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Hybrid algorithm for fault node recovery and energy efficiency in wireless sensor networks

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Abstract

The Wireless Sensor Networks (WSNs) are designed for the monitoring of remote areas in various places with a variety of different applications. The main challenges with the WSN are energy efficiency and fault recovery. In order to optimize the network lifetime of the WSN, fault node recovery and energy efficient clustering are required in order to efficiently utilize the energy supply device of battery-powered sensors. The purpose of this paper is to develop a hybrid algorithm that combines the K-means clustering technique with fault node recovery in the WSN in order to reduce energy consumption and extend sensor lifetimes. A hybrid algorithm combine's fault node recovery with energy-efficient clustering methods in order to reduce energy usage. We are using Grade Diffusion (GD) with Genetic Algorithm (GA) to detect fault nodes. In complex or large WSNs, K-means clustering can be used to reduce the complexity of the hybrid algorithm in order to reduce its complexity. As the hybrid algorithm is used for identifying fault nodes and replacing nodes with neighbor nodes, it is primarily used for the computation of grade values. With the proposed fault node recovery and energy efficient clustering methods, the energy consumption of each node can be minimized and the network lifetime can be improved as well. Using the MATLAB platform, we compared the suggested method to several existing ones including "Low Energy Adaptive Clustering Hierarchy (LEACH), Hybrid Hierarchical Clustering Approach (HHCA), Novel Energy Aware Hierarchical Cluster (NEAHC), and Heuristic Algorithm for Clustering Hierarchical

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Protocol (HACH)", among others in terms of residual and consumption energy, as well as receiving packet data.

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Keywords: *Genetic algorithms, Energy-efficient, Faulty nodes, Grade diffusion, Genetic algorithms, Sensor networks, Energy-efficient.*

1. Introduction

In recent years, there has been significant interest in the research of Wireless Sensor Networks (WSNs) due to their numerous advantages and their applicability across a variety of fields including "weather prediction, intelligent transportation systems, vehicle detection, industrial performance monitoring, health management, smart administration, and environmental surveillance" [1]. A WSN consists of multiple sensor nodes which are compact electronic devices with limited battery power. These sensors are crucial to the network's structure as they function autonomously without requiring human supervision. In addition to energy, these sensors possess the capability to process data and store information, which is vital for prolonging the network's operational lifespan [2]. These sensors are designed to function independently across different applications for extended periods, thereby mitigating issues related to unavailability and the need for battery replacement. Additionally, the implementation of fault-tolerant node recovery and energy-efficient clustering strategies is essential for the optimal functioning of WSNs [3, 4].

Several factors can negatively impact the performance of a Wireless Internet Network [5]. These factors include deployment strategies, geographical location, connection quality, network coverage, measurement accuracy, and the reliability of both software and hardware components. In a Wireless Sensor Network (WSN), node failures present a significant challenge, as they can lead to performance issues and prevent the network from meeting the expected quality standards. In order to enhance the efficiency of the "Wireless Sensor Network (WSN)", it is essential to address and rectify these issues. Addressing these issues mitigates the depletion of battery life and minimizes the unnecessary expenditure of energy in faulty nodes. The user's text is "[6-7]". The primary objective is to achieve fault node recovery and enhance energy efficiency in "Wireless Sensor Networks (WSNs)" in order to optimize overall system performance. The primary issues in the WSN are fault recovery and energy efficiency [8]. In mobile node networks, the base station is responsible for providing unrestricted energy supply to the network. A failure node refers to a situation when the base station can provide electricity to the node [9, 10]. To prolong the lifespan of the nodes, it is important to prevent the unnecessary supply of energy.

Two main techniques are introducing the energy consumption in the WSN such as nodes sleep active method and clustering methods [11]. Clustering is a frequent and efficient method for reducing unwanted energy consumption of the WSN nodes. Before the clustering parts, the fault node diagnosis with replacement is main task in the WSN, which method also mostly avoided the unwanted consumption of the energy [12, 13]. After that, the energy consumption optimally reduced by reduces data sent to the data center and aggregate data with easier scalability and network management. Many methods are developed by the researchers, that methods are not considered the fault node recovery methods it only contains the energy efficient clustering techniques [14, 15]. This paper outlines a fault recovery strategy and an energy-efficient clustering method for wireless sensor networks (WSNs) designed to address the aforementioned challenges. These approaches aim to effectively resolve the issues highlighted, ensuring improved network performance and reliability.

The main contribution of the paper can be presented as follows,

- To develop the hybrid algorithm of node replacement and energy efficient clustering methods in WSN.
- To develop the GD algorithm which used to find the non-functioning node and select the sink node-based grade values in WSN.
- To develop K-means clustering which used to clustering and cluster head selection and GA used to find optimal path selection progress for reducing energy consumption in WSN.
- A comparison is made between the suggested technique and the current models of "LEACH, HHCA, NEAHC, and HACH" in order to evaluate the effectiveness of the new method.
- To analysis the proposed method with the performance metrics such as Data transmission round, Residual Energy, Packet delivery ratio, energy consumption.

The study is structured as follows: Section 2 of the paper provides an overview of the previous work on energy clustering techniques and fault node recovery strategies. The final part presents comprehensive details on the proposed clustering strategy and fault node recovery mechanism. The article provides a comprehensive account of the implementation results and performance metrics of the proposed technique in section 4. In section 5, the study closes by discussing the potential future applications of the suggested approach.

Literature Review:

A number of clustering and fault node replacement algorithms for WSN have been developed by the researchers. Some of the works are reviewed below.

Seema Dahiya et al. [16] The present research unearths an efficient Self-Organizing Cluster based Greedy First Search Opportunistic Routing Protocol to manage energy-centric Wireless Sensor Networks (WSNs). To control energy distribution, the protocol is divided into four states, namely death, guard, active, and sleep. It uses K-means method with greedy best search algorithm to optimize the d Faction detection rates, neighbor node analysis and the remaining energy. The proposed opportunistic routing algorithm clearly works best in repairing the coverage holes and even recovers hole pair in order to prolong the network lifetime. During the experiments, the efficiency of the protocol implemented in the heterogeneous as well as in the homogeneous network environment is confirmed.

Sercan Yalcin et al. [17] This paper proposes the pi Bacterial Inspired Optimization algorithm for detecting mobile faults in WSNs by Analyzing voltage values and sensor health. Cluster heads are selected using intersection pivots, and data packets are collected via mobile sinks. The method effectively diagnoses and eliminates software and hardware faults, enhancing network functionality and reliability.

Somaye Jafarali Jassbi et al. [18] The proposed methodology enhances energy efficiency in wireless social networks using the HEED clustering technique combined with the sleep-wake up strategy. Backup cluster heads are selected based on defective node detection within clusters, and faulty nodes are replaced with member nodes. Weighted median analysis is used to identify cluster head nodes as fault nodes, which are isolated and replaced during the transition from sleep to active mode, ensuring efficient fault management and energy optimization.

Karl E. Prikopa et al. [19], This research introduces fault-tolerant least squares solutions using gossiping in WSNs, leveraging the Gossip-Based

Least Squares Solver (GLS-IR) to address over-determined linear systems. Iterative refinement merges two variations to enhance accuracy, maintain system stability, and reduce communication costs. Gossip-based methods enable distributed aggregation and seamless communication between nodes, allowing for immediate error detection and substitution with neighboring nodes.

Usha Mohanakrishnan et al. [20], introduces the Modified Cognitive Tree Routing Protocol (MCTRP), which integrates the Genetic Whale Optimization Algorithm to improve energy efficiency in WSNs within a VANET. The protocol uses cognitive radio technology to optimize spectrum utilization by identifying and efficiently managing occupied channels. A tree-based routing structure facilitates efficient data transmission, with the genetic algorithm combined with whale optimization for optimal root channel selection. This integration ensures effective spectrum allocation, enhancing the routing protocol's performance and energy efficiency.

The above reviewed methods were used for optimal energy consumption and fault node recovery methods with replacement which were implemented in the study. It has been reported that the authors of [16] developed a method to solve the problem of energy consumption in WSNs called "Self- Cluster-based organization The approach of replacing failure nodes was not considered in the Greedy Best-First Search Opportunistic Routing (SOCGO)". The researchers in [17] have devised a technique for identifying defective nodes that draws inspiration from microbes. Nevertheless, although this technology may be used in real-time situations, the network's lifespan and the processing of sent data are currently not efficient. In a previous study [18], it was reported that HEED was created to enhance the energy efficiency of WSN by addressing the issue of picking cluster heads. However, this process was found to be time-consuming. In their work, the authors have introduced GLS-IR as a technique for resolving over-determined linear systems. However, it should be noted that the approach incurs significant communication costs. In their research [20], the authors introduced MCTRP as a method to enhance energy consumption in WSNs. However, due to the intricate network structure and the variability in node capacity, energy efficiency could not be attained. To address these limitations, a new technique was devised. The comprehensive procedure and system framework of the suggested architecture are outlined in the next section.

In the past, defect detection in Wireless Sensor Networks (WSNs) has mostly depended on statistical methods, such as probabilistic approaches and strategies based on thresholds or accounts. Nevertheless, these systems have several disadvantages, including the uncertainty in selecting suitable threshold values and establishing the frequency of the detection process. As a result, machine learning methods have become a potential option for detecting defects in Wireless Sensor Networks (WSNs). This review examines many research that have used statistical and machine learning approaches for defect detection.

Methodology

This paper is specifically aimed for improving the WSN's performance and energy utilization in node fault recovery techniques and clustering. WSNs employ high-performance sensors for remote event sensing with different kinds of distributions: random, linear, and uniform. Faulty nodes can waste network energy by using power unnecessarily and thus power management is very important [21]. The proposed method in fact also employ a Grade Diffusion (GD)-based technique to identify the faulty nodes by evaluating their grade values. K-means clustering is used to form clusters, while the GA is used to optimize the route selection in order to reduce energy utilization [22]. This approach benefits in power control, fault tolerance, load balancing and reliable communication, thus enhances the cluster performance and longevity of the network. The proposed structure of WSN and the routing mechanism are shown in the Figure 1 below.

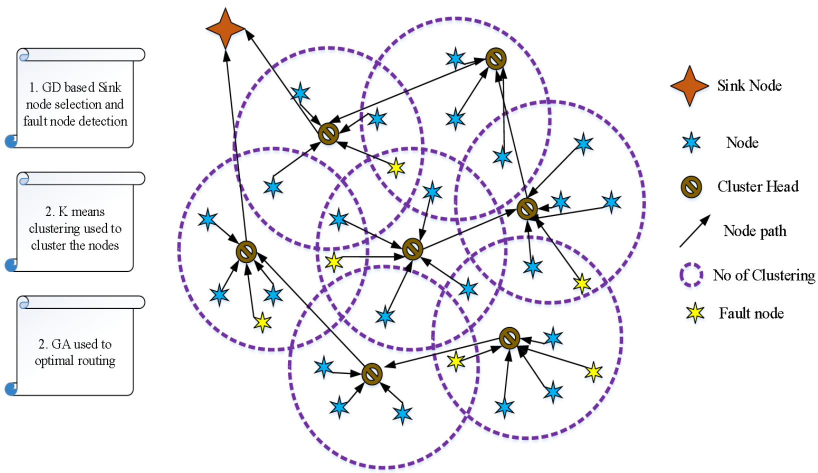

Figure 1

System Architecture in Fault Node recovery with Clustering

Network Model:

In the basics of the proposed Wireless Sensor Network (WSN) model, there will be 100 static nodes geographically dispersed in a sensing field. They postulate include the static positioning of the sink and the sensor nodes, bi-directional links, and the nodes with accurate location information that can reach the sink node. Data collection proceeds in rounds and a cluster head is responsible for a cluster and it sends data to the sink node using one-hop links. The model uses the Grade Diffusion (GD) technique for selecting an efficient high-energy sink node and identifying faulty nodes. Defective nodes are removed and the other nodes are clustered according to the distance and the K-means clustering weights. The cluster heads that are chosen on the basis of high energy help in managing the data aggregation and also preventing the redundancy. The Genetic Algorithm (GA) aims at minimizing energy consumption when selecting the routes for recovering faults in order to improve the performance of the network [23].

3.1 *Fault Node Recovery Algorithm*

This paper seeks to design a WSN with a fault node replacement mechanism utilizing both the GD and GA techniques in order to preclude unnecessary energy dissipation in applications like event detection. The GD algorithm minimizes data packet loss, and optimizes node lifespan, where failed nodes are replaced by suitable neighboring nodes that have high grade values, and higher energy and load capacities. The GD algorithm determines Payload values, Neighbour Nodes, Routing Tables and grade values to isolate and replace nonfunctional nodes. Neighboring nodes without grade values are replaced by nodes with larger amounts of energy and smaller loads to facilitate effective relay functions. It also transmits query and grade creation packets so that the sink node can process the data received in an efficient manner and hence optimize energy use and network operation [24].

In this study, a unique fault node recovery approach is presented. "This method combines the concepts of genetic algorithm and grade diffusion (GD). Over the course of the wireless sensor network (WSN), the GD algorithm is responsible for initializing the payload value, neighbour nodes, routing table, and grade value of every sensor node. It is the responsibility of this algorithm to carry out the initialization step. While the wireless sensor network (WSN) is in operation, the GD method makes it feasible to calculate the fault node or the sensor node that is not operating correctly. This is accomplished via the use of the GD algorithm". By computing the parameter B^th using the equation shown below, it is possible to ascertain the location of the fault node [25].

$$B^{th} = \sum_{a=1}^{MAX\{G\}} T^{a} \tag{1}$$

$$T^{a} = \begin{cases} 1 & \frac{M_a^{Pre}}{N_a^{Ref}} < \alpha \\ 0 & \text{otherwise} \end{cases} \tag{2}$$

"Where, M_a^{Pre} A sensor node's grade value can be referred to as the number of sensor nodes that are currently operating on a time-based basis, B^{th} In addition, this value can also be referred to as the sensor node grade value, the N_a^{Ref} the number of sensor nodes with grade value is represented as a number of sensor nodes with grade value. Parameters are used to calculate the grade value, and can be expressed as a value between 0 and 1. The number of sensor nodes operating for each grade value should be 1 and this condition should also be considered to be larger than zero".

From the computation, B^{th} is more than the zero means, the sensor node requires to replacement for enhancing the performance of the network structure. The fault node or non-functioning node can be replaced with the functional nodes that are selected by the GA algorithm. Finally, the GA is used to replace the fault node from the WSN network [27]. The GA is replacing the fault node by optimal path process. If a greater number of nodes are considered means, it is complex to replace the fault node from the WSN. So, the k means clustering is developed in this paper. The K-means clustering can be operated in the complex network architecture and it WSN structure can be divided in to number of clusters with cluster head. It is creating simple structure to operate the GA for selecting optimal path to remove or replace the fault node or non-functioning sensor node in WSN. The K-means clustering process to reduce the energy consumption of each sensor in the nodes. The detail description is presented in the below section [26].

3.2 *Energy Efficient K-means Clustering Algorithm*

The K-means clustering approach partitions the WSN into many clusters, which may then be used to determine the most efficient route selection scheme using the GA algorithm. In addition to decreasing the energy use of individual nodes, the clustering process should also minimize unnecessary energy consumption. When it comes to the Wireless Sensor Network (WSN), "the K-means clustering algorithm has the capability to generate clusters in order to reduce the amount of energy that is used". In this article, a collection of essential information about the use of energy in Wireless Sensor Networks (WSNs) is presented.

3.2.1. Energy Consumption Model

The WSN communication channel consists of a transmitter and a receiver. The transmitter device draws power from the sensor node to activate and sustain the amplification circuit. Conversely, the recipient may expend energy to receive packets wirelessly by using radio equipment. During the communication time, the communication entities are separated based on a comparison of distances versus threshold distances. The calculation of energy consumption for open space used the energy expenditure calculations. The multipath design was used for the multipath design. Consequently, "the architecture of the cluster head to sink node connection for data aggregation features was derived from this. The calculation of energy expenditure may be determined using equation (3), which includes the variables of distance (d) and length (L)".

$$e^{TX}(L,D) = Le^{EIE} + Le^{FS}D^2 \quad D \ll D^O \tag{3}$$

Where, e^{FS} can be "referred as the volume of transmitter amplifier expenses at the condition of free space model, e^{TX} referred to as the energy utilized up to transport packet data at the length. L. The transmitter and receiver power consumption mainly based on the digital modulation and digital coding. e^{EIE} Can be referred as the energy used up through receiving or transmitting electronic circuit to operate solitary bit data. The power amplifier can be consumed power based on the distance among the sender and receiver in the communication period" [23]. The communication distance is denoted by D which is less than the D^0 parameter. Subsequently, the calculation of energy may be undertaken, taking into account the model for power loss in free space. As previously said, when the distance is greater than the reference distance, we may consider using the multipath mode for energy consumption. This can be determined using the equation shown below:

$$e^{TX}(L,D) = Le^{EIE} + Le^{MP}D^4 \qquad D \ll D^O \tag{4}$$

Were, e^{MP} can be described as the volume of transmitter amplifier expenses at the condition of multipath model. The received side energy consumption is presented as follows,

$$e^{RX}(L,D) = Le^{ElE} \tag{5}$$

Where, e^{RX} can be described as the can be used as the "energy used up to receiving packet data" at the length L and L can be defined as the data packet length in terms of number of bit in communication. The computation of the D^0 is presented as follows,

$$D^0 \frac{\sqrt{e^{FS}}}{\sqrt{e^{MP}}} \tag{6}$$

The purpose of this part is to offer a complete evaluation of the total energy consumption of multipath models and free space models. Both the transmitter and the receiver use electricity in order to carry out their respective functions inside the sensor node. There is a possibility that the use of the K-means clustering technique might successfully reduce the amount of energy that the sensor node consumes. Within the next section, we will conduct an in-depth analysis of the K-means clustering procedure.

3.2.1. Process of K-Means Clustering

The proposed K-means energy-efficient clustering aims to reduce energy consumption, enhance scalability, select optimal cluster heads, and minimize internal operational costs. It ensures equitable communication between cluster members and sink nodes while preventing node overload. Dynamic adjustments to cluster head selection during runtime are integral to the process, with the sink node determining cluster head parameters. Optimal packet size is carefully managed to reduce energy usage and avoid packet loss or overload, improving WSN efficiency. This strategy applies the K-means clustering algorithm to maximize cluster development, optimize packet size, and extend sensor node functionality in resource-constrained networks.

Phase 1: Initialization

From the sink node, "an initialization request, also known as an IRQ is sent to the sensor nodes that are located in the network field. In this case, the broadcast message is received by these sensor nodes. The sink node is the recipient of the initialization reply message (IRP) which indicates that it is the obligation of the remaining node to transmit it. This particular communication is referred to as the reply message, and it contains the information about the initialization. There is information about the nodes that is included in the IRP message". This information includes the position of the sensors as well as the quantity of energy that the nodes use.

Phase 2: Formation of cluster

The building of clusters is accomplished by the use of K-means clustering during this phase, which makes it one of the most straightforward techniques to unsupervised learning. The dataset is partitioned into K clusters via the clustering technique, and the value of K may be determined by applying equation (7) to their respective values. The K-means clustering algorithm displays a greater degree of both intra-cluster similarity and inter-cluster variance than other clustering methods. The clusters each have their own unique processes, which are described in the following manner:

Step 1: Calculation of K value

"Computation of the k value presented in the below equation",

$$K = \sqrt{\frac{n}{2\pi}}\sqrt{\frac{\varepsilon e^{FS}}{e^{MP}}} \quad \frac{F}{XSN^2} \tag{7}$$

Where, XSN^2 "It is possible to specify the usual distance between sensor nodes and sink nodes, as well as the dimensions of the network architecture and the sensor nodes that are included inside it, as the average distance between all of the sensor nodes and sink nodes. There was just one factor that influenced the number of clusters in the network topology, and that was the value of k".

Step 2: Computation of distance

For the purpose of computing the distance between the sensor nodes and each of the cluster centers, the Euclidean distance may be used. To determine which node should be assigned to the cluster center that is closest to it, the Euclidean distance may be calculated by utilizing the equation that is provided below.

$$X^{CC} = \sqrt{\sum_{a=1}^{n}(X^a - X^c)} \tag{8}$$

Where, X^c can be "described as the coordinates of cluster centers, X^a can be described as the coordinate of sensor node a in addition X^{CC} can be described as the distance of node to cluster center".

Step 3: Computation of New cluster center

The "new cluster centre for the whole collection of sensor nodes that are included inside the cluster groups is produced by the calculation of the mean values that are contained within each cluster".

Step 4: Termination condition

Once the new centres have been computed for each cluster, step 2 may proceed using the calculated centres. If the variation in cluster formation among sensor nodes is seen, go to step 3. Otherwise, terminate the procedure.

Phase 3: Selection of Cluster head

During the process of cluster building using k-means clustering, the task of identifying cluster heads is an extremely important one. The two processes that came before it are responsible for the formation of the clusters. The selection of the cluster head is comprised of this stage, which takes place inside the clusters. The cluster head may be identified by comparing the weight functions of two clusters.

$$W^{na} = S^1 * E^{na} + S^2 * D^{CC} \tag{9}$$

$$W^S = S^1 * e^{TX} + S^2 * Avg(D^{CC}) \tag{10}$$

Where, "e^{TX} can be referred as the energy used up to transmitting packet data at the length L, W^S can be described as the cluster head with the standard weight of a node, D^{CC} can be described as the distance among the a^{th} the node to the cluster center and S^1, S^2 are considered as the constants the $a = 1, 2, 3 \ldots n$. The cluster head selection process is illustrated in the Figure 2".

First, with the help of the K-means clustering the clusters are created. In this phase, the cluster head can be computed from the respective clusters of the algorithm. Each of the cluster and node weights is calculated and then compared to the other weights. The node weight which is almost equal to the standard weight can well be said to be the cluster head of respective clusters. With the behaviour routing tables that have been updated in the cluster sensor nodes, the cluster head data has been relayed to the cluster sensor nodes via the sink node. In the process of creating clusters and cluster heads the "K-means clustering algorithm" is used. The GD algorithm enables the identification of the fault node or the non-functioning node. The GA is aiming at improving the path selection process with replacement of the faulty node. The process of the GA is provided in the following section.

3.3. *GA based Optimal Path Selection*

The K-means clustering technique is utilized in WSN to form clusters, reducing network complexity and enhancing energy efficiency. After clustering, the Genetic Algorithm (GA) identifies faulty nodes and selects optimal paths, minimizing energy consumption and improving fault recovery. Fault nodes are identified using grade and energy levels, with low-grade nodes being replaced. GA, an evolutionary algorithm, optimizes fault replacement and path selection using binary-encoded chromosomes, maximizing fitness values through iterative processes. GA operates in five phases Initialization, Fitness Function, Selection, Crossover, and Mutation to compute optimal solutions. It ensures efficient fault recovery and energy-efficient routing in clustered WSNs.

Step 1: Initialization

The user selects or modifies the number of chromosomes, with each chromosome representing sensor nodes (faulty or healthy). Chromosome length is set to 20, and genes are randomly initialized to binary values (1 for faulty, 0 for healthy), addressing 5 non-functioning nodes.

Step 2: Fitness function

The fitness function replaces faulty nodes and selects optimal paths for WSN. It evaluates performance using total sensor nodes, optimal paths, and grade values to ensure effective path reuse and node replacement.

$$F^N = \sum_{a=1}^{MAX\{G\}} \frac{P^a \times tp^{-1}}{N^a \times tn^{-1}} \times a^{-1} \tag{11}$$

When referring to the Wireless Sensor Network (WSN), the word "tp" makes reference to the total number of sensor nodes in the WSN as well as the combined count of the optimal paths that were selected.

Step 3: Selection

The selection process retains high-fitness genes while eliminating low-fitness ones using the elitism strategy. After removing low-fitness genes, the process advances to crossover, maintaining only the best genetic material.

Step 4: Crossover

One-point crossover is applied to create new chromosomes by exchanging genetic material between parent chromosomes. Two offspring are generated, with the crossover rate determined by fitness values and roulette wheel selection.

Step 5: Mutation

Mutation introduces new genetic variations and prevents rapid convergence by randomly altering genes. This step ensures optimal fitness values are achieved, improving the algorithm's adaptability.

4. Performance Evaluation

This section evaluates the proposed "fault node recovery and energy-efficient clustering" method using MATLAB R2016a. The approach, tested against LEACH, HHCA, NEAHC, and HACH, assesses performance based on energy metrics, fault nodes, alive nodes, and data delivery. The GD algorithm identifies faults and selects a high-energy sink node, while K-means clustering reduces network complexity and optimizes routing. The simulation includes 500 nodes, a 1000x1000m area, 1J initial energy, a 10kb packet size, one sink node, and five clusters.

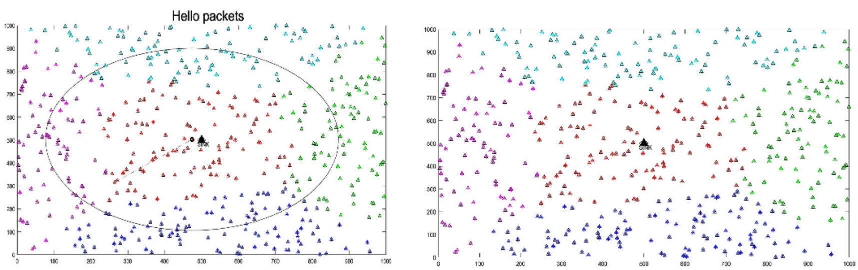

Figure 2

Network creation model with sink node selection

The enhanced GD algorithm integrates an initial K-means clustering step in order to create better energy efficient and fault tolerant WSNs. The GD algorithm chooses a high-energy node, and K-means clustering, forms 500 sensor nodes into five groups, where each head node communicates with the sink node, thus making complex work easy and saving energy. Energy consumption and residual energy are examined in 10 rounds and the proposed method satisfies 0.5 J residual energy in the fifth round compared with the other methods that are LEACH (0.35J), HHCA (0.39J), NEAHC (0.4J) and HACH (0.45J). It enhances energy utilization, failure tolerance, and network durability over comparable methods.

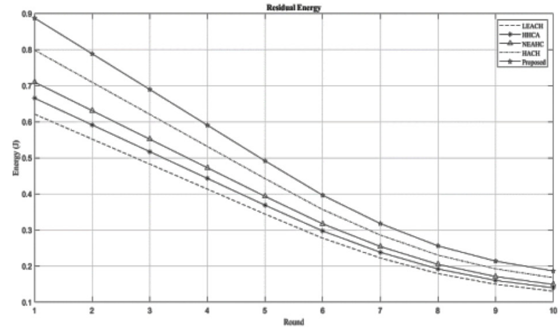

Figure 3

Analysis of Residual energy

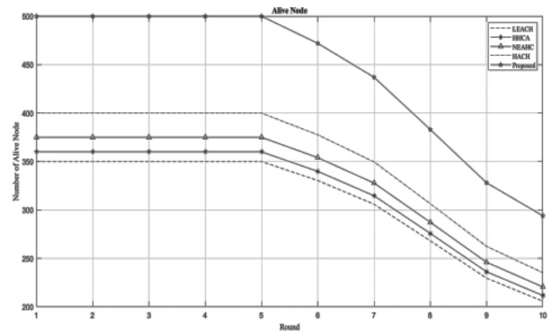

Figure 4

Analysis of Alive node

The evaluation in Figures 3 and 4 shows the frequency of alive and fault nodes in the WSN in terms of rounds. In the fifth round the proposed method preserves all 500 nodes as alive and clearly outperforms LEACH, HHCA, NEAHC and HACH algorithms, which have 350, 325, 375, and 400 alive nodes respectively. The fault nodes identified and replaced by the GD algorithm also guarantees unhampered communication. Unlike other techniques that distribute energy to the defective nodes like in LEACH (150 numbers) HHCA (175 numbers) NEAHC (125 numbers) and HACH (100 numbers); the present algorithm does not happen like that. However, in SiNoW, the failed node is efficiently replaced using the GA for path selection while comparing effectively against other techniques in terms of fault recovery and energy consumed. Also, at the end of the fifth round, the fault node is well handled so that WSN has a low energy consumption and all nodes are efficiently utilized.

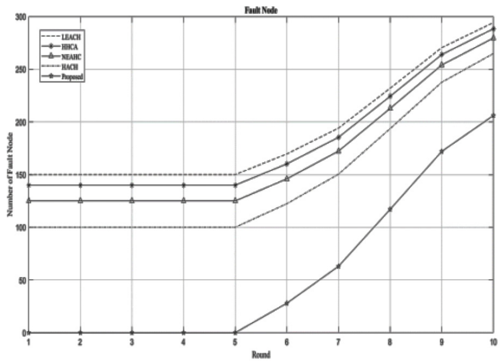

Figure 5

Analysis of fault node

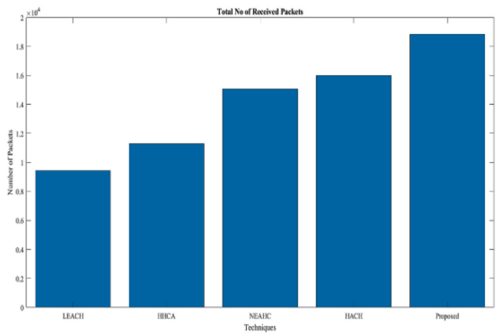

Figure 6

Analysis of received packets

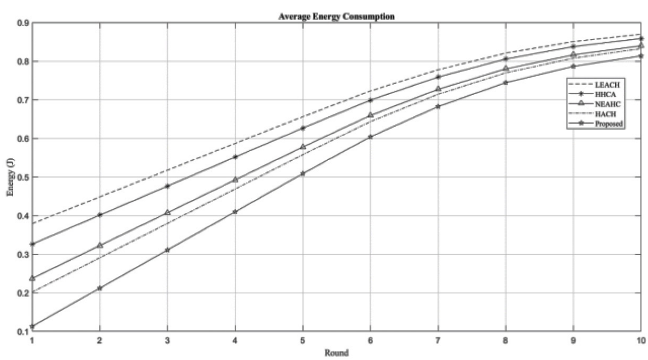

Figure 7

Analysis of energy consumption

The proposed algorithm outperforms existing methods (LEACH, HHCA, NEAHC, HACH) in packet delivery and energy efficiency for Wireless Sensor Networks (WSNs). It successfully delivers 18,000 packets without data loss, compared to 8,000 (LEACH), 11,000 (HHCA), 15,000 (NEAHC), and 15,250 (HACH), demonstrating superior efficiency in data transmission.

In terms of energy consumption during the third round, the proposed method records 0.3J, significantly lower than LEACH (0.55J), HHCA (0.48J), NEAHC (0.4J), and HACH (0.38J). This highlights its energy-efficient approach. The algorithm effectively integrates fault node recovery, K-means clustering, and Genetic Algorithm (GA) optimization, ensuring better performance and reduced energy usage in WSNs

5. Conclusion

This research provides a hybrid approach that "incorporates K-means clustering in order to greatly minimize the amount of energy that is used by wireless sensor networks, hence extending the amount of time that these networks are able to function. The Grade Diffusion (GD) approach was used in order to identify fault nodes and sink nodes within the network. Subsequently, the K-means clustering technique was utilized in order to arrange the network into clusters, and the selection of cluster heads was based on the energy levels of the nodes. "The suggested method was evaluated by comparing it to other methods that are already in use, such as LEACH, HHCA, NEAHC, and HACH, as well as a Genetic Algorithm (GA) approach that is used for selecting and replacing fault nodes in wireless sensor networks. This was done in order to determine how successful the new method is. In terms of fault node recovery and energy-efficient clustering, the results of the simulation suggested that our solution is superior to the alternatives that are currently in use. Using a variety of indicators, including energy consumption, packets received, fault nodes, active nodes, and residual energy, a comprehensive analysis of the method's performance was carried out. By comparison, the energy levels for LEACH, HHCA, NEAHC, and HACH were 0.55J, 0.48J, 0.4J, and 0.38J, respectively". The suggested method had an energy consumption of 0.3J, which was much lower than the other algorithms".

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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