Tuijin Jishu/Journal of Propulsion Technology
ISSN: 1001-4055
Vol. 45 No. 1 (2024)

SMART Clustering: A Methodical Approach to Increasing Energy Efficiency in Diverse Wireless Sensor Network

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Abstract: - Wireless Sensor Networks represent a significant area of research involving a multitude of sensor nodes distributed across a geographical area, operating with limited battery power. These networks are often deployed in challenging environments, making energy conservation a critical challenge. To address this, clustering has been identified as a highly effective technique for reducing energy consumption. This research introduces a novel clustering approach aimed at decreasing energy consumption and extending the overall lifetime of the network, particularly crucial for deployments in inaccessible areas. The proposed approach incorporates heterogeneity to enhance the stability and energy efficiency of randomly deployed sensor nodes. We assessed the effectiveness of the proposed protocol through simulations and compared it with well-established distributed protocols. The results demonstrate the efficiency of our approach in terms of the stability period, residual energy inside the network, and the number of cluster heads generated inside the network. Additionally, the proposed method exhibits improved performance in the number of dead nodes and overall network lifetime.

Keywords: *Quality of Service (QoS), Hierarchical, node degree*

1. Introduction

Wireless Sensor Networks (WSN) are rapidly advancing in wireless communication systems and micro-electromechanical systems. These networks consist of compact, battery-operated sensor nodes (SN) and are characterized by three fundamental principles: wireless data transmission, computation on sensed data, and data sensing from the external environment. The collaborative functioning of nodes in accomplishing tasks defines WSN, where nodes manipulate physical parameters like humidity, pressure, and temperature. These networks find applications in various fields such as crisis management, military, and defense systems. In WSN, challenges include limited energy resources and a large number of nodes, necessitating energy-efficient routing protocols for transmitting sensed data packets to the base station. Various effective routing protocols establish communication paths between sensor nodes and the base station. To optimize Quality of Service (QoS) parameters, cross-layer techniques combine replacement information across different communication protocol layers. Routing protocols are categorized into flat and hierarchical types based on the network structure. Flat routing protocols involve each sensor node performing a similar role, reducing network overhead. In contrast, hierarchical routing protocols divide nodes into clusters, with cluster heads acting as leaders. Each cluster consists of a few sensor nodes and the respective cluster head receives sensed data from its sensor nodes. Despite the advantages of clustering-based energy-efficient protocols, challenges such as data routing to the base station, cluster maintenance, optimal cluster numbers, and appropriate cluster head selection have been identified [1-4]. In recent years, evolutionary methods have demonstrated improved performance in engineering applications, addressing some of these challenges. Wireless sensor networks exhibit heterogeneity by incorporating regular and diverse nodes. Regular nodes specialize in sensing and data reporting, while diverse nodes possess augmented energy or communication capabilities, contributing to computational, link, and energy resource variety. The impact of diverse sensor networks extends to improving network lifespan, ensuring reliable data transmission, and minimizing latency. Energy emerges as a critical resource, posing challenges when replacing non-rechargeable batteries in sensor nodes is impractical. The mission duration of a sensor node varies based on application requirements. The principal design challenge for wireless sensor networks is achieving energy efficiency, and influencing decisions at the physical layer and higher-level protocols. The Medium Access Control (MAC) layer is pivotal, with contention-based MAC approaches leading to energy overheads and delays. Contention-free MAC protocols regulate medium access, eliminating collisions, and enabling sensor nodes to power down during inactivity. Cluster heads play a vital role in efficiently facilitating communication between sensor nodes and the base station. Introducing diverse nodes can extend the network's lifetime, encompassing nodes with varying computing power and sensing range. Existing clustering techniques like LEACH may not efficiently save energy in diverse networks, necessitating tailored energy clustering protocols. Wireless sensor networks can be classified into homogeneous and diverse types based on data collection methods. A homogeneous network features sink and sensor nodes with equal capabilities, using flat or hierarchical topologies [5-8]. In contrast, a diverse sensor network includes fixed or mobile sinks, regular sensor nodes, and advanced sensor nodes with enhanced processing and communication capabilities. With the advancement of ad-hoc networks, including Mobile Ad-hoc networks (MANET) and Vehicular Ad-hoc networks (VANET), the development of Wireless Sensor Networks (WSNs) has been driven by the need for easy implementation in harsh environments, sensing physical phenomena, and delivering high performance. WSNs consist of multiple sensor nodes collaborating to perform tasks and wirelessly transmitting data to a sink node. These sensor nodes have multiple sensors, a transceiver, a processing unit, a memory unit, and a power supply. To enhance network efficiency, addressing energy, network lifetime, and scalability challenges is crucial. Clustering plays a vital role in achieving scalability, fault tolerance, data aggregation, and energy efficiency objectives. Re-clustering ensures fault tolerance when Cluster Heads (CHs) fall below an energy threshold. Uneven clustering achieves load balancing, and the deployment of diverse nodes must be optimized to balance cost. This work presents a clustering approach in a diverse network with energy-based heterogeneity [9].

Contribution:

i. A load-balanced clustering is designed to minimize the load on clusters near the BS, improving network connectivity, energy efficiency, and network lifespan.
ii. Heterogeneity is introduced to the network, considering deployment and cost issues. The inclusion of different node types, based on application requirements, allows the network to operate for longer durations.
iii. The approach is designed for the network with the BS at the center of the network, utilizing multi-hop communication to reduce energy consumption.

This Novel SMART clustering method dramatically increases power economy plus network performance. This technique optimizes the decision-making process for cluster head nodes for network interaction by taking into account variables such as starting energy, residual energy, hop count, and node degree. This strategy improves network stability, extends its lifetime, and assures balanced load distribution by rotating cluster head responsibilities depending on calculated function values. Furthermore, by utilizing node degree and calculated weight value and intra-distance between nodes and the sink, the developed method efficiently minimizes energy expenditures for a wide range of nodes, hence contributing to total energy conservation. Through about a 1.3-fold increase in cluster rounds over a well-known protocol, the simulation results show that SMART Clustering: A Methodical Approach to Increasing Energy Efficiency in Diverse Wireless Sensor Network performs better, demonstrating its superiority in energy efficiency and network survival period.

2. Literature Survey

In the domain of Wireless Sensor Networks (WSNs), the critical challenge revolves around addressing concerns such as energy conservation, scalability, and the constraints of limited network resources. The central focus is on augmenting energy efficiency through strategic clustering methodologies, where specific nodes are designated as Cluster Heads (CHs), endowed with heightened power capabilities to effectively mitigate the risks associated with energy depletion across the entire network. Exploring the spectrum of clustering techniques reveals a myriad of meticulously devised schemes and protocols, categorized based on the control process or algorithmic type. The control processes within clustering unveil three distinctive approaches: centralized, distributed, and hybrid. In the centralized paradigm, the Base Station (BS) or sink assumes the responsibility of selecting CHs, resulting in notable examples like LEACH-C, Energy Efficient Load Balancing Clustering protocol (EELBC), and Energy Efficient Dynamic Clustering (EEDC). However, centralized control incurs increased overhead, compelling nodes to transmit comprehensive network information to the BS. Distributed control methods, represented by Low Energy Adaptive Clustering Hierarchy (LEACH), offer a reduction in overhead as nodes communicate directly among themselves. Other noteworthy distributed algorithms include the Distributed Weight-based Energy-efficient Hierarchical Clustering protocol (DWEHC) and Power-Efficient and Adaptive Clustering Hierarchy protocol for wireless sensor networks (PEACH) [10]. Hybrid approaches, exemplified in the work of WSN are possible with the aim to strike a balance between minimizing energy consumption and maximizing network lifetime [11]. Innovative avenues explore residual energy-based CH selection mechanisms, incorporating fuzzy logic, as seen in the works of Mahboub et al. (2019). Fuzzy logic becomes a valuable tool in handling uncertainties and instability within the network, showcased in FUZZY-LEACH and similar endeavors. Transitioning to the algorithmic realm, clustering emerges as a potent strategy for enhancing energy efficiency in both homogeneous and heterogeneous networks. Algorithmic types are categorized as probabilistic or non-probabilistic. Probabilistic clustering, a form of distributed clustering, selects CHs based on a probability function and predefined CH percentage. Noteworthy protocols in this domain include LEACH and Hybrid Energy Efficient Distributed Clustering (HEED) for homogeneous networks, while heterogeneous networks commonly employ Distributed Energy Efficient Clustering (DEEC), Enhanced DEEC (EDEEC), and Energy-efficient Heterogeneous Clustered Scheme for Wireless Sensor Networks (EEHC)[13-16] . In these protocols, the selection of CHs is contingent upon a probability value defined by a threshold. Given the inherently higher energy consumption by CHs during data collection, processing, and transmission to the BS, strategically balancing the network load becomes paramount. The selection of an appropriate type and number of CHs is pivotal in reducing overall energy consumption and enhancing the network's lifespan. This entails distributing high-energy nodes in areas with high traffic and allocating a greater number of CHs in densely populated regions, ensuring the holistic efficiency of the network.

Recent years have witnessed a surge in algorithmic innovations aimed at addressing various wireless sensor network protocols. Notably, heterogeneous wireless sensor networks, comprising a mix of normal and heterogeneous nodes, have gained prominence. The Heterogeneous LEACH protocol finds diverse applications, and researchers have proposed alternative approaches, such as two-level hierarchies and probability-based clustering. The work by Loscri et al. introduces a novel LEACH-based protocol with primary and secondary cluster heads, reducing energy consumption and improving data aggregation efficiency[17]. Similarly, Qing et al. present a distributed energy-efficient clustering protocol, DEEC, where cluster heads are elected based on the ratio of residual energy to the network's average energy, significantly extending the network lifetime. In the quest for effective clustering protocols, researchers have introduced several innovative solutions. Heinzelman et al. presented the pioneering LEACH protocol, utilizing a random distribution of Cluster Heads (CHs) to address challenges in large geographical deployments. Manjeshwar and Agrawal proposed the Threshold Sensitive Energy Efficient Sensor Network Protocol (TEEN), incorporating soft and hard thresholds for data transmission between sensor nodes. Bandyopadhyay and Coyle introduced the Energy Efficient Hierarchical Clustering (EEHC) algorithm, a distributed and randomized approach to organizing sensors into energy-efficient clusters. Younis et al. presented the Hybrid Energy Efficient Distributed (HEED) scheme, aiming to overcome the limitations of existing protocols by selecting CHs based on residual energy and intracluster communication cost. Smaragdakis et al. introduced the Stable Election Protocol (SEP) for two-level heterogeneous wireless sensor networks, categorizing nodes based on initial energy to prolong stability. Soro and Heinzelman proposed the Unequal Clustering Size (UCS) bi-layered model to achieve uniform energy consumption among CHs, though facing scalability challenges. Mao Ye et al. developed the Energy-Efficient Clustering Scheme (EECS), electing cluster heads based on the highest residual energy. Qing et al. introduced the Heterogeneous Distributed Energy-Efficient Clustering (DEEC) protocol, selecting CHs based on the probability ratio of residual energy to the average energy. Chen et al. proposed the Unequal Cluster-Based Routing (UCR) protocol to address hotspots in multi-hop routing in clustered WSNs [14-19]. In the pursuit of addressing the challenges presented by existing protocols, a novel approach named SMART Clustering (SC) is proposed. SMART Clustering takes into account real-time attributes of deployed sensor nodes, along with a weighted function incorporating residual energy, hop count, initial energy, and node degree. This proposed protocol aims to overcome limitations observed in EEHC and HEED protocols, showcasing its effectiveness through comprehensive testing.

2.1 Hybrid Energy-Efficient Distributed Clustering (HEED)

O. Younis et al. [13] improve the LEACH protocol by using residual energy, node degree, or density as the main parameters for cluster formation to achieve power balancing. This protocol was proposed with three main parameters: The first parameter is to enhance network lifetime by distributing energy consumption, clustering terminates within a fixed number of iterations third minimum control over heads and fourth the cluster heads were well distributed. The algorithms proposed in this protocol periodically select cluster heads based on the two basic parameters. The first primary parameter is the residual energy of each node; the second parameter is the intra-cluster communication cast as a function of cluster density or node degree. The primary parameter selects an initial set of cluster heads probabilistically which secondary parameter is breaking ties. HEED is not able to fix the cluster count in each round and it is also not aware of heterogeneity.

2.2 Energy Efficient Hierarchical Clustering (EEHC)

Energy Efficient Hierarchical Clustering (EEHC) [16] is a randomized, distributed clustering algorithm designed to extend network lifetime. In this algorithm, sensor nodes are organized into clusters with a hierarchy of cluster heads. Cluster heads collect information from nodes within their clusters and send aggregated data to the base station through the hierarchy. The algorithm is based on two-stage clustering: single-level and multi-level clustering. During the single-level clustering stage, each sensor node becomes a cluster head based on a pre-defined probability (p) and announces itself as the volunteer cluster head to its neighbors within k-hops distance. Nodes receiving this announcement become members of the closest cluster. If a node does not hear any announcement within a preset time interval (t), it becomes a forced cluster head. The time interval (t) is calculated based on the duration for a packet to reach a node that is k-hops away. The energy consumed for sending information to the sink depends on parameters p (probability value) and k. In the second stage, the same process is applied from bottom-up to multi-level clustering. Assuming there are h levels in a clustering hierarchy, with level-1 being the lowest and level-h being the highest, level-1 aggregates data from its cluster members and sends it to level-2 cluster heads, and so on. Finally, level-h cluster heads send the aggregated data to the base station. The cost of transmitting information to the base station includes the power consumed by sensor nodes to send data to level-1, then the energy used by level-1 cluster heads to reach the base station via h-hop cluster heads at different hierarchical levels. The EEHC algorithm can be executed periodically for load balancing or triggered when the energy level of the cluster head falls below a certain threshold.

2.2.1 Conclusion and Proposed Novel Approach: SMART Clustering (SC)

In conclusion, the landscape of wireless sensor network clustering protocols has seen significant advancements, with researchers addressing challenges related to energy efficiency, scalability, and network constraints. While existing protocols exhibit merits, novel approaches such as SMART Clustering (SC) have been proposed to overcome identified limitations. SC incorporates real-time attributes and a weighted function, presenting a promising avenue for further exploration and refinement in the quest for energy-efficient and robust clustering protocols in wireless sensor networks.

Here, SMART Clustering is elucidated as follows:

- ✓ S: Scalable Cluster Head Selection and Management through Algorithmic Refinement and Tuning
- ✓ M: Maximizing Communication Efficiency and Network Lifetime for Optimal Resource Utilization
- ✓ A: An Advanced Approach to Clustering Algorithm Design for Energy-Aware and Reliable Networking
- ✓ R: Resourceful Optimization Strategies for Enhanced Scalability and Improved Network Performance

- ✓ T: Tailored Techniques for Cluster Head Selection Considering Energy Efficiency, Load Balancing, and Communication Effectiveness

3. System Model

3.1. Problem Formulation

For this investigation, the following assumptions have been established:

i. It is assumed that sensor nodes remain stationary.
ii. Each sensor node is uniquely identified by an ID.
iii. The Base Station (BS) is centrally positioned within the network.
iv. The BS is unrestricted by constraints related to energy, memory, and computation.
v. While all nodes share identical processing and communication capabilities, they differ in terms of their energy supply.
vi. Nodes are capable of calculating their distances to the BS and neighboring nodes, and links exhibit symmetry between nodes.
vii. The distribution of nodes is random.
viii. Nodes are equipped with GPS for updating their information in one scenario and are without GPS sensitivity in another.

3.2. Network Model

This study explores a network featuring heterogeneously distributed nodes, where the selection of Cluster Heads (CHs) is determined by probability values. The heterogeneity is characterized by varying energy efficiencies among nodes, with some nodes identified as more energy-efficient compared to the norm, albeit in smaller numbers. The introduced network model aligns with existing literature and is formulated based on diverse node populations. Specifically, we incorporate three types of nodes: normal, advanced, and super. The total number of nodes is denoted as 'T_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 'N'. The standard node is characterized by an initial energy 'Ne' and a percentage population factor 'n'. Higher-type nodes, referred to as super nodes, have a population value of 's', and an energy value of 's_e' that is greater than the normal node energy. For a normal node, the energy value is 'Ne', calculated based on the population factor 'n' and the total number of nodes T_N [13-17]. The energy contribution from each node is outlined as follows:

The energy calculation for a standard node is determined by:

$$E_N = n.\ Ne.\ N;\ \text{Where, } n= (1\text{-}a\text{-}\ s) \quad (1)$$

The energy of an advanced node is computed as:

$$E_a= a.\ (1+a_e).\ N_e.\ N \quad (2)$$

The energy provided by a supernode is given by:

$$E_s= s.\ (1+s_e).\ N_e.\ N \quad (3)$$

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

$$E_{NT} = E_N+ E_a+ E_S \quad (4)$$

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

$$E_{NT} = (N_e\ (n+ a\ (1+a_e) + s(1+s_e))).\ N \quad (5)$$

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:

$$E_{NT} = (n.\ Ne\ (1+ 3a+5s)).\ N \quad (6)$$

3.3. Energy Utilization Model

The main objective of this presentation is to communicate the data exchange between two sensor nodes, with emphasis on specific communication attributes. The propagation model is categorized into two classes: direct and multipath, which are determined by a communication distance threshold. The sender node typically consumes more energy when transmitting collected data. This energy consumption is a result of expected power usage at the modulator, energy dissipation in the environment, and energy dissipation at the transmitting amplifying section of the antenna. On the other hand, the receiver only incurs energy consumption in the radio electronics, but this occurs beyond the threshold distance 'd_0'. In the context of data communication, when the communication distance 'd' less than the threshold distance for direct communication, energy expenses can be calculated based on the multipath propagation model. Nearby data communication is initiated for a data packet of ‘L’ (in bits) using radio link features similar to those described in existing. The energy model presents various communication attributes such as 'E_{TX}' representing the cost of transmitting a data packet, 'E_{RX}' for receiver energy consumption, 'E_{elec}' for energy consumed by radio electronics, 'E_{mp}' for energy cost in the multipath model, and 'E_{fs}' for energy required in free space propagation. Additionally, 'E_{DA}' refers to 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 following section focuses on the calculation of different attributes used in the energy model, starting with the determination of 'd_0' as outlined below.

The energy expended by the transmitter for a packet of length ‘L’ over a distance ‘d’,

$$d_0 = \sqrt{}E_{fs} / E_{mp} \quad (7)$$

$$E_{TX} = L \cdot E_{elec} + L \cdot E_{fs} \cdot d^2 \qquad \text{if } d \leq d_0 \quad (8)$$

$$E_{TX} = L \cdot E_{elec} + L \cdot E_{mp} \cdot d^4 \qquad \text{if } d \geq d_0 \quad (9)$$

Energy computation at the receiving node involves...

$$E_{RX} = L.\ E_{elec} + L \cdot E_{DA} \quad (10)$$

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

$$E_{Relay} = E_{RX} + E_{TX} \quad (11)$$

4. Methodology

The main objective of the proposed design is to leverage the heterogeneity of 3-level nodes while validating the introduced protocol. Simultaneously, we aim to assess improvements in energy efficiency and evaluate multiple performance criteria. Our focus lies in managing energy consumption during data relay to the sink node and analyzing various performance metrics. To achieve this, we actively rotate the role of Cluster Head (CH) and monitor the remaining network energy. After measuring the node degree (incoming node) and by combining weight value based on function **f**((initial energy, hop count), residual energy). Nodes with higher values of weight function and node degree will be responsible for selecting a node as a cluster head for the particular round in the network. If there are multiple nodes with the same value of node degree and weight function, then nodes that have less attempt of CH’s selected as CH. If the node has better value of the combination will be selected as master CH as compared to their slave CH those are selected randomly. To ensure adherence to boundary conditions and prevent placement at the network's edge, the selected CHs must fulfill specific criteria. Our protocol design involves dividing the network into eight equal zones relative to the base station (BS). The average value of combination function f(Weight-Vlaue, Node degree) of each zone serves as a threshold for selecting CH. The ultimate CH acts as a relay element, providing support to the secondary-level CH in data communication. It should be noted that in this scheme, we strive to minimize assigning the CH role to nodes located near the network boundary [13-16].

5. Proposed Protocol

By carefully selecting nodes for the CH function and implementing effective load balancing, the proposed protocol and its implementation enhance the energy efficiency of the tested network model. The current CH selection process considers factors such as energy consumption, node degree, and value about a threshold. This approach ensures a well-distributed network load, resulting in balanced node degrees at each head level. Consequently, the cluster size is systematically managed, leading to improved network management of residual energy through energy expenditure regulation, as opposed to relying on chance. It's crucial to note that sensor nodes in the transmitting mode consume significantly more energy than other processes. To address this, we intend to utilize multi-hop communication with remote nodes to conserve energy. In this strategy, a temporary CH is deployed within each zone (determined by the node index value), and a primary CH is selected based on the network's highest weight to alleviate the Cluster Head (CH) burden. Each secondary CH node in a zone transmits collected data to the primary CH, facilitating future connection with the Base Station (BS). When a node's communication distance from the BS is greater, it directs the gathered data to a neighboring node based on the node weight. Conversely, information can be directly sent through the BS using the same approach employed by Cluster Members (CM) to relay data to either the CH or the primary CH. In our previous research, we evaluated various clustering-related aspects of wireless sensor nodes, emphasizing the importance of selecting relay nodes that consume the least amount of energy while transmitting observed signals. The chosen Cluster Head (CH) must have a calculated weight magnitude exceeding the threshold value, excluding other nodes, and is deliberately positioned away from the network's border with assigned CH duties. During the initial rounds, a considerable number of nodes may have a higher weight value than the ideal cluster node value. To address this, we apply the normal HEED approach in the first several rounds of 500 cluster cycles. In this phase, our primary focus is on a query-based approach suitable for monitoring structural health or medical applications [1-4]. The supporting parameters of the clustering process are determined based on the factors described earlier.

5.1. Result

In this section, our objective is to provide a detailed explanation of the simulation parameters and performance criteria. The implemented protocol undergoes rigorous testing and validation using a predefined set of standard parameters, as outlined below. The practical constraints for the subsequent parameters fall within the range of 0 to 100000. The specifics regarding the performance parameters employed in the validation process are detailed as follows:

I-Stability: This metric measures the number of cluster rounds that occur before the first operational node fails within the network.

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

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.

The experimental verification process involves testing the suggested implementation against predetermined simulation parameters represented by the dataset in Table 1. The network configuration consists of 200 nodes randomly arranged in a 200m x 200m layout. A percentage population factor, represented as a = 0.2 and s = 0.1, is applied in the context of the 3-level network model for all 200 nodes. The energy value increases by a factor of 1.5 to 2 as more node types are added, with nodes categorized as super, advanced, and normal, corresponding to different energy levels.

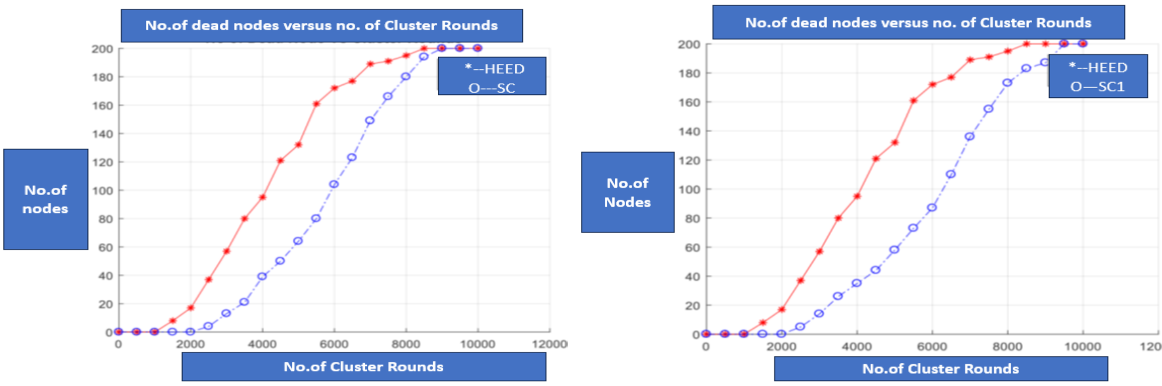
Table 1: List of Simulation Parameters with values

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

5.2. Discussion

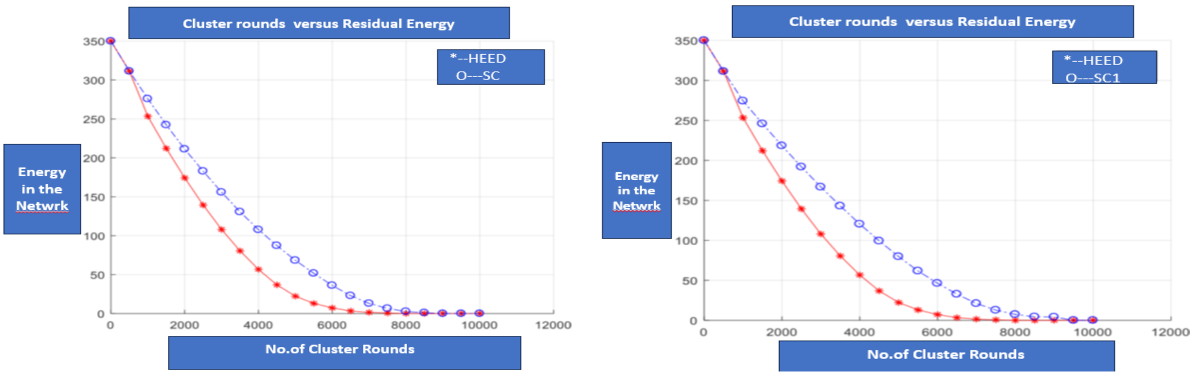
The suggested implementation is currently undergoing validation at different phases. Initially, we analyze the performance under the condition that nodes are randomly deployed and have their location information and unawareness. The results of the implementation and testing are presented in Figures 1 to 6 and recorded in Table 2. Utilizing the centrally located Base Station (BS), a source with significant processing and energy capacity, we employ the received signal strength indicator (RSSI) of nodes for applications to achieve location insensitivity. The Hybrid Energy Efficient Distributed Clustering (HEED) architecture concept of clustering, established by the authors in [13], is used as a point of comparison for our implementation. Details of HEED present an approach based on residual energy and node degree in selecting Cluster Heads (CH). Premature node depletion may occur if the resulting cluster head has a greater node degree in an arbitrarily large cluster, further taxing the CH. Uneven load distribution across nodes may result from the selected Cluster Head coming from separate zones, leading to imbalance, shortened stability, and lifespan due to needless energy use. Consequently, both energy stores and throughput quickly exhaust. HEED fails to fully exploit the usage of heterogeneous sensor nodes in Wireless Sensor Networks (WSN) and is unable to differentiate between nodes' capabilities. In contrast, Stable Clustering (SC) initiates better performance for various energy level nodes or heterogeneous networks, suggesting handling heterogeneity through a SMART approach, mainly using advanced or super nodes systematically in WSNs. The suggested approach selects the CH based on initial, residual, hop count, and node degree values, reducing the chances of selecting CHs with less potential. The Energy-efficient Heterogeneous Clustering protocol (EEHC) emphasizes energy awareness and attempts to solve energy balancing across the network with the try of proper usage of high-energy nodes [16]. However, increased energy consumption may occur for nodes set at a long distance from the BS. Unlike previous upgrades, our proposal carefully chooses an appropriate Cluster Head (CH) to optimize energy use, considering factors like node degree, and energy availability, and ensuring the chosen CH is less utilized or attempting to utilize and away from the network boundary. In the first stage, the suggested approach outperforms HEED and Energy-efficient

Heterogeneous Clustering in terms of stability and lifetime, as CH nodes inside zones submit collected data to the principal CH for relaying data packets to the BS, creating a more balanced configuration. Since nodes in the suggested framework are location-sensitive, available energy consumption is much less than with the previous location-unaware nodes method. However, location-unaware nodes save energy in the SC1 approach, lowering the node death rate compared to the prior design with location-aware nodes as in SC. In addition to increasing network connectivity, this slowdown lowers energy depletion proportionately. Through partitioning networks, clusters are bounded to finite sizes instead of arbitrary ones, extending the total survival time of the network. Consequently, 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 the number of cluster heads 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 Table 2.



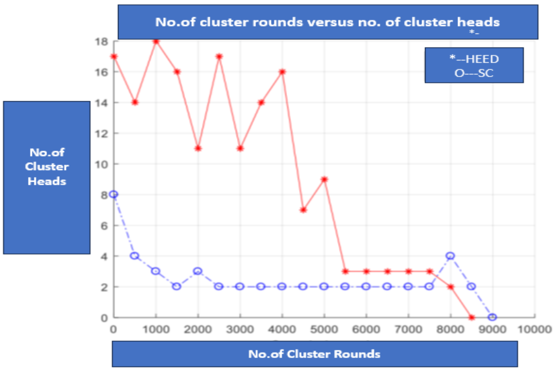
1(a) 1(b)

Figure 1 illustrates a graph depicting the correlation between the number of cluster rounds and the count of deceased or dead nodes in the HEED protocol. The graph presents comparisons between the Location-aware and location-insensitive approaches, specifically denoted as SC and SC1, shown as 1(a) and 1(b), respectively.

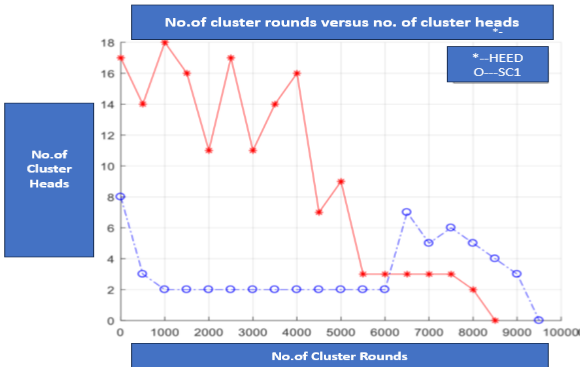


2(a) 2(b)

Figure 2 displays a graph illustrating the relationship between the number of cluster rounds and the residual energy or the remaining energy in the network within the HEED protocol. The graph compares the Location-aware and location-insensitive approaches, represented as SC and SC1, respectively, labeled as 2(a) and 2(b).

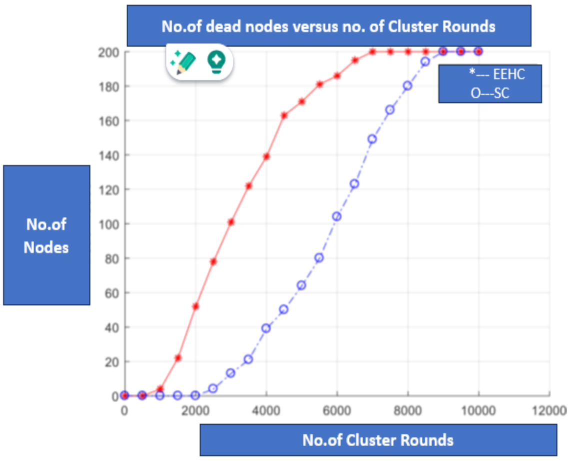


3(a)

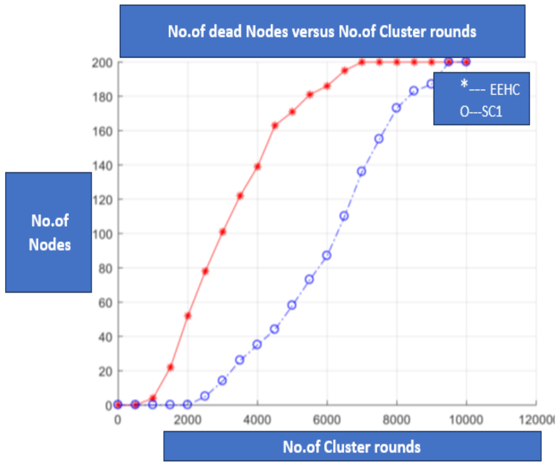


3(b)

Figure 3 presents a graph that illustrates the correlation between the number of cluster rounds and the count of cluster heads in the HEED protocol. The graph compares the Location-aware and location-insensitive approaches, represented by SC and SC1, respectively, labeled as 3(a) and 3(b).

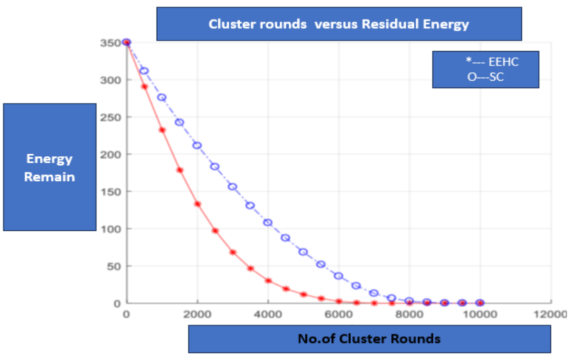


4(a)

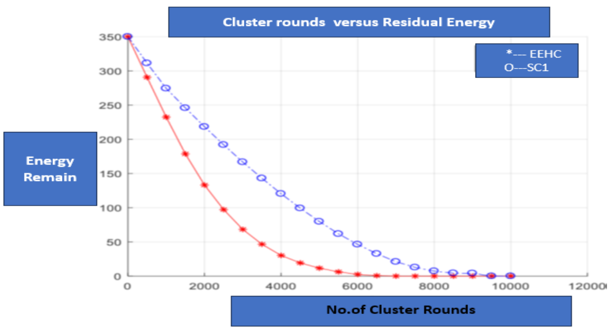


4(b)

Figure 4 depicts a graph illustrating the relationship between the number of cluster rounds and the count of deceased nodes in the EEHC protocol. The graph compares the Location-aware and location-insensitive approaches, denoted as SC and SC1, respectively, and labeled as 4(a) and 4(b).

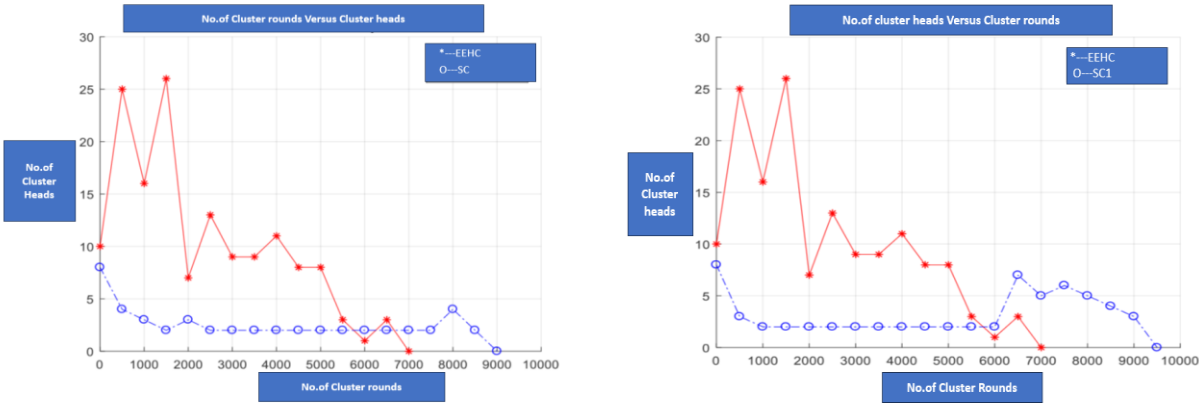


5(a)



5(b)

Figure 5 presents a graph illustrating the relationship between the number of cluster rounds and the residual energy or the remaining energy in the network within the EEHC protocol. The graph compares the Location-aware and location-insensitive approaches, represented as SC and SC1, respectively, labeled as 5(a) and 5(b).



6(a) 6(b)

Figure 6 presents a graph that illustrates the correlation between the number of cluster rounds and the count of cluster heads in the EEHC protocol. The graph compares the Location-aware and location-insensitive approaches, represented by SC and SC1, respectively, labeled as 6(a) and 6(b).

In Table 2 above, the deployed nodes exhibit both location-aware and location-insensitive characteristics in the context of random node deployments, represented as SC and SC1.

Table 2: Performance parameters recorded based on location sensitivity

Parameters	HEED	EEHC	SC	SC1
3-Node Network				
Stability Period	1020	820	2080	2200
Lifetime	7046	7020	9030	9781

The recorded readings reveal that the proposed 3-level node architecture, utilizing the suggested scheme with random deployment, outperforms the existing HEED and EEHC by 84% and 66%, respectively, in terms of stability. This indicates a superior clustering scheme compared to HEED and EEHC. Consequently, the suggested design results in an overall improvement of more than 75% in lifetime.

5. Conclusion

Therefore, combining stability and energy efficiency enhances the entire parameter set of a multilayer node network. The suggested protocol efficiently selects the optimal node for the Cluster Head (CH) role, simplifying network management. A crucial step is taken to reduce the energy required for data transmission from the CH to the sink node. This suggested configuration achieves more reliable cluster communication and improved load balancing. Hence, the suggested SMART Clustering approach performs exceptionally well in the field of Heterogeneous WSN. The overall node connectivity, load balancing, and energy efficiency of the CH significantly enhance network residual energy. Furthermore, the suggested design excels in various performance parameters, including increased stability, a longer lifespan, energy efficiency, and enhanced faithfulness, as evidenced by the controlled form of cluster head count.

Future enhancements may include a fuzzy algorithm to optimize CH energy within the multilevel network. Additionally, an Ant-based communication strategy is another potential system that could complement this architecture.

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