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# Green Optimization with Load balancing in Wireless Sensor Network using Elephant Herding Optimization

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**Abstract:** Wireless sensor networks (WSNs), which provide sensing capabilities to Internet of Things (IoT) equipment with limited energy resources, are made up of specialized transducers. Since substitution or re-energizing of batteries in sensor hubs is extremely difficult, power utilization becomes one of the pivotalmattersin WSN. Clustering calculation assumes a significant part in power management for the energy-compelled network. Optimal cluster head selection suitably adjusts the load in the sensor network, thereby reduces the energy consumption and elongates the lifetime of assisted sensors. This article centers around to an appropriate load balancing and routing technique by the utilization recently developed of Elephant Herding Optimization (EHO) algorithm that alternates the cluster location amongst nodes with the highest energy. The Scheme considered various parameter residual energy, initial energy and an optimum number of cluster head for the next cluster heads selection. The proposed model increases the lifetime of the network by keeping more nodes active even after the 2700th round. The experiment results of the trials show that the proposed EHO-based CH selection strategy outperforms the cutting-edge CH selection models.

**Index Terms:** Wireless Sensor Networks, Energy Optimization, Cluster Head, Elephant Herding Optimization.

## 1. Introduction

WIRELESS sensor networks (WSNs) are self-coordinated autonomous, self-overseeing network framework that contains tremendous disseminated sensor nodes (SNs) [1]. It is an imperceptible however intelligent network which is programmed and sensed to the physical phenomenon such as temperature, position, height [2]. These sensors have the ability to operate without the assistance of a person communicated through the use of embedded technologies. WSN nodes typically have limitations like the availability of an energy supply and the ability to communicate or perform computations. As a result, energy efficiency is a very important aspect for WSN-based routing protocols that need to increase communication throughput and network longevity, and as a result, attract major research interest [3].

Power consumption reduction has always been a major concern while designing WSNs. Recent research findings have generated a variety of suggestions for lowering energy use and extending network longevity for efficient resource utilization. Clustering of sensors is quite possibly of the most over whelming utilized strategy [4]. The IoT network is organized into a number of clusters, each of which consists of a cluster head and a large number of nodes. The cluster head is determined by a variety of performance indicators like remaining power, load, etc. furthermore, every node transmit their sensed data to the cluster head and the aggregated data from nodes by the cluster head is moved to the base station [5]. Base station can transmit the data to the gateway node or to the cloud sever and lastly, the data transmit to the end user as demonstrate in Fig. 1.

A well-known clustering method called LEACH (Low Energy Adaptive Clustering Hierarchy) [6] takes energy into account while routing data hierarchically. For each round, the protocol stochastically chooses a CH at random. To gather the sensed data, the CH connects with each member node of the cluster. The CH gives its associated cluster member TDMA (Time Division Multiple Access) schedules. During the designated time slot only, the member node is permitted to communicate data. Prior to interacting with the sink node, the data is then compressed and redundant data is analyzed. Compared to direct or multi-hop transmission, the LEACH algorithm extends the network's lifetime, although it still has a lot of restrictions. Since cluster heads are chosen at random, correct distribution and the best outcome are not guaranteed. When it comes to being chosen as CH, nodes with lower energy levels have the same priority as those with greater energy levels [6]. Numerous strategies have been developed to solve these drawbacks, including the Power Efficient Gathering Sensor Information Systems (PEGASIS) [7], the Hybrid, Energy-Efficient, Distributed Clustering (HEED) [8], and the Energy Efficient Clustering Scheme (EECS), an enhancement of LEACH [9].

Multi-objective optimization problems are exceptionally well suited for meta-heuristic optimization estimations. Different optimization techniques and evolutionary algorithms are applied to tackle such sort of issue. A smooth balance between exploration and exploitation is achieved by swarm-based algorithms which successfully avoid the local optimal constraints. Swarm algorithms that are bio-inspired and biomimetic have a high potential to improve network performance. Numerous studies have also used biomimicry to address the sensor network's clustering and routing issues. These algorithms gain from the way of behaving of the fishes, birds, bugs, and so forth.

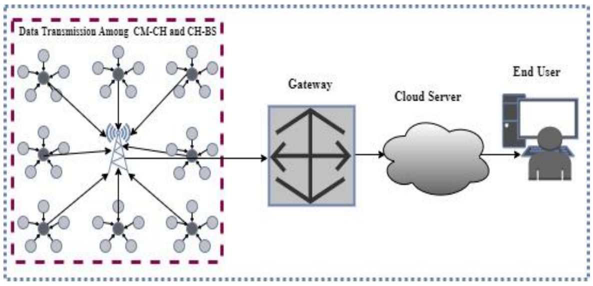


Fig.1. Data Transmission

Additionally, a number of criteria impact how long a network will last. With regard to these parameters, the main problem and concern for any WSN networks is to ensure reduced energy consumption and increased IoT network lifespan. In any network, when the network's load, data traffic, and temperature all rise as the number of dead nodes rises. As a result, an effective energy optimization framework is very necessary to address energy optimization problems in the IoT environment. In light of the aforementioned problems, this article proposes a remedy while simultaneously underlining the value of the article discussed in the subsection of this section.

The optimal CH is chosen by utilizing the EHO algorithm to build an energy improvement model.

- The flooding of transmitting packets that are taken into account for computation is replaced by an effective route broadcasting approach. As a result, energy usage is dropped considerably.
- Keeping an ideal number of nodes active that lowers the load, that lengthening network lifespan.
- The fitness function employed for the CH selection and route optimization algorithm is also provided with the well-defined formulation of linear programming.
- Execution assessment and result examination have been conducted and performance of the scheme is examined with some notable benchmark techniques.

The rest of the paper is organized as: Section 2 is centered on around related work. Section 3 explores network structure and system model. The assumptions related to proposed model is discussed in Section 4. The proposed model is exploring in Section 5. Results estimation and execution assessment are talked about in Section 6. End and future viewpoint are given Section 7

## 2. Related Works

The related research on clustering and routing in sensor networks is reviewed in this section.

Low-energy versatile grouping order (LEACH) is one of the earliest yet notable information conglomeration algorithm [6], and a few exploration works have been introduced in view of that. In such manner, LEACH-B (LEACH-Balanced) is an upgraded variant of LEACH that was introduced by Tong et al. [10]. There are three primary phases to the LEACH-B protocol: Cluster formation, CH election, and data communication. It is a decentralized method for cluster creation [10]. LEACH-B starts out the same as the LEACH method for the initial CH choice. LEACH-B then includes a second step that incorporates the energy that is still usable. According to LEACH-B, there will be an equal number of CH in each round. The better LEACH (I-LEACH) [11] clustering and routing algorithm picks the cluster head based on the amount of energy left, the node's position in the network, and the number of neighbors from whom it selects CHs. Similar to many clustering routing protocols, the I-LEACH approach consists of three parts: CH selection, cluster building, and data transfer. The authors in [54] created a brand-new mechanism called V-LEACH (Vice

Cluster-Head-LEACH) [12] to cut down on this energy use and stop CHs from losing energy quickly. The VH-LEACH technique, an enhanced variant of V-LEACH, was suggested by the authors of [13]. This protocol's major objective is to change the CH election. Based on the greatest quantity of leftover energy, the CH is chosen via the VH-LEACH algorithm [4].

The energy-efficient CH selection method PSO-ECHS, which is based on particle swarm optimization (PSO), selects a CH based on an objective function dependent on RE, inter-cluster distance, and intra-cluster distance. Based on PSO, the imbalanced and risk-tolerant clustering model PSO-UCF [15] seeks to resolve the imbalanced clustering protocol in order to prolong the life of the network. This technique used an unequal clustering approach to stabilize the inter- and intra-cluster energy intake. Two linear programming formulations for cluster construction and routing have been provided in TPSO-CR [16]. In this case, the objective model for CH selection worked well for both data communication and energy efficiency. The calculations are based on a plausible network model. To identify an energy-efficient CH with rapid global convergence, HSA-PSO [17] employs a hybridization of PSO with the harmony search algorithm (HSA). The method utilizes PSO and HSA's benefits. The hybridization showed to be superior to PSO alone because HSA searches only within the restricted zone while PSO searches by movement, but PSO still has the issue of exploration and exploitation when seeking the local optima. To maximize the use of energy in WSN systems, authors in [18] present a Sailfish Optimizer (SFO) routing algorithm and clustering algorithm.

An energy aware approach for a heterogeneous network environment comprising super, advanced, and normal nodes was put forth in [19]. The super nodes choose optimal CHs in a centralized manner, whereas the other nodes choose them in a decentralized manner. Using Network Simulator 2.35, the procedure was carried out and the network's performance was estimated based on throughput and the proportion of dead nodes to total rounds. The suggested model performed better than the current models as well. The cluster construction technique, COARP [20] uses cuckoo search optimization to find the ideal CH. The algorithm used the residual energy and the distances between and within clusters as the specifications for the fitness function for the CHs selection process. Each time the COARP algorithm runs, Cuckoo Search is responsible of choosing the CH. The clustering and routing method for sensor networks, E-OEERP [21], also prohibits residual nodes formation in the network. PSO is utilized in this technique to cluster data, while gravitational search algorithm (GSA) is used to route data across clusters in the network.

In the sensor-enabled Internet of Things, iASEF [22] utilized atom search optimization for clustering and electromagnetic force optimization for routing. Authors used inter-cluster routing in order to deliver the packets from CH to BS. It has been demonstrated that combining these two optimization strategies produces a better result than using the other baseline algorithms. The proposed iASEF method has been examined using a variety of network situations and performance measures. Another routing path selection method, ACOHCM [23] combines the advantages of the ACO and lowest hop count. The approach exhibits greater load balancing and maintains a diverse topology. The clustering and routing mechanism, iCSHS [24] extend the life of networks. The uniform distribution of CHs in the network field is the main goal of this strategy. Both the CH selection and the route selection for packet transmission use the improved cuckoo search optimization.

For an IoT large-scale sensor network, CSFO-CR [25] offered a chaotic sailfish optimization founded energy utilization minimization. The recommended model partitioned the network region into hexagons and grouped sensors to lessen the power utilization. In the sensor network, the chaotic sailfish optimization algorithm successfully identified the optimal CH and data transmission path. In SLDD [26], author proposed a novel load balancing method that makes use of super connections' strong ability to drain data and maintain load balance. It is an effective early intervention method that, in large-area networks, is more realistic and workable. In [27], presupposes a heterogeneous network with sensor nodes that have varying amounts of processing power and energy. There are several high-performance nodes planted next to one another. The nodes with the highest starting energy and processing levels are chosen. The cluster head (CH) nodes are chosen from the set based on the geographical properties. In [28], authors describe a swarm-based PSO-DEC technique for cluster head selection. By considering other fitness function characteristics besides residual energy, this enhanced approach has eliminated some shortcomings of the previous protocol.

## 3. Network Structure and System Model

Urban regions need modern infrastructures and sufficient services to meet the needs of the city residents due to the rapid increase in population density. Henceforth, WSN requires developments in communication technology for the execution of the various applications of it [2].

A sensor network consists of numerous cheap, widely dispersed sensor nodes with a powerful BS. It is assumed that every sensor in the network field has been randomly placed. All of the sensor nodes, including the BS, are in fixed places. Because the sensors are homogeneous, each node in a given network area has the same original energy [1, 3]. Each node in the network has the ability to communicate with other nodes if they are within range. While the battery in the BS can be recharged, the battery in the sensor’s node cannot. The base station receives the data from the cluster member nodes once CH obtains it.

Sensor nodes used their energy for data gathering, processing, and transmission, however the majority of their energy was used for data transmission and reception. This approach therefore concentrated on energy loss during network data exchange. In this section, the basic framework and operational model of a network are provided, along with a discussion of the communication energy model for calculating the power dissipation of sensors in sensor networks. We implemented the energy concept put forth in [6] into practice. furthermore, distance to be traverse by information is the significant justification behind energy utilization, this factor is taken into account by the given approach.

Let $dis_{TH}$ be the threshold distance. In our model, if the radio range is less than $dis_0$, a sensor node's energy consumption is proportionate to $dis^2$, and if it is more than $dis_0$, the sensor node's energy depletion is proportionate to $dis^4$: The following is an expression for a node's overall power usage during the transmission of a b-bits data packet:

$$E_{T_S X}(b, dis) = \begin{cases} b \times E_{elec} + b \times \varepsilon_{fs} \times dis^2, & if \ d < dis_0 \\ b \times E_{elec} + b \times \varepsilon_{mp} \times dis^4, & if \ d \geq dis_0 \end{cases} \tag{1}$$

The target nodes' energy consumption is calculated using the following equation when they receive b-bits data packets.

$$E_{R_c X} = b \times E_{elec} \tag{2}$$

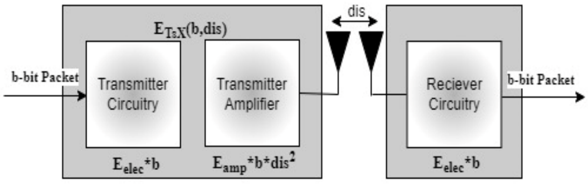


Fig.2. Radio energy model

In the equation above, $E_{elec}$ stands for the energy loss incurred by the node when sending or receiving b-bits data packets. The transmission amplifier coefficients for the free space and multipath models, respectively, are $\varepsilon_{fs}$ and $\varepsilon_{mp}$ . $\sqrt{\varepsilon_{fs} / \varepsilon_{mp}}$ is the value of $dis_0$. The radio energy model is shown in Fig. 2.

## 4. Preliminaries

Finding the optimal CH in any cluster is a challenging task. Generally, in WSN, CH depends on factors including energy, network load, and distance. Speed and Distance are the two main determinants of the propagation delay. Therefore, in order to achieve good performance, we must choose the appropriate CH in a way that minimizes network-wide propagation time. As a result, in order to increase the network lifetime and performance, we must choose a CH node that has the highest energy, lowest load, and closest distance to the base station. Eq. (3) illustrates the optimal objective function to exceed the network's efficiency:

$$\begin{aligned} OOF_i &= r_1 \times OOF_{Energy} + r_2 \times OOF_{Load} \\ &+ r_3 \times OOF_{Distance} \end{aligned} \tag{3}$$

where, the sum of the weighted parameters is equal one and the weighted parameters are α, β and γ.

Energy Parameter: After sending and receiving every packet, a node expends a set amount of energy. As a result, this leftover energy significantly contributes to increased network lifetime and performance. The energies of the CH and node should be changed after each packet transmission and reception. The optimal CH should have a high node energy. A CH should always have a higher energy value since it is held more responsible than a cluster member for data gathering, data aggregation, and cluster control. As a result, the CH should have a larger energy power than the other members in its cluster.

$$OOF_{Energy} = \sum_{i=1}^{nt} \frac{1}{RE_{CH_i}} \tag{4}$$

Here, $RE_{CH_i}$ is the RE of the i$^{th}$ CH and $n_t$ is the total number of CHs.

Distance Parameter: From the literature it is notified that the optimal cluster head considered, the one which has the shortest distance between the node and sink node. The Eq. (5) objective function for distance is used to indicate the separation between CH and both node and BS.

$$OOF_{Distance} = \sum_{i=1}^{n_t} dis(CH_i, BS) \tag{5}$$

Sensor load: When choosing the best CH, the load related to sensor nodes should be as low as possible. For the performance study, the data pertaining to Load are input into sensor as a parameter.

## 5. Proposed Model

**Elephant Herding Optimization [29]:** Elephants are gregarious creatures who live in groups with other females and their offspring. An elephant clan is made up of several elephants and is headed by a matriarch. Male members typically reside elsewhere, while female members choose to live with family. They will slowly become free of their families until they leave their families totally.

We preferred to simplify the elephant herding behavior into the following idealized principles in order to make it tackle all types of global optimization problems.

- There are several clans within the elephant population, and each clan has a set number of elephants.
- Every generation, a predetermined number of male elephants will disperse from their family group and live alone in an area separate from the main elephant herd.
- The matriarch of each clan is in charge of the elephants living there.

Operator for updating clans: Elephants in each clan are led by a matriarch in accordance with their normal behaviors [30]. As a result, matriarch $c_i$ has an impact on each elephant's new position $c_i$. Equation (6) can be used to calculate the elephant j in clan Equation can be used to calculate the elephant $j$ in clan $c_i$.

$$X_{new,c_i,j} = X_{c_i,j} + \alpha \times (X_{best,c_i} - X_{c_i,j}) \times r \tag{6}$$

Where, elephant $j$ current position in clan $c_i$ is indicated by the variables $X_{new,c_i,j}$ and $X_{c_i,j}$ respectively.

The scale factor [0,1] establishes matriarch $c_i$ impact on $X_{c_i,j}$. A scale factor, $r \in [0,1]$, is indicated by the notation $a \in [0,1]$. Equation (7) can be used to determine the optimal elephant for each clan.

$$X_{new,c_i,j} = \beta \times X_{center,c_i} \tag{7}$$

Where $\beta \in [0,1]$ is a parameter that governs how the $X_{center,c_i}$ affects the $X_{new,c_i,j}$. The information that all the elephants in clan $c_i$ collected is used to create the new individual $X_{new,c_i,j}$ in equation (7).

The central member of clan $c_i$ is known as $X_{center}$. For the $d^{th}$ dimension, it can be computed using Equation (8).

$$X_{center,c_i,d} = \frac{1}{n_{ci}} \times \sum_{j=1}^{n_{ci}} c_i, j, d \tag{8}$$

where $1 \leq d \leq D$ denotes the dimension in the dth location and $D$ is the overall dimension. The number of elephants in clan $c_i$ is known as $n_{ci}$. The $d^{th}$ of the elephant individual $c_{ij}$ is $c_i$, $j$, $d$.

Operator for Separating: When resolving optimization issues, the separating process through which male elephants depart from their family group can be modelled as a separation operator. Equation (9) illustrates how the elephant individual with the worst fitness in each generation implements the separation operator.

$$X_{worst,c_i} = X_{\min} + (X_{\max} - X_{\min} + 1) \times rand \tag{9}$$

Where, $X_{max}$ denotes the individual's upper bound and $X_{min}$ denotes the individual's lower bound. The weakest member of clan $c_i$ is identified by the name $X_{worst,c_i}$. A stochastic distribution between 0 and 1 is known as Rand [0,1].

Algorithm 1: Elephant Herding Optimization Algorithm [29]

*begin*
Initialization, Set iterations $G = 1$; population $P$, $maxGen$
while do
Sort p according to fitness
for $c_i$ do
for elephant j in $c_i$ do
Generate $X_{new,c_i,j}$ and update $X_{c_i,j}$ using Eq. (6)
if $X_{c_i,j} = X_{best,c_i}$ then
Generate $X_{new,c_i,j}$ and update $c_i, j$ using Eq.(7)
end if
end for
end for
for all $c_i$ do
Replace the worst individual $c_i$ using Eq. (9)
end for
Evaluate each elephant individual according to its position
$T = T + 1$
end while
*end begin*

In order to collect data and transfer it to the associated CH, sensor nodes are initially placed in sensing areas. The CH then gathers data from various nodes inside a cluster and transmits it to the BS. All nodes in the network used to send data to the BS because there was no CH mechanism in the workings at the time. Data duplication, packet loss, and node failure management happened as a result of the BS becoming overloaded. All of these problems are resolved and the network's endurance is increased by selecting the ideal CH. The EHO algorithm has a number of benefits, including a higher rate of convergence, enhanced threshold coefficients, increased system effectiveness, and avoidance of the trap at local and global minima. In the suggested model, the advantages of the EHO algorithm are used to select the best CH. The system's performance suffered as a result, and the network's life expectancy was decreased. Based on the fitness function of each node, the best node among the cluster of nodes is chosen as a CH. The EHO method is used to determine each node's fitness function based on performance indicators such load, residual energy, and distance. The best node picked as a CH is nearer to the BS, has more residual energy, a lower temperature, and a lower load. If a node in a cluster has enough residual energy relative to other nodes, it will receive high priority over nodes with less residual energy. The nodes that are closest to the base station will receive preference in some scenarios where a group of nodes have the same remaining energy. The suggested model for the best CH selection is shown in Fig. 3.

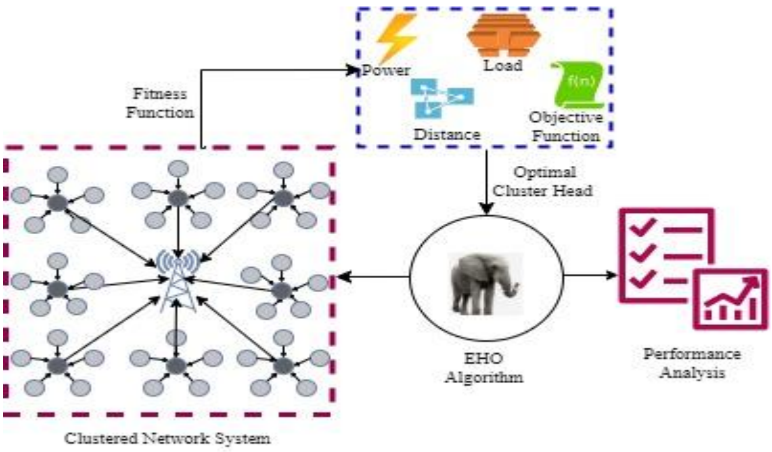


Fig.3. General illustration of optimal cluster head selection by EHO

## 6. Result Analysis

The proposed work is tested using the MATLAB R2016A. The proposed model's effectiveness is evaluated in comparison to various schemes for the best CH selection, that includes the genetic algorithm (GA) [31] and Biogeography based optimization [32]. For the proposed EHO-based model, the following parameters were used to simulate the IoT network. Figure 4 shows the node deployment in network area.

- Sensing area: 100 × 100 square meters (as represented in Fig.4.
- Initial energy of the network: 1 Joule.
- Total number of rounds: 3000.
- Packet size: 4000 bits.
- Free space energy: 10 peta joules/bit/square meter.
- Data Aggregation energy: 5 nano joules/bit/signal.

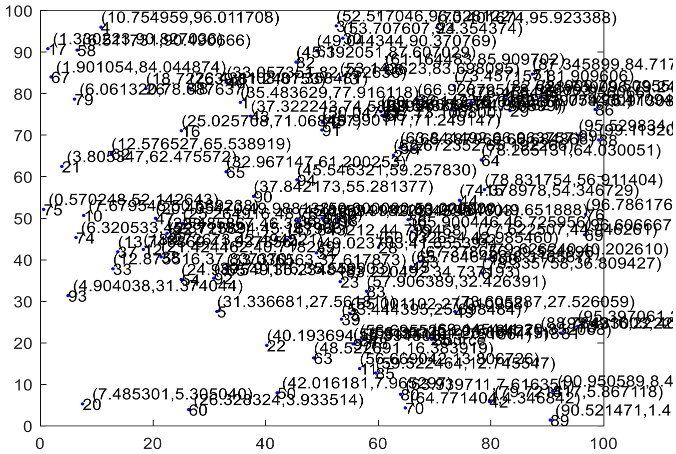

Fig.4. Node deployment in network area

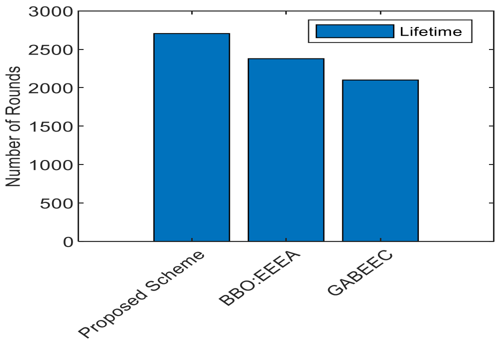


Fig.5. Number of rounds VS lifetime

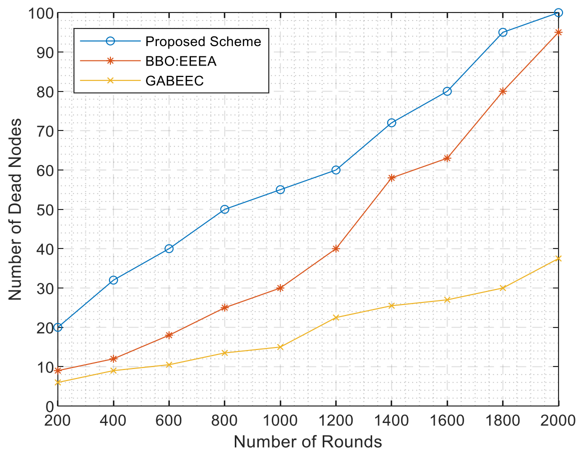


Fig.6. Number of rounds VS number of dead nodes

The following parameters are used to measure the proposed model performs: network lifetime, number of alive nodes and residual energy. The number of rounds until entire nodes totally lower their energy is the network lifespan. To measure the network longevity, we utilize Last Node Die (LND). The energy in the network is a factor for sensor node's functioning. The moment the energy is depleted, these sensors will stop functioning. These sensor's battery life and residual energy will decrease as a result of their constant ambient data sensing. How long the IoT network lasts depends on how much leftover energy is there. The lifespan of a network is determined by the total number of active anodes. When nodes do compute, some energy is used; a node is deemed dead when its battery is completely exhausted.

The number of alive nodes determines the network's life time.

Performance Analysis Based on Lifetime: Fig. 5. Shows the network lifetime. The network's lifespan is shown in Fig. 7 and 8 to be longer when the BS is in the middle as opposed to on a corner. We investigate the network longevity using the Last Node Die method (LND). Figure5 shows that in our situation, the last node passes away after around 2700 rounds of our method, compared to 2378, and 2100 for the algorithms for proposed algorithm, BBO: EEEA and GABEEC respectively.

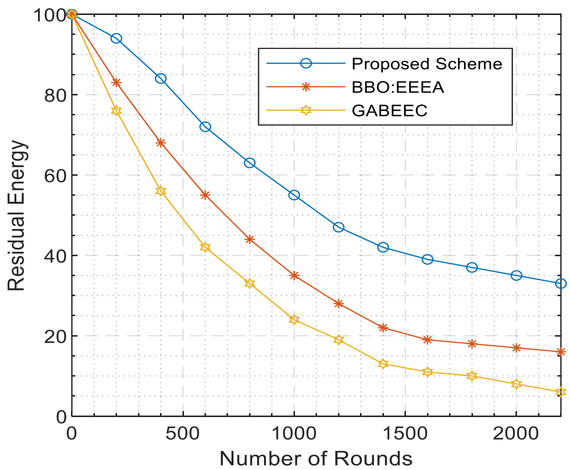


Fig.7. Number of rounds VS residual energy

Performance Analysis Based on Dead Nodes: The suggested model's performance analysis is based on the number of dead nodes in each round. In terms of the number of dead nodes per number of rounds, Fig. 6 displays the outcomes of the simulation run for the suggested scheme and the baseline methods. The result analysis reveals that as the number of rounds rises, dead nodes also rise. For instance, according to Fig. 6, the numbers of dead nodes at round 1200 for the propose protocols, BBO: EEEA and GABEEC around 60, 40 and 17.

Performance Analysis Based on Energy: Fig. 5 displays the performance of each model taken into account based on residual energy. Fig. 7 demonstrates that the recommended EHO-based model has more residual energy than the other models as the number of rounds rises. The proposed model will, in comparison to the previous models, have a larger percentage of active nodes in each cluster, which decreases each node's load and thus lowers its energy consumption. The results of the simulations demonstrate that our method, outperforms the standard techniques and has a longer last node life. This is because the suggested method selects the CH using an EHO-based CH selection algorithm, which aims to prevent residual nodes by selecting the CHs in a way that assures none of them are within communication range of one another. This prolongs the network's overall lifespan by maintaining the equilibrium between power depletion among CHs. Fig. 7 show the results of RE for various numbers of rounds. Fig. 7 demonstrates how our suggested model, lost nearly 55% of its starting energy at around 1000, compared to other models like the BBO: EEEA, GABEEC, which reduced their energy by about 35% and 25% respectively.

## 7. Conclusions

The various application saves quite a load of money by extending the life of sensor networks. IoT networks must effectively manage the load placed on its sensor nodes if they are to live longer due to the networks' sensors' constant generation of massive volumes of data. In support of this, the optimal CH in each of the clusters in the IoT networks is chosen in this work using a nature-inspired method called EHO. An optimal CH can transfer packets to the BS more rapidly, balance the load on the sensor nodes, reduce energy consumption, reduce network stress, and overall lengthen the life of the network. The recommended model is assessed using a variety of parameters, including temperature, the quantity of active nodes, residual energy, and load. The proposed scheme is performing 11% and 22% better than BBO: EEEA, GABEEC respectively, in terms of network lifetime. Henceforth, the proposed EHO-based model outperforms the current methods due to its quick convergence rate and capacity to avoid becoming stuck in local optima.

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