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Research Article

An Energy-Efficient Reliable CH Selection Algorithm using Harmony Search Algorithm for WSNs

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ABSTRACT

Energy restrictions in wireless sensor networks (WSNs) stem from the finite and non-renewable power sources of sensor nodes. One popular topology control method for WSNs that attempts to lower energy consumption and increase scalability is clustering. Nodes outside of a cluster in clustered WSNs send sensing data to a designated cluster head (CH). After processing the data, the CH transmits it to the base station (BS) either directly or via a series of hops. However, due to the additional effort required for data gathering, aggregation, and communication with the BS, CHs use more energy compared to non-CH nodes. Establishing an energy-efficient cluster is challenging, especially considering the inherent fault tolerance of WSNs, where sensor nodes are susceptible to failures. This study introduces the Energy-Efficient Harmony Search-based Reliable CH Selection technique (EHSRC). Our CH selection technique considers parameters such as residual energy, connection lifetime, and base station connectivity rate. It is based on the Harmony Search algorithm (HSA), a popular metaheuristic methodology for addressing many NP-Hard problems. In order to identify the optimal selection of sensor nodes for CH roles, a fitness function is developed which considers the parameters indicated earlier. Our study presents a fault tolerance approach that uses a genetic algorithm to manage unforeseen CH failures. The network is arranged using an energy-efficient distance-based clustering technique, and backup nodes are chosen for each cluster head using a well-known genetic algorithm (GA) based on association coverage and packet loss probability. This technique helps to pinpoint problems with cluster heads and get communication back up and running. Experimental results reveal that our suggested technique performs better than previous fault-tolerant clustering algorithms, indicating that it is effective in improving the energy efficiency and dependability of WSNs.

Keywords: WSN, Clustering, Cluster head selection, HSA, GA, Fault-tolerant, Energy efficiency.

I. Introduction

WSNs have attracted a lot of attention because of its many uses, which include environmental monitoring, medical care, military surveillance, and disaster assistance [3]. A target region is covered by a large number of small, autonomous, low-power sensor nodes that are manually or randomly assembled to form WSNs [4]. These sensor nodes collect, analyze, and send local data to a remote base station (BS), also known as a sink. The limited and non-replaceable power sources of the sensor nodes are their main disadvantage. As a result, controlling sensor node energy consumption emerges as the primary responsibility for maintaining WSN sustainability [5].

It has been shown that clustering may effectively lower WSNs' overall energy usage [6]. The given Figure 1 shows the usual topology of a clustered WSN.

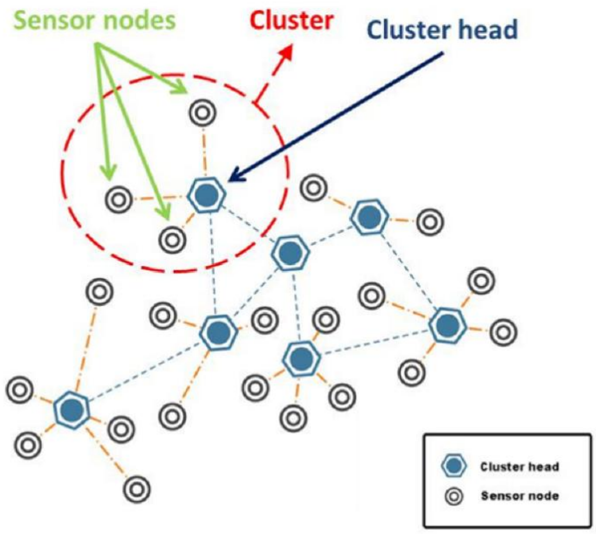

Fig 1: Network topology of a clustered WSN

In a cluster-based WSN, sensor nodes are organized into distinct clusters, with each cluster being overseen by a CH. Every sensor node is assigned to a certain cluster. There are many benefits to using a cluster-based WSN, such as lower energy usage, maintained communication capacity, and improved network scalability overall [7]. In contrast, the CH in the clustering strategy takes on additional duties, such as receiving sensed data from its member sensor nodes, processing the data, and then sending it to the BS after aggregating the data to remove redundant and uncorrelated data.

Cluster head failure is a common problem in WSNs due to the limited battery life of sensor nodes [8]. Data from other sensor nodes in the cluster must be gathered, processed, and sent to the base station by CHs. The cluster's sensor nodes might lose network connection and perhaps lose data in the case of a cluster head failure. This situation poses a significant challenge for applications such as environmental monitoring and security surveillance [9].

CH failure also increases network latency, as sensor nodes need to find a new cluster head to connect to, causing increased latency [10]. Additionally, cluster head failure reduces network throughput, as sensor nodes may need to reduce their transmission rate to avoid overloading with the new cluster head. These problems have a substantial effect on WSN performance and sensor network efficiency as a whole.

There are a number of ways to mitigate the impact of cluster head failure in WSNs. One promising approach is to use a fault-tolerant clustering algorithm [11]. These algorithms select multiple cluster heads for each cluster, so that if one CH fails, the other can take over. The major issue with the existing fault-tolerant clustering algorithms is that they are often complex and computationally expensive. This can make them difficult to implement and deploy in real-world WSNs.

Swarm intelligence algorithms can be used to address this issue by providing a more efficient and scalable way to implement fault-tolerant clustering. Swarm intelligence algorithms are inspired by the collective behavior of social insects, such as ants and bees. These algorithms are able to solve complex problems by using simple rules and interactions between individuals. One way to use swarm intelligence algorithms for fault-tolerant clustering is to use them to select the cluster heads. Swarm intelligence algorithms can be used to find a set of cluster heads that is distributed evenly throughout the network and that has a high level of connectivity. This can help to improve the reliability and resilience of the network.

In this paper, we introduce a novel algorithm called the Energy-Efficient Harmony Search-based Reliable CH Selection Algorithm (EHSRC). Our proposed CH selection algorithm is based on the HAS, and considers parameters such as the Base Station Connectivity Rate, link lifetime, and residual energy. The fitness function is enhanced for optimal CH selection. A genetic algorithm-based fault tolerance solution is suggested to tackle the problem of abrupt CH failure. The well-known GA uses packet loss probability and associate coverage to choose a backup node configuration. This approach helps in identifying faults in cluster heads and restoring communication.

Contributions

- The proposed energy-efficient CH selection algorithm can help to improve the energy efficiency of the network by selecting CHs that are well-distributed throughout the network and have a high level of connectivity.
- HSA is a metaheuristic algorithm that is widely used to solve complex problems. The proposed HSA-based CH selection algorithm can help to improve the energy efficiency and reliability of WSNs by selecting a set of optimal and reliable CHs.
- The energy efficiency and fault tolerance feature of the proposed EHSRC algorithm can help to increase the network throughput of WSNs by ensuring that CHs are selected in a way that minimizes the distance between CHs and BS and maximizes the link lifetime.
- The fault tolerance technique using a genetic algorithm can help to improve the reliability of the network by quickly and efficiently selecting a new CH to replace a failed CH.

II. Related work

The authors created a grid-based routing method for WSNs [12] in an effort to reduce energy consumption and increase the lifetime of sensor nodes (SNs). A Grid Coordinator guides the fuzzy rules-based routing process, which uses a fuzzy inference method to choose the best path. The goal of the fuzzy inference system's rule formulation is to reduce the number of hops involved in the routing process. Sensor networks with mobile nodes are not a good fit for the grid-based routing method, even if they perform very well in terms of energy conservation and WSN longevity.

In order to increase the lifetime of the network, [13] introduces an intelligent virtual force-based clustering for energy-efficient routing (VFICEER) in MWSNs. The first clustering is done using the k-means clustering algorithm to get the first cluster heads. Iteratively, this procedure is carried out until all SNs are included in the cluster heads. Nodes that are closest in distance are selected to be included as member nodes in each cluster head. Furthermore, by following spatiotemporal rules and restrictions, cluster-based routing is used to handle target coverage and network connection problems. The suggested routing algorithm's main benefits are a significant increase in the network's lifetime and effective mobility management. Additionally, there has been a noticeable improvement in the measures that determine the quality of service, such as improved packet delivery ratio (PDR), decreased latency, and higher dependability.

For WSNs in the Internet of Things (IoT), a Neuro-Fuzzy Rule-Based Clustering and Routing Protocol is presented in [14] to improve overall network performance. By examining factors including CH energy, CH-to-sink distance, node mobility, and cluster head degree, this unique protocol uses a neuro-fuzzy technique to understand network features. The network is trained using a convolutional neural network, and weight modification is accomplished using fuzzy rules. fuzzy reasoning technique forms a resilient cluster to enable cluster-based routing. Learning-based fuzzy rules are included in the proposed protocol, which shows improved performance in terms of energy consumption and network lifespan. On occasion, however, the protocol fails to fulfill the assumption of node trustworthiness, which poses a constraint.

A method for managing topology energy-efficiently using clustering was presented in the work of Din et al. [15]. They proposed a multi-tiered clustering design that included routing both inside and across clusters, choosing forwarding nodes, and changing cluster heads. By installing a routing table at every node, forwarding nodes may be changed. Although the findings show that the suggested strategy uses less energy, there is no proof to support the idea of extending network lifespan, and control overhead is not examined in the research.

Haseeb et al. [16] suggested using SEHR in 2020 to improve the general performance of WSNs by identifying and stopping data tampering. The technique uses artificial intelligence (AI) heuristic assessment to combine dependable and perceptive learning. Heuristics are used in this method to find and stop data breaches. On the other hand, the accuracy of data categorization using the existing metaheuristic approach is low. This technique has to be improved in the key generation part since the counter block makes it possible to identify the key value. The routing efficiency and energy consumption of sensor nodes might be improved by accounting for asynchronous operations.

A succinct summary of techniques using low-energy adaptive clustering hierarchy (LEACH) and bioinspiration was presented by Behera et al. in 2022 [17]. The authors examine the benefits and drawbacks of various methods, delve into the underlying presumptions of these approaches, and go into great detail about the CH selection criteria. Understanding routing protocols with various topologies, creative tactics, and enhanced effectiveness in the context of WSNs was the goal. Performance characteristics of several protocols, including resilience, scalability, and packet-delivery rates, were examined. It was also recommended to investigate cryptographic techniques for verified encryption in WSNs in order to improve network security and privacy.

Reference [18] states that in 2023, the WSN will be responsible for organizing and gathering sensed data prior to transmission to the BS. Since sensor nodes have limited battery life, finding efficient ways to collect and send data becomes essential to maintaining sensor network uptime. The particle swarm optimization (PSO) approach was used to create the WSN clusters in this investigation. Moreover, fuzzy logic-based energy-efficient routing protocol (E-FEERP) was introduced. The E-FEERP technique takes into account a number of variables to optimize data transmission from the CH to the BS, including communication quality, node density, average distance between SNs as well as the BS, along with battery energy.

These variables were taken into account in the study that used Fuzzy Multi-criteria Clustering and Bio-inspired Energy-efficient Routing (FMCB-ER), a hierarchical routing algorithm [19]. The objectives were to increase the lifespan of the network and extend the operational period of the WSN applications. To establish robust clusters, a grid-based clustering strategy has to be used. An adaptive fuzzy multi-criteria decision-making (AF-MCDM) technique was developed using fuzzy AHP and TOPSIS to facilitate the selection of the optimal CH. This process contained six sub-criteria and included three key factors: energy, Quality of Service (QoS), along with node location. The optimal route for data transmission from the sink to the CH was determined using the Emperor Penguin Optimization (EPO) once the CH was selected. The proposed approach, which included characteristics such as energy consumption, node lifespan, throughput, jitter, packet delivery ratio, delay, and the number of active and idle nodes, was assessed and compared with other existing routing systems.

The researchers' suggested strategy [20] offers an energy-aware routing algorithm and a technique for lowering control overhead with the goal of extending the network lifetime of software-defined multihop wireless sensor networks (SDWSNs). Optimizing energy usage in WSNs for the Industrial Internet of Things (IIoT) is the main goal. The newly proposed solution makes use of this global view point; however, it comes with added control overhead related to a centralized controller offering a full picture of the sensor network. By choosing from a range of possibilities the paths with the greatest residual energy level for each sensor node, it establishes energy balance across the network. Once the crucial activities in SDWSNs that drain energy have been identified, a data packet aggregation strategy is put in place to lessen their effects. Additionally, control overhead is reduced by keeping an eye on the routing tables of sensor nodes using a simple checksum mechanism.

The PSO algorithm was used to construct the Particle Swarm Optimization Routing Protocol (MPSORP) [21], a multipath protocol, using an optimization approach described in the paper. The applicability of MPSORP was extended to Internet of Things (IoT) applications based on WSN, which are characterized by increased traffic loads and unequal network flow. Tests of the developed methodology's effectiveness were carried out using a range of configurations and parameters in the NS-2 simulator. In addition, a comparative study was conducted to evaluate MPSORP's efficacy against AODV and DSDV routing protocols.

The research team in the studyintroduced the MHSEER (meta-heuristic-based secure and energy-efficient routing) protocol for WSN-IIoT [22]. The protocol determined which packets to advance based on the number of hops, connection integrity metrics, and total residual energy. Data encryption was implemented using counter-encryption mode (CEM) for increased security. To achieve reliable learning using the suggested approach, a meta-heuristics study was a necessary step in the procedure. Two phases went into designing the protocol. Using a heuristic approach, the initial step selected more dependable data routing options. The second stage, which incorporated a simple and random CEM, prioritized security. The following protocols were compared to the MHSEER protocol: secure and energy-aware heuristic-based routing (SEHR), secure energy-aware meta-heuristic routing (SEAMHR), heuristic-based energy-efficient routing (HBEER), and secure trust routing protocol for low power (Sectrust-RPL). The assessment included many parameters, including the energy consumption, throughput, packet loss ratio, network latency, and the presence of bad routes.

III. System model

Network model

- Within WSN, sensor nodes exhibit homogeneity with respect to starting energy and processing capability.
- The Euclidean distance formula is used to calculate the distances between sensors.
- Sensor nodes are positioned arbitrarily across the sensing region and don't move once they are in place.

Energy usage model

The performance of WSN is significantly influenced by their energy consumption. The techniques implemented in the network continually attempt to decrease energy usage to increase system lifespan. Figure 2 shows the WSNs' energy model.

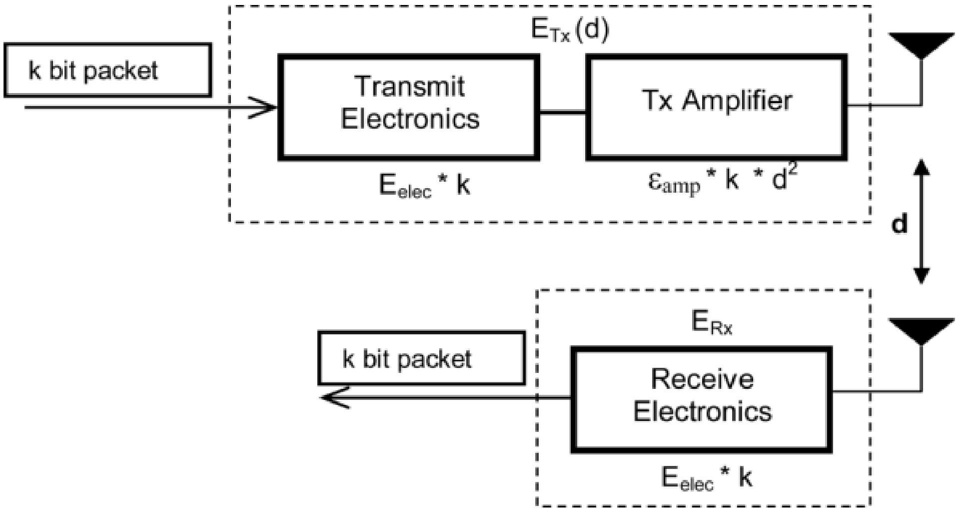

Fig 2: energy usage model in WSN

WSNs employ radio frequencies to facilitate node-to-node communication. The energy consumption of data transmission and reception is computed using an energy model. The energy model includes two channels: the free space channel and the multi-path fading channel. The channel to be used is determined by the distance (d) between the transmitter and receiver with respect to a threshold of d_0. If the distance is shorter than the threshold, the multi-path fading channel is utilized; otherwise, the free space channel is used. The energy required by the model to convey a k-bit message over a d-distance is represented by the following formula.

$$E_T(k,d) = \begin{cases} kE_{elec} + k \in_{fs} d^2, & d \leq d_0 \\ kE_{elec} + k \in_{mp} d^4, & d \geq d_0 \end{cases}$$

where E_{elec} is the energy needed for the electronic circuit, d_0 is the threshold, $\in_{mp}$ is the energy needed for the multi-path channel, and $\in_{fs}$ is the energy needed for the free space. The following is the equation for the energy needed to receive k bits of data:

$$E_R(k) = kE_{elec}$$

The energy required for an electronic circuit (E_{elec}) is determined by a number of variables, including signal dispersion, digital coding, modulation, and filtering. Whether in free space ($\in_{fs}*\ d^2$) or multi-path settings ($\in_{mp}*\ d^4$), the amplifier's energy consumption depends on the bit error rate and the distance between the transmitter and receiver.

Proposed fault tolerant CH selection algorithm

In this section, we describe the proposed EHSRC (Energy-Efficient Harmony Search-based Reliable CH Selection) Algorithm. The proposed CH selection method relies on the HSA and considers factors such as Base Station Connectivity Rate, link lifetime, and remaining energy. The fitness function is enhanced to make better choices for CHs. To address the problem of unexpected CH failures, a fault tolerance strategy using a GA is suggested. This well-established GA is used to select a group of backup nodes based on factors like associate coverage, and packet loss probability. This approach helps in identifying issues with cluster heads and restoring communication.

An overview of HSA

The dependable optimization method Harmony Search (HS) was developed with influence from jazz musicians' improvisational approaches. Using a technique known as "Harmony Memory," the algorithm produces arbitrary answers that are compared to the least advantageous option that is kept in memory. The least advantageous option is replaced if a new one turns out to be better. Until a predetermined end point is achieved, this iterative process continues. An overview of the HSA may be seen in Figure 3.

HS is good at finding global solutions to problems, which is why it is used to select a set of preliminary nodes that can be considered as candidate cluster heads in the Firefly algorithm.

Here is a more detailed explanation of the steps involved in the basic HS algorithm:

1. Harmony Memory (HM) Initiation: The HM for the optimization problem is composed of a collection of arbitrary solutions.
2. Creation of a New Harmony: Using the Harmony Memory Consideration Rate (HMCR) and the Pitch Adjustment Rate (PAR) as guidelines, notes are chosen from the HM to create a new harmony.
3. Evaluation of the New Harmony: The freshly produced solution is assessed using the fitness function.
4. Harmony Memory Update: The weakest solution is replaced if the new solution outperforms the others inside the HM.
5. Repeat steps 2-4 until the termination requirements are met.

The HS algorithm provides a flexible optimization solution for a wide range of problems. It is renowned for its simplicity and efficacy. It becomes especially helpful in circumstances where achieving a global solution creates obstacles, as shown in activities like the selection of cluster heads within a wireless sensor network.

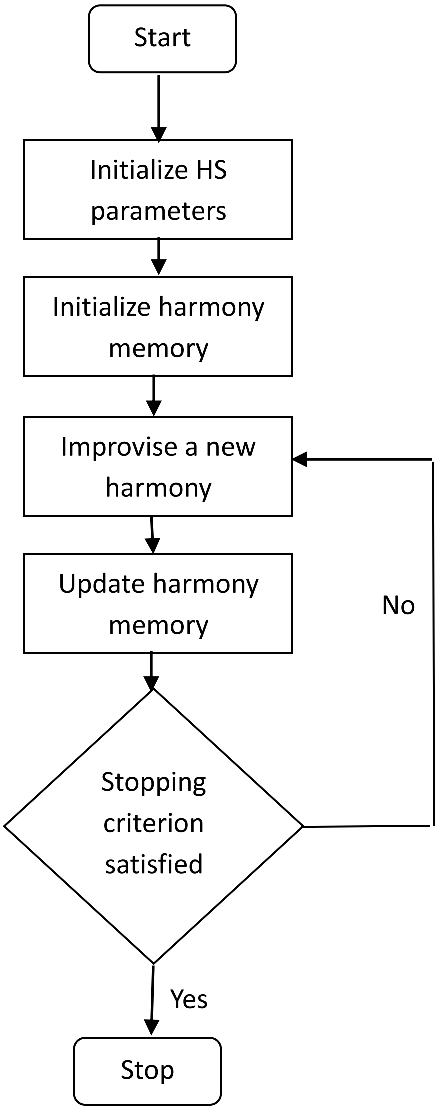

Fig 3: An overview of the Harmony Search Algorithm

HSA-based CH selection algorithm

Representing Harmony memory & initialization

The very first step is representation of HM. At the time the CH selection process, the total amount of CHs in the network matches the harmony dimension. Let $HM_i = (HM_i^1, HM_i^2, \ldots . HM_i^m)$ be i_th harmony, where every position $HP_i^1 = (x_i^d, y_i^d), \forall_i\ 1 \le \mathrm{i} \le \mathrm{H_{ms}}, \forall_i\ 1 \le d \le m$ indicates a sensor node's node id in the network.

Supposing there are 100 sensor nodes, 10% of them are CHs. Consequently, the size of each harmony is the same as the quantity of CHs, or 10. Currently, each harmonic is initialized with a random number between 1 and 100, also known as the node id.

Improvisation of Harmony

The harmonic improvisation procedure in the context of choosing the CH is as follows:

a. New Harmony Generation
b. Pitch Adjustment Rate
c. Updating Memory

New Harmony Generation

Either the random selection technique or the harmony memory concept may be employed to generate a new harmony vector. While the choice at random procedure, a new harmony is formed employing node IDs from one to a maximum number of nodes (n). The resultant new harmony, assuming 100 nodes overall, is represented by the symbol.

$$HM_{NH} = (HM_{NH}^{1}, HM_{NH}^{2}, \dots . HM_{NH}^{m})$$

Where $HM_{NH}^{d}, \forall_i \; 1 \leq d \leq m$ is selected at random from a range of 1 to 100. Afterward, it is matched with its corresponding coordinates.

Pitch adjustment Rate (PAR)

Each HM_{NH}^{d} represents the coordinates of a sensor node that has been selected as the network's CH. During pitch adjustment, the coordinates of CHs are adjusted using the accompanying equation.

$$x_{rand}^{i} \leftarrow x_{rand}^{i} + \omega$$

where ω represents random number between (0,1) and x_{rand}^{i} represents randomly picked harmony.

A sensor node may or may not be able to be located at the newly pitch-adjusted position. Consequently, the sensor node closest to the updated position is selected as the new CH. So, after pitch adjustment, the (x_i, y_i) becomes $(x_i + \omega, y_i + \omega)$.

Updating Memory

First, the proposed fitness function is used to calculate the harmony HM_{NH}'s fitness. The improvised harmony's (HM_{NH}) fitness value is then contrasted with the worst (HM_{WT}) in HM. HM_{NH} takes the place of HM_{WT} in HM if it turns out to be better than the worst harmony.

Fitness function

To choose a set of sensor ideal nodes as CHs, a fitness function is created utilizing Base Station Connectivity Rate, link lifetime, and residual energy parameters.

Base Station Connectivity Rate: The set of sensor nodes that are situated less than or equal to d_0 from the BS is shown in the image. In this case, a larger number confirms that nodes are using less energy while transferring data to the base station since it indicates that the nodes are closer to the BS. It is computed as

$$f_1 = BSR = \frac{(D_{i2BS}) \leq d_0}{T_{CHs}}$$

Where, D_{i2BS} - the distance between the node i and the BS, T_{CHs} – total number of CHs.

Link lifetime: - The link lifetime is a measure of how long two nodes can communicate with each other reliably. It is calculated based on the distance between the two nodes, the quality of the communication channel, and the amount of interference in the network. Selecting cluster heads with the highest average link lifetime can help to improve the performance of the network.

$$f_2 = LT = \frac{2 \times ((RS_x + RS_n))}{C + P_{sn} + P_{rc} + R + \|D_x - D_n\|}$$

The energy levels of the CH (n) and the ordinary node (x) in this situation are represented by the symbols RS_n and RS_x, respectively. The x^{th} node's packet sending and receiving rates are denoted by P_{sn} and P_{rc}, respectively. R stands for the transmission range, C for a constant value, and $\|D_x - D_n\|$ for the distance between the cluster head node and the ordinary node x.

Residual energy: During the data transmission phase, the selected CH receives data from non-CH nodes and, after aggregation, transfers it to the BS. CH needs more residual energy to do these activities. Therefore, a sensor node with more energy leftover makes a superior CH.

$$f_3 = RE = \sum_{i=1}^{m} \frac{1}{E_i}$$

Every one of the non-conflicting goal functions listed above is subject to the normalizing function, ensuring that it minimizes them effectively, considering the different range of values for each objective, thereby minimizing them into a single objective function. Finally,

$$F_i = \alpha_1 \times f_1 + \alpha_2 \times f_2 + \alpha_3 \times f_3$$

Where $\sum_{i=1}^{3} \alpha_i = 1; and\ \alpha_i \in (0,1)$. Then the node with $min(F_i)$ is selected as optimal CHs.

GA based fault-tolerance

A GA is a search heuristic that uses natural selection to find optimal solutions to problems. It is particularly effective for complex problems with multiple objectives or numerous possible solutions. GAs maintains a population of chromosomes, which are selected at each iteration to generate a new population. The fitness function evaluates the new population, and the best chromosomes are used to generate the next population. This procedure keeps on until a predetermined end point is reached, either the ideal fitness level or the maximum number of iterations.

Selection of the backup nodes

Chromosomes, which are genetic information strings stored in alleles, are necessary for the application of the GA for the selection of backup nodes. Ordering difficulties are the context in which permutation encoding is utilized, where each chromosome represents a place in a sequence, such as task sequencing problems or the traveling salesman problem. Additionally, random numbers between 0 and 1 are used as sorting keys. Notably, unlike parameter optimization problems, permutation problems cannot be handled using generic recombination and mutation operators. These steps make up this approach's technique.

A powerful search technique, GA is employed for addressing large-scale optimization problems. It leverages biological evolution models, incorporating processes such as crossover, mutation, and selection, to identify solutions that are close to optimal.

The solution variables or chromosomes in this approach are the transformation probabilities ($\omega_1 and\ \omega_2$). By optimizing these factors, the ideal solution will be reached.

The node's associated coverage value and packet loss probability are evaluated to calculate the fitness function (F_t), and the resultant value is then updated inside the individual.

"Associate coverage" refers to the sector-shaped area that an adjacent node covers inside a node's sensing area. The associate coverage of nY for nX in the case when two nodes, nX and nY, are separated by a distance of c is represented by the central angle 2ρ.

$$\rho = \frac{d^2 + nX^2 + nY^2}{2nXd}$$

Packet loss probability is the fraction of the total transmitted packets that did not arrive at the receiver. It is a measure of the unreliability of a network and can be caused by a variety of factors

$$plp = \frac{p_l}{p_s}$$

p_l - Number of packets lost p_s- Number of packets transmitted

Based on the estimated fitness F_t, the population transforms into the future generation.

The Roulette-Wheel selection technique is used to estimate recombination and cross individuals by selecting chromosomes with higher F_t values for generating new offspring.

For F_t chromosomes, the selected probability δ_i is evaluated as $\delta_i = \frac{F_t}{\sum F_t}$.

The process of creating new people is accomplished by combining parents with a certain probability using the two-point crossover technique.

Every bit in a person goes through the mutation process after the crossing.

In order to prevent duplication and increase genetic variety in the progeny, randomly chosen genes inside an individual are replaced with the mutation probability throughout the mutation process.

In the end, the best backup nodes (BNs) for each cluster are chosen according to how well they can search globally.

Algorithm

Initialize parameters and harmonies

Generate random vectors

    Calculate fitness of all harmonies

End

Improvisation of Harmony

    If $rand < Harnomy_{rate}$

        Select HM_{NH}

    Else

        Generate new random HM

    End If

Adjust the PAR of HM_{NH}

Calculate fitness F_i

    If $(HM_{NH} > HM_{worst})$

        Replace HM_{NH} with HM_{worst}

    End if

Select CHs from $min(F_i)$

GA based fault tolerance

Initialize population

Compute individual fitness

While (not stopping condition) do.

    Select parents from population.

    Execute crossover & mutations.

    Compute fitness of each individual.

    Replace the parents.

End

IV. Results and analysis

Simulation setup

Using NS2 simulation, the suggested DDFCH's performance is assessed and contrasted with that of FMCB-ER, EARSD, MPSORP, and MHSEER. Sensor nodes are randomly deployed throughout a 1000 x 500 m network region. Every sensor node has a constant starting energy of 100 joules upon startup. There are 50 to 250 nodes in the network. A CBR (constant bit rate) traffic agent is used to guarantee steady traffic during data transmission. The protocol used for data transfer is UDP. Table 1 lists all of the experimental parameters in detail.

Table 1: The experimental parameters

Parameter	Value
Network area	1000 m x 500 m
Number of nodes	50 to 250
Cluster size	4
Initial energy	100j
Packet size	1024 bytes
Routing protocol	AODV

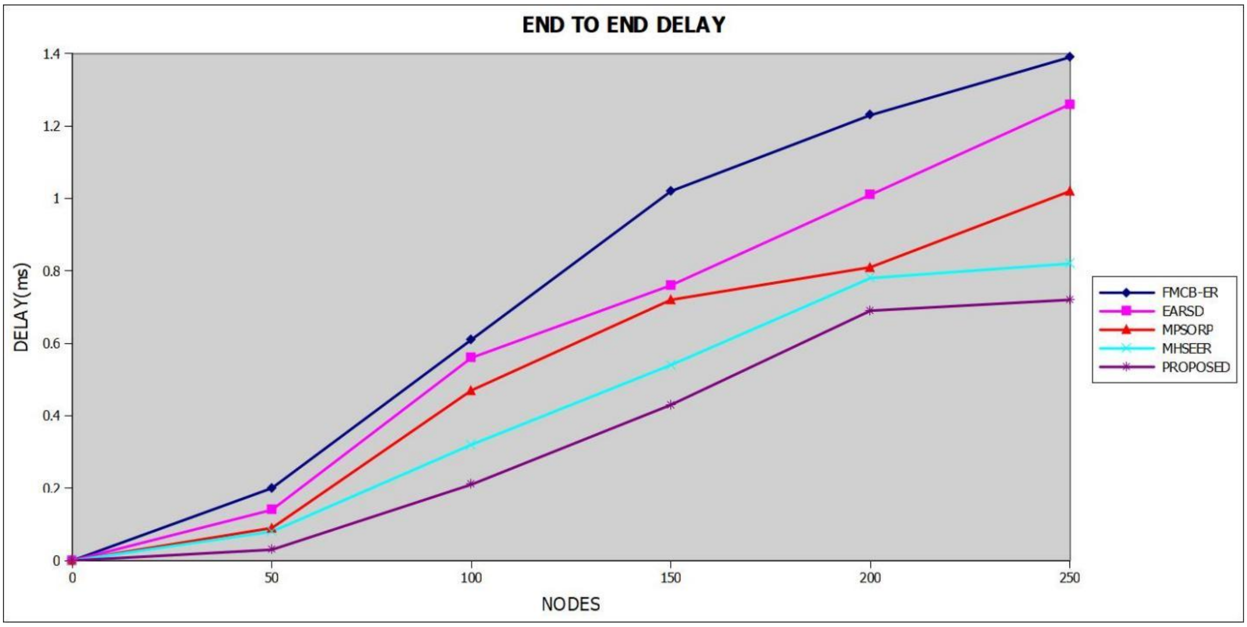

Fig 4: Performance evaluation of Delay

End-to-end delay refers to the time it takes for a packet to travel from its source to its destination within a network (Fig 4). The evaluated values of end-to-end delay time for the proposed method are presented in Table 2. The method's stable CH selection, incorporating multiple selection parameters, reduces communication distances, leading to faster delivery of data packets. Additionally, the CH selection based on multiple parameters chooses low-overhead CHs, contributing to the minimization of end-to-end delay in the proposed method. The network experienced a minimum average delay of 0.72 ms, showcasing improved performance compared to previous methods, which exhibited higher delays of up to 1.39 ms.

Table 2: Analysis of Delay comparison of proposed with existing methods

NODES	FMCB-ER	EARSD	MPSORP	MHSEER	PROPOSED
50	0.2	0.14	0.09	0.08	0.03
100	0.61	0.56	0.47	0.32	0.21
150	1.02	0.76	0.72	0.54	0.43
200	1.23	1.01	0.81	0.78	0.69
250	1.39	1.26	1.02	0.82	0.72

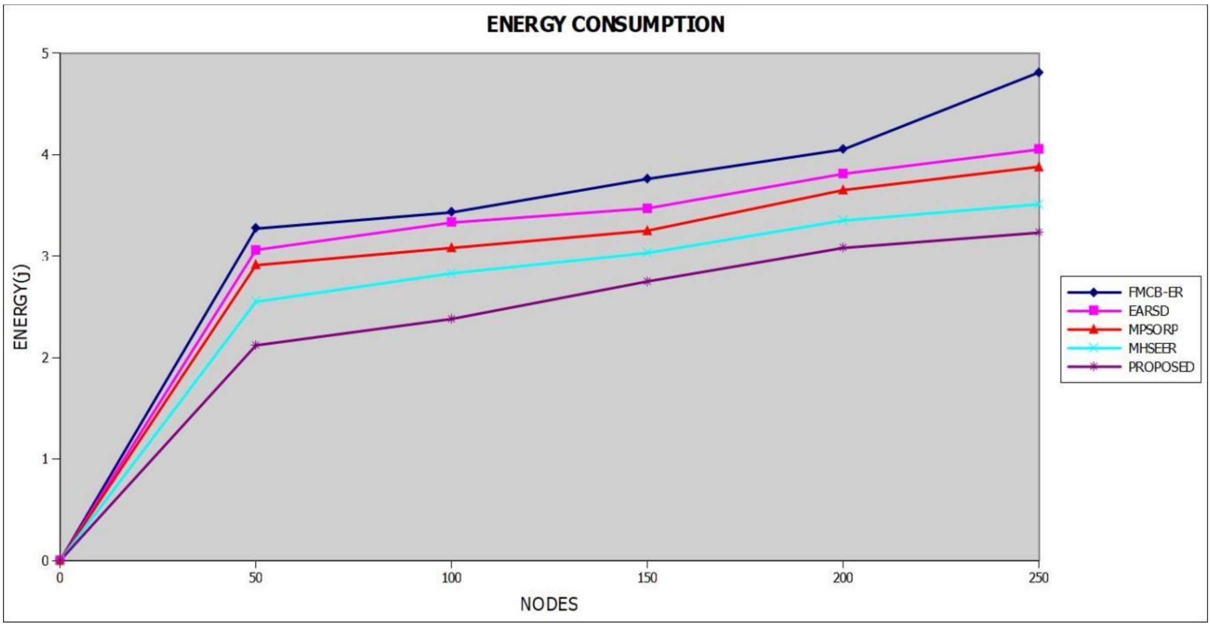

Fig 5: Energy consumption analysis

The sensor nodes have a starting energy of 100j for network operations, and with every network action, their energy is depleted. Energy optimization is essential for long-term network operation. When CHs are selected using the HSA and backup CHs are wisely chosen, data aggregation is improved and energy-intensive tasks such as retransmission are avoided. Consequently, the suggested network displays little energy use. The suggested strategy yielded an average energy consumption rate of 3.2j. Figure 5 shows a study of energy, while Table 3 offers a thorough breakdown of energy levels.

Table 3: Analysis of Energy consumption comparison of proposed with existing methods

NODES	FMCB-ER	EARSD	MPSORP	MHSEER	PROPOSED
50	3.27	3.06	2.91	2.55	2.12
100	3.43	3.33	3.08	2.83	2.38
150	3.76	3.47	3.25	3.03	2.75
200	4.05	3.81	3.65	3.35	3.08
250	4.81	4.05	3.88	3.51	3.23

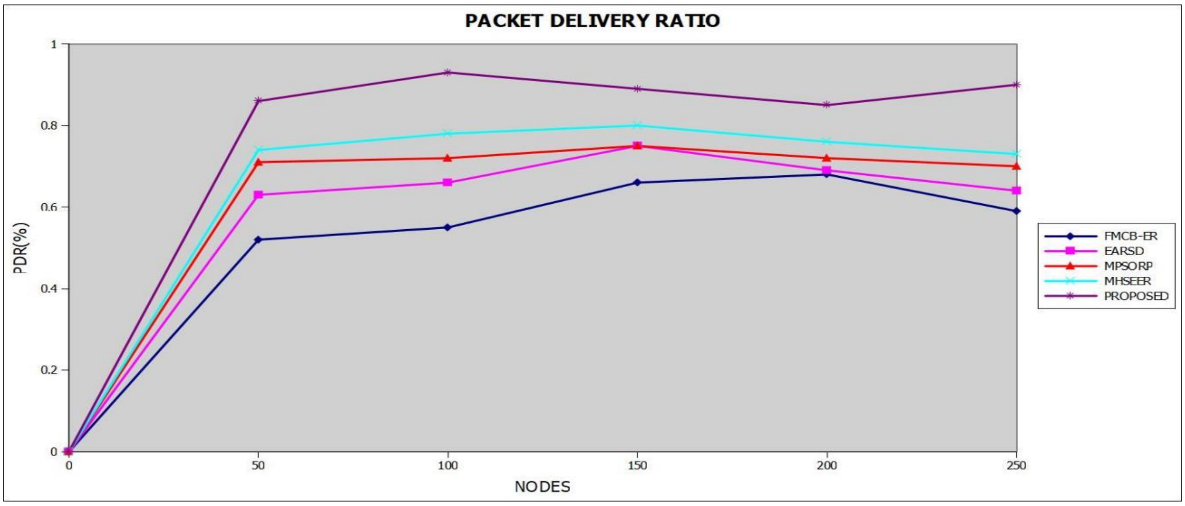

Fig 6: Packet delivery ratio

Figure 6 shows the PDR, which is the percentage of data packets that arrive at their destination that were originally sent by the sender. An improved relay selection process and efficient data aggregation lead to a higher delivery rate. The method includes choosing balanced and fault-tolerant CHs in addition to trustworthy CHs to guarantee continuous data forwarding by sensor nodes. The suggested technique outperformed previous approaches, which had an average PDR rate of 0.59%. Its maximum PDR of 0.90% is attained; the relevant figures are shown in Table 4.

Table 4: Analysis of PDR comparison of proposed with existing methods

NODES	FMCB-ER	EARSD	MPSORP	MHSEER	PROPOSED
50	0.52	0.63	0.71	0.74	0.86
100	0.55	0.66	0.72	0.78	0.93
150	0.66	0.75	0.75	0.8	0.89
200	0.68	0.69	0.72	0.76	0.85
250	0.59	0.64	0.7	0.73	0.9

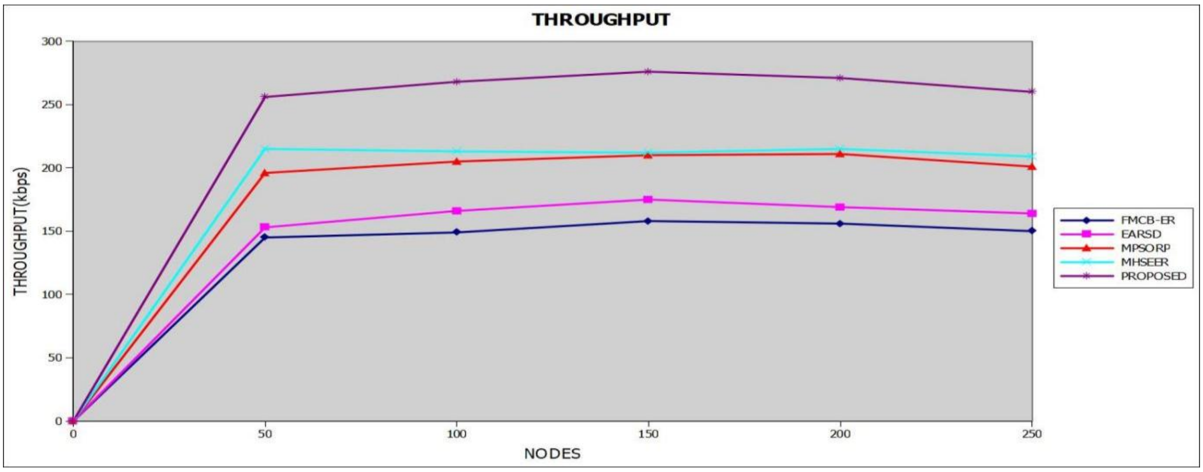

Fig 7: Network performance

When it comes to effective data aggregation, the best CH are chosen using the HSA, and backup CHs are chosen based on coverage. Throughput is the total number of data units a node can process in a given amount of time. The findings shown in Table 5 confirm that the suggested strategy outperforms current methods in terms of throughput rate. While other approaches showed lesser throughput rates, the suggested method continuously maintained the best throughput rate throughout the testing, reaching up to 260 kbps. An overview of the overall functioning of the network is shown in Figure 7.

Table 5: Analysis of Throughput comparison of proposed with existing methods

NODES	FMCB-ER	EARSD	MPSORP	MHSEER	PROPOSED
50	145	153	196	215	256
100	149	166	205	213	268
150	158	175	210	212	276
200	156	169	211	215	271
250	150	164	201	209	260

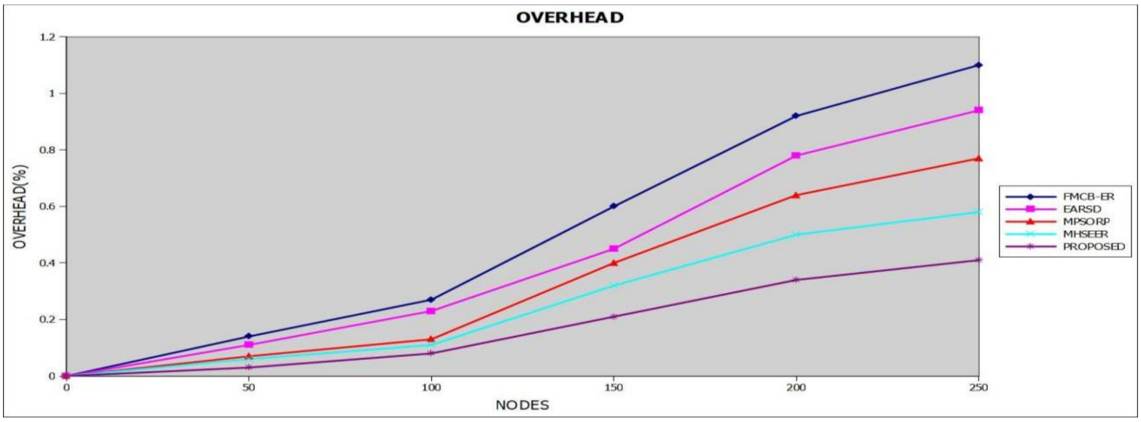

Fig 8: Routing overhead

The results of the simulated network overhead are shown in Figure 8 above. The amount of control packets that are sent across the network to carry out its operational duties is referred to as overhead. The overhead for the suggested strategy was around 0.40%. Frequent cluster head failures are less likely when base station coverage rate and connection lifetime are taken into account during the head selection process. This reduces the frequency of control packet broadcasts. As a result, the suggested strategy successfully keeps the overhead at a minimum. The values for routing overhead are shown in Table 6.

Table 6: Analysis of Overhead comparison of proposed with existing methods

NODES	FMCB-ER	EARSD	MPSORP	MHSEER	PROPOSED
50	0.14	0.11	0.07	0.06	0.03
100	0.27	0.23	0.13	0.11	0.08
150	0.6	0.45	0.4	0.32	0.21
200	0.92	0.78	0.64	0.5	0.34
250	1.1	0.94	0.77	0.58	0.41

V. Conclusion

The EHSRC is a novel solution for WSNs that addresses energy constraints due to limited power sources for sensor nodes. The EHSRC uses the HSA as a metaheuristic approach to optimize the selection of sensor nodes as CHs, minimizing energy consumption and enhancing network efficiency. The study also emphasizes the importance of fault tolerance in WSNs, introducing a fault tolerance technique using a GA to detect faults in cluster heads and facilitate network communication restoration. Experimental results confirm the effectiveness of the EHSRC algorithm, demonstrating its superiority over existing fault-tolerant clustering approaches.

Compliance with Ethical Standards

Conflict of interest : The authors declare that they have no conflict of interest.

Human and Animal Rights: This article does not contain any studies with human or animal subjects performed by any of the authors.

Informed Consent: Informed consent does not apply as this was a retrospective review with no identifying patient information.

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Availability of data and material: Data sharing is not applicable to this article as no new data were created or analyzed in this study.

Code availability: Not applicable

Generative AI writing: We haven't used any such tools for writing this document.

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