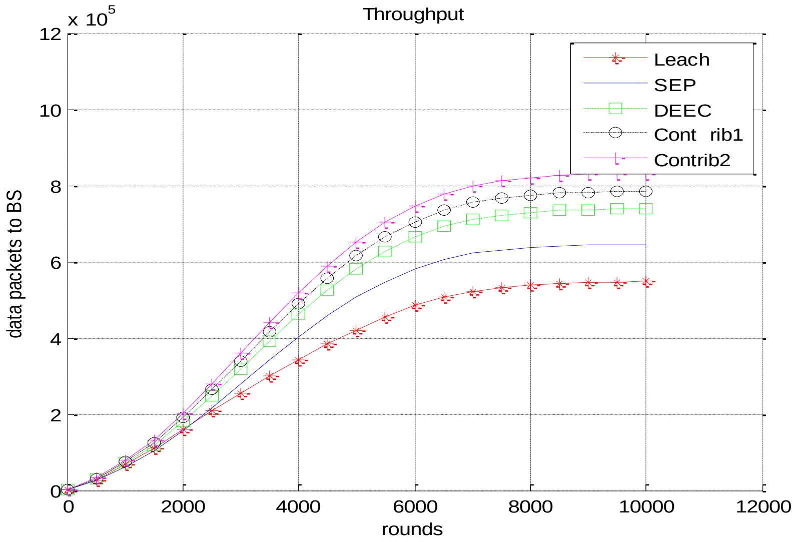

Figure 3 The quantity of data packets transmitted in each cluster round.

Recorded readings from the simulation ground concerning the above figure or graph are presented effectively in the form of the following record table in the form of Table 2.

Table 2: Parameters for varied deployment strategies over cluster round

Parameters	LEACH	SEP	DEEC	Contrib1	Contrib2
Record for three-level randomly deployed network					
Stability Period	1190	1430	1787	2467	2757
Lifetime	8245	8900	9190	9276	9469
Record for three-level uniformly deployed network					
Stability Period	1590	1920	2056	2679	3002
Lifetime	8468	9309	9508	9945	10460

In the above table 2, Deployed nodes are location-aware and with fixed epoch periods in the form of contrib1. Secondly, deployment with location-insensitive nodes and with varied epoch values as contrib2.But, here percentage population factor is utilized as 0.2,0.1, and 0.7 for super, advanced, and Normal nodes respectively. Concerning the same strategy, we are presenting more records in the form of various strategies in the form of the following table such as 3 and 4.

Table 3: Performance parameters recorded based on location sensitivity

Parameters	**LEACH**	**SEP**	**DEEC**	**Contrib1**	**Contrib2**
Record for three-level node network					
Stability Period	914	1281	1526	2153	2343
Lifetime	6638	8414	8743	8863	9063

Here in Table 3, the contrib1 (Contribution 1) label is for a location-sensitive node with a fixed epoch and contrib2 for a location-insensitive node with varied epoch for nodes with a population factor of 0.1,0.2, and 0.7 for Super, Advanced, and Normal nodes respectively [9].

Table 4: Performance record for node heterogeneity with random deployment

Parameters	**LEACH**	**SEP**	**DEEC**	**Contrib1**	**Contrib2**
Three types of node heterogeneity					
Stability Period	1060	1406	1787	1987	2177
Lifetime	7106	8840	9090	9115	9209
Four types of node heterogeneity					
Stability Period	1782	1978	2378	2612	2781
Lifetime	8439	10421	10611	11108	11928
Five types of node heterogeneity					
Stability Period	3030	2800	3190	3460	3580
Lifetime	10045	13005	12402	13565	15478

In summary, we discovered that the suggested design outperformed the 3-level network model in terms of stability and lifetime by more than 70 and 90 percent, respectively. In contrast, the stability and longevity of the suggested 4-level network model outperform the previously reported protocol by more than 75 and 85 percent, respectively. Consequently, the suggested design yields an overall improvement of 85 % in a lifetime and more than 72% in stability.

5. Conclusion

Hence, a multilayer node network's whole parameter set is improved when stability and energy efficiency are combined. The suggested protocol chooses the best node for the CH job and makes network management easier. Reducing the amount of energy needed for data transmission from CH to the sink node is a crucial step. More reliable cluster communication and improved load balancing are achieved with this suggested configuration. Therefore, the suggested CMEN in Wireless Sensor Network for Multiple Goals performs better for multilevel clustering techniques across a range of network dimensions. The CH's overall node connectivity, load balancing, and energy efficiency significantly increase network throughput and residual energy. Furthermore, the suggested design performs far better when it comes to a variety of goals, including increased stability, a longer lifespan, energy efficiency, and increased faithfulness in the form of increased throughput.

We will integrate a genetic algorithm to optimize the CH energy and the energy inside the multilevel network. Another system that might work well with this architecture is a PSO-based communication strategy.

References

[1] W. R. Heinzelman, A. Chandrakasan, H. Balakrishnan, Energy- Efficient Communication Protocol for Wireless Microsensor Networks, 33rd Annual Hawaii International Conference on System Sciences, Maui, 2000.

[2] M. Perillo, Z. Cheng, W. Heinzelman, On the problem of unbalanced load distribution in wireless sensor networks. Proc. of IEEE GLOBECOM Workshops on Wireless Ad hoc and Sensor Networks, 2004.

[3] O. Younis and S. Fahmy, HEED: A hybrid, energy-efficient, distributed clustering approach for ad-hoc sensor networks,". IEEE Trans. Mobile Comput., 2004.

[4] G. Smaragdakis, I. Matta, A. Bestavros, SEP: A Stable Election Protocol for clustered heterogeneous wireless sensor network. Second International Workshop on Sensor and Adhoc Network Protocols and Applications,2004.

[5] L. Qing, Q. Zhu, and M. Wang, Design of a distributed energy-efficient clustering algorithm for heterogeneous wireless sensor network, Elsevier, Computer Communications, 2006.

[6] D. Kumar, T. C. Aseri, R.B. Patel, EEHC: Energy efficient heterogeneous cluster scheme for wireless sensor networks. Elsevier. Comp. Comm., 2009.

[7] F. Farouk, R. Rizk, F.W. Zaki, Multi-level stable and energy-efficient clustering protocol in heterogeneous wireless sensor networks, IET Wireless Sensor Systems,2014.

[8] N. Javaid, M. Babar Muhammad, Imran, M. Guizani, Z. Ali Khan, T.A. Alghamadi, and M. Llahi, An energy-efficient distributed clustering algorithm for heterogeneous WSNs, EURASIP Journal on Wireless Communications and Networking. Springer,2015.

[9] S. Purkar, R. Deshpande, Dynamic Clustering Protocol to Enhance Performance of Heterogeneous Wireless Sensor Network, Adhoc & Sensor Wireless Networks, 2019.

[10] E. Umargono, J.E. Suseno, S.K.V. Gunawan, K-means clustering optimization using the elbow method and early centroid determination based on mean and median formula, 2nd Int. Semin. Sci. Technol. (ISSTEC 2019), Atlantis Press (2020),2020.

[11] A. Ghosal, A. Nandy, A.K. Das, S. Goswami, and M. Panday, A short review on different clustering techniques and their applications, Emerg. Technol.Model. Graph., Springer,2020.

[12] B.A. Hasan, T.A. Rashid, and H. K. Hamarashid, A novel cluster detection of COVID-19 patients and medical disease conditions using improved evolutionary clustering algorithm star, Computers in Biology and Medicine,2021.

[13] N. M. Labib, N. F. Omran, E. M. Mohamed, and N. M. Abdelnapi, Design of an enhanced threshold sensitive distributed energy efficient clustering routing protocol for WSN-based IoT, 2022.

[14] I. Banerjee and P. Madhumathy, QoS enhanced energy efficient cluster based routing protocol realized using stochastic modeling to increase lifetime of green wireless sensor network, Wireless Network,2023.

[15] Rathore R.S., Sangwan, S., Prakash S., Hybrid WGWO: Whale grey wolf optimization-based novel energy-efficient clustering for EH-WSNs. EURASIP J. Wirel. Commun. Netw. 2020.

[16] Fang W., Zhang W., Yang, W.; Li Z., Gao W., Yang Y., Trust management-based and energy efficient hierarchical routing protocol in wireless sensor networks. Digit. Commun. Netw. 2021.

[17] Daniel A., Baalamurugan K.M., Vijay R., and Arjun, K.P., Energy aware clustering with multihop routing algorithm for wireless sensor networks, Intell. Autom. Soft Comput. 2021.

[18] Zachariah U.E. and Kuppusamy L., A hybrid approach to energy efficient clustering and routing in wireless sensor networks, Evol. Intell. 2021.

[19] Hou Y., Gao H., Wang Z., and Du C., Improved Grey Wolf Optimization Algorithm and Application. Sensors 2022.

[20] Mandli Rami Reddy, M. L. Ravi Chandra, P. Venkatramana and Ravilla Dilli, Energy-Efficient Cluster Head Selection in Wireless Sensor Networks Using an Improved GreyWolf Optimization Algorithm, Computers 2023.

[21] Venkatesan Cherappa et.al, Energy-Efficient Clustering and Routing Using ASFO and a Cross-Layer-Based Expedient Routing Protocol for Wireless Sensor Networks, Sensors 2023.

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