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Gaussian Harris Hawks Optimizer (GHHO) Based Cluster Head Selection (CHS) And Enhanced Energy Harvesting Clustering (EEHC) Protocol for WSN

L. Lakshmaiah
Research scholar
Department of Information Technology
Annamalai University
lakshman222@gmail.com

Dr. K Raja, Assistant Professor,
Department of Information Technology, FEAT, Annamalai University
rajakapit@gmail.com

Dr. B. Rama Subba Reddy
Professor and Dean CSE
Narasimha Reddy Engineering College, Hyderabad
rsreddyphd@gmail.com

Abstract: Designing routing protocols for Energy Harvesting- Wireless Sensor Network (EH-WSN) has two key challenges like improving harvested energy utilization and examination harvested energy utilization. However, the clustering and routing phases of the clustering-based routing protocols employed in EH-WSN need a lot of message overhead. Cluster Head Selection (CHS) is a crucial component of clustering that improves energy efficiency. An Enhanced Energy Harvesting Clustering (EEHC) protocol with two phases for cluster setup and data transmission is presented in this research. Sensor nodes are grouped into clusters during cluster construction, and CHS using the Gaussian Harris Hawks Optimizer (GHHO) algorithm is used for data transmission. Hawks chasing behaviours serve as the search agent in the GHHO algorithm, while prey serves as the ideal CH position. Data from each cluster node is collected by CHS, which then sends the aggregated data to the base station. Following CHS, connecting Cluster Member (CM) to a suitable CH is done using a variety of factors like energy, distance to neighbours, distance to the Base Station (BS), node density, and Signal-to-Noise Ratio (SNR). Each CM awakens during its designated working time slot during the DT stage, and transfers the data it has gathered towards the CH of the same cluster. A mobile sink is employed to enhance network performance and relay transmission distance is changed to match the amount of gathered energy. Residual Energy (RE), Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), Network Lifetime, and average delay are metrics used to measure the results of clustering methods.

Index Terms: Energy Harvesting- Wireless Sensor Network (EH-WSN), Cluster Head Selection (CHS), Gaussian Harris Hawks Optimizer (GHHO), routing selection, dynamic data transmission, and mobile sink.

1. INTRODUCTION

Wireless Sensor Network (WSN) has been applied in various applications like environmental monitoring, agriculture, tracking, military surveillance, smart homes, and more [1]. WSN gathers necessary information in a distributed manner by deploying an assortment of low-power sensors [2]. The primary energy source for WSN nodes is the battery, and the battery energy consumption is closely correlated with the lifespan of the WSN. The lifetime of the conventional WSN is typically recognized to be constrained since of the controlled battery usage of its sensor nodes [3]. EH-WSN is the name given to WSN that use energy harvesting technology. Energy harvesting modules on the sensor nodes in the EH-WSN allow them to draw power from sources like solar, thermal, vibrational, and RF energy [4].

The network would be considered dead when the WSN available sensing coverage fell below the threshold coverage. The communication protocol, traffic load, and node topology [5, 6, 7] will all have an impact on the energy consumption of nodes simultaneously. The primary cause is the reception and transfer of information. In order to prevent the hotspot nodes from being prematurely depleted [7, 8], it is essential to maintain a balance in the traffic load. This will extend the Maximum Lifetime Coverage (MLC) of the WSN. The MLC problem of WSN can be considerably optimized through the design of communication protocols.

A significant research challenge in the area of WSN that has not yet been completely investigated is ensuring the network longevity. A predictable and assured network lifetime is more crucial in some applications than a long network lifetime. For successful node energy management in WSN employing various clustering strategies has been developed recently [8, 9, 10]. Clustering model in which nodes are clustered which have been used for data communication. WSN organizes nodes into clusters, with each cluster having a coordinator

(CH) in charge of collecting data from the nodes and transmitting it to the sink/ Base Station (BS). To meet the coverage requirement, sensors are frequently placed close together. This allows some nodes to enter the sleep state, which results in significant energy savings.

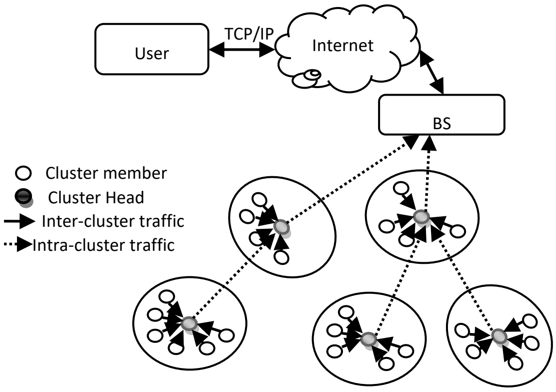

FIGURE 1. CLUSTERING WIRELESS SENSOR NETWORK (CWSN) MODEL

The remaining nodes are referred to as Cluster Member (CM), whereas the dominating node, CH is chosen from among the alternate nodes. Equal Clustering is the process of creating clusters in a system with an even number of nodes, whereas Unequal Clustering is the method of forming clusters through an uneven no. of nodes. A CH is chosen from each cluster in accordance with the predetermined parameters. Figure 1 illustrates the clustering architecture. CH may be chosen at random or in accordance with one or more criteria. Lifetime of WSN is influenced by CH selection. The best CH is closest to the BS, generally neighbour nodes, and has the maximum Residual Energy (RE). In WSN, CH election, security, routing, data transmission, and data management plays a significant role. It is considered as Non-deterministic Polynomial (NP) problem which is solved by metaheuristic methods. Energy harvesting techniques like clustering and routing are still difficult to perform due to energy usage, and network lifetime maximization.

In this paper, Enhanced Energy Harvesting Clustering (EEHC) protocol is introduced for EH-WSN. Two major steps like cluster-route formation and data transmission has been presented in this protocol. Gaussian Harris Hawks Optimizer (GHHO) has been introduced for CHS and simultaneously working on CH selection, the proposed methodology lowers the overall message overhead. In the data transmission phase, a mobile sink is used to increase network lifetime while relay transmission distance is changed to match the amount of gathered energy. Additionally, by offering a CHS system for extending network lifetime and lowering energy expenditure, it increases network lifetime.

2. LITERATURE REVIEW

Hybrid Whale and Grey Wolf Optimization (WGWO) based clustering mechanism for EH-WSN was proposed by Rathore et al. [11]. The methods like whale and grey wolf has been combined to improve the performance of the clustering. When evaluating the algorithm, the proposed hybrid WGWO technique has considerably greater exploitation and exploration capabilities than the conventional and different current metaheuristic algorithms. Hybrid WGWO based clustering mechanism has been proposed based on cluster formation and dynamic CH selection. Result of this clustering mechanism is compared to other conventional routing protocols.

With the least amount of routing overhead, Nisha and Basha [12] introduced the Triangular Fuzzy-based Spectral Cluster Routing (TF-SCR) mechanism to increase network lifetime and successfully packet transmission in WSN. Preprocessing, clustering, and post-processing are the three major steps in the TF-SCR mechanism. In the preprocessing, TF-SCR mechanism is used for determining the remaining energy and received signal strength of each sensor node. After preprocessing, then it executes spectral clustering which clusters the sensor nodes according to the RE level. In post-processing step, triangular fuzzy membership function is used to choose the sensor node by highest RE and signal strength as the CH for routing. It achieves WSN routing in energy-efficient manner. TF-SCR mechanism, several sensor nodes and data packets are used together with parameters like energy utilization, network lifetime, routing overhead, and reliability.

To extend the network lifetime of EH-WSN, Bahbahani and Alsusa [13] proposed a Low Energy Adaptive Clustering Hierarchy (LEACH) based clustering protocol. According to each node unique capacity for energy harvesting, the duty cycling is used to rotate the CH role across the nodes in order to ensure with the purpose of every energy consumption is distributed between the nodes. In an EH-WSN, the ideal number of clusters is examined in terms of bandwidth utilization, latency, and energy consumption. GreenCastalia simulations show that the proposed protocol works better by throughput and network lifetime when compared to other methods, particularly under highly constrained energy settings.

Zhang et al [14] proposed a clustering routing in Energy Harvesting- Wireless Sensor Network (CREW) for uneven harvested energy among sensor nodes. The phases of cluster construction and data transmission make up CREW. CREW divides the network into unequal clusters during the cluster building and chooses the CH based on the RE and energy gain of the nodes respectively. These two new concepts like Network Gradient and Waiting Time for Cluster Head Competition are used for cluster formation. An adaptive inter-cluster communication system has been used for data storage and utilizes the energy harvested through the packet transmission. This protocol is able to give successful clustering routing for the EH-WSN and works better than other techniques.

Low Energy Adaptive Clustering Hierarchical based modified cluster-head selection method (LEACH-M) routing was proposed by Zhao et al. [15]. The CH threshold was optimized using ZigBee Distributed Address Assignment Mechanism (DAAM), which takes into account both RE and node network. Additionally, LEACH-M routing successfully balanced the network energy load and significantly increased energy efficiency by utilizing a CH competitive mechanism. The proposed approach can enhance the amount of data received at base stations while reducing energy consumption, according to simulation findings in Network Simulator (NS-2.35).

Energy- Efficient Cluster Head Selection (EECHS) scheme was developed by Ren and Yao [16]. The scheme classifies every node in a cluster into three categories: Scheduling Node (SN), CH, and CM. By designating a corresponding CM as the new CH in the CH selection stage based on the findings of the monitoring, the SN lowers the energy utilization related with CH selection. CHS is transferred between the CH to the SN, freeing up more CH energy for data transmission. Proposed system is simulated through experiments, and it shows that the proposed system has an effective CHS scheme for EH-WSN. It is capable to utilize the reduced energy usage than similar methods.

Energy-Efficient Multi Attribute-based clustering system for energy harvesting (E^2-MACH) has been proposed which tackles energy efficiency and communication reliability. E^2-MACH was proposed by Haq et al. [17]. It employs accurate CH selection criteria depending on a weighted function specified by a number of parameters (statistics, neighborhood density, current RE, and energy harvesting). It is used to save node energy and reduced usage of energy between the nodes. The proposed system has achieved in increasing network throughput, energy consumption, lifetime, and reduced PLR.

A Novel Energy Harvesting Clustering Protocol (NEHCP) was proposed by Sah and Amgoth [18]. The hierarchical clustering routing algorithm, which employs solar EH is the foundation of the NEHCP. The BS receives the information gathered from the sensor nodes via the CH. It includes of three phases like start-up, setup, and data transmission. Additionally, the distinctive quality of EH-WSN produces results that are more effective in terms of network longevity. Results show that it significantly improves the EH-WSN network efficiency while having a higher ability to balance energy consumption.

Hybridization of the Metaheuristic Based Cluster Routing (HMBCR) technique for WSN was proposed by Al-Otaibi et al. [19].The method starts with a clustering procedure based on Brainstorm Optimization with Levy Distribution (BSO-LD) by fitness function with parameters (energy usage, distance to neighbours, distance to the BS, and network load). Water Wave Optimization with a Hill-Climbing (WWO-HC) has been introduced for optimal route selection in routing. HMBCR technique is used to assure the energy efficiency and network lifetime when compared to other methods.

Arjunan and Sujatha [20] proposed a Fuzzy-based Unequal Clustering and Hybrid data transmission with Ant colony optimization based Routing (FUCHAR) for increasing the network lifetime. Inter-cluster routing process is performed by the Ant Colony Optimization (ACO) algorithm from CH to BS and Fuzzy Logic (FL) for CH selection. This protocol includes cluster maintenance, inter-cluster routing, and CH selection. Additionally, this protocol transmits data in a hybrid way which combines proactive and reactive behavior. In addition to the regular data transmission, a threshold scheme is used towards broadcast/ close at rapid changes in the environment. Cross-layer cluster maintenance has also been introduced for uniform load distribution.

3. PROPOSED METHODOLOGY

In this paper, Enhanced Energy Harvesting Clustering (EEHC) protocol is introduced with two phases like cluster setup and data transmission. Sensor nodes are grouped into clusters during cluster construction, and CHS using the Gaussian Harris Hawks Optimizer (GHHO) algorithm is used for data transmission. Hawks' chasing behaviours serve as the search agent in the GHHO algorithm, while prey serves as the ideal CH position. Data from each cluster node is collected by CHS, and then it sends the aggregated data to the BS.

When CHS is chosen, attaching Cluster Member (CM) to a suitable CH is then done using a variety of factors. Each CM awakens during its designated working time slot during the DT stage and transfers the data it has gathered to the CH in the same cluster.

3.1. WSN MODEL FOR EH-WSN

EH-WSN consists of N stationary sensor nodes and a sink with a lot of resources. A CH and numerous CM are found in each of the several clusters that make up the whole EH-WSN. Sensing and transmitting the data to their CH are the primary duties of CM. The CH then communicates the aggregated data to the sink after aggregating the data it has received from the CM or another CH. EH-WSN system has includes the following features,

(1) The nodes cannot move after they are deployed because it is a static network.

(2) Each node has a distinction $ID_i(1 \leq i \leq N)$ is aware of both its own and the sink positions. Localization methods or GPS at deployment can both determine the position.

(3) The transmission power of each node has been varied based on the distance among the receiver and itself in the deployment area. dis_{max} and dis_{min} is denoted as the maximum and minimum distances among the node and sink.

(4) All nodes limited rechargeable battery capacity, designated as En_{cap} are the same for all of them. Node i remaining energy is denoted by the symbol En_i. En_0 is denoted as the initial energy of the node.

3.2. ENERGY UTILIZATION AND HARVESTING MODEL

A first-order radio model is presented to anticipate harvesting. The distance among nodes i and j will be indicated as dis_{ij}. The energy used to transport k-bit data from node i to node j is as follows,

$$En_{tx}(k, dis_{ij}) = k \times En_{elec} + \begin{cases} \varepsilon_{fs} \times dis_{ij}^2 & dis_{ij} < dis_0 \\ \varepsilon_{mf} \times dis_{ij}^4 & dis_{ij} \geq dis_0 \end{cases} \quad (1)$$

En_{elec} is stand for the amount of energy used by digital circuitry when sending or receiving a single bit of data. The transmission and receiver energy to move a packet by length of k is specified as En_{tx} and En_{rx}. It is described as follows,

$$En_{rx}(k, dis_{ij}) = k \times En_{ele} \quad (2)$$

where the propagation loss coefficients are ε_{fs} and ε_{mf} .The transmission distance dis_{ij} and a predetermined threshold, $dis_0 = \sqrt{\frac{\varepsilon_{fs}}{\varepsilon_{mf}}}$, n=2 if $dis_{ij} < dis_0$ and n=4 determine the value of n, with n=2 if dis_{ij} dis_0 and n=4 in all other cases [18]. Expected value of the node i harvested energy at time slot t+1($EH_i^{exp}(t+1)$) . It is described as follows,

$$EH_i^{exp}(t+1) = \alpha \times EH_i^{exp}(t) + (1-\alpha)EH_i^{rel}(t) \quad (3)$$

where $EH_i^{exp}(t)$ and $EH_i^{rel}(t)$ is denoted as the expected and real value of EH value of node i at time slot t respectively, $\alpha \in (0,1)$ is the weight parameter. Thus the predicted EH of node i in timeslot t+1($EH_i^{Pre}(t+1)$) has been computed by changing $EH_i^{exp}(t+1)$ on energy acquisition. It is described as follows,

$$EH_i^{pre}(t+1) = \varphi_i(t) \times EH_i^{exp}(t+1) \quad (4)$$

Equation (5) can be used to calculate the revision factor of node i at t ($\varphi_i(t)$),

$$\varphi_i(t) = \frac{EH_i^{exp}(t)}{EH_i^{exp}(t)} \quad (5)$$

For cluster formation, data from this optimal energy model is employed.

3.3. SYSTEM MODEL

In order to select an initial CH for each cluster, CE must first partition the entire monitored area into a number of irregular clusters. The DT and CH selection (CHS) comprise the DCS. Data from the CM are gathered using the DT. In order to work sustainably in the EEHC, CM utilizes various sample rates due to the unsteady and unevenly gathered energy. Some related methods determine the CM sampling rate [20]. The CH continues to work in this stage by listening and receiving data. CH aggregates the received data and subsequently it sends the data to the sink at the final stage of every data reception phase. CHS is prompted to elect a new CH if RE of the present CH is lesser than the predetermined threshold.

3.3.1. Cluster Establishment (CE)

CE is used for the first clustering at this stage. Its major role is to choose a first CH for every cluster after splitting the EH-WSN into several irregular clusters. The sink sends a message $\mathrm{Partion}_{\mathrm{Cluster}}(\mathrm{dis}_{\max}, \mathrm{dis}_{\min})$ to the entire nodes for clustering after they have all been deployed. Since all deployed nodes are inside the sink transmission range, all nodes can receive $\mathrm{Partion}_{\mathrm{Cluster}}(\mathrm{dis}_{\max}, \mathrm{dis}_{\min})$. Then node i determines its distance from the sink based on the received RSSI_i signal. Subsequently, node i sends a message for clustering called $\mathrm{Cluster}(\mathrm{i}, \mathrm{dis}_{\mathrm{is}}, \mathrm{En}_{\mathrm{i}}, \mathrm{Ra}_{\mathrm{i}}^{\mathrm{C}})$, where $\mathrm{Ra}_{\mathrm{i}}^{\mathrm{C}}$ stands for node i competitive radius has been determined using the equation (1),

$$\mathrm{Ra}_{\mathrm{i}}^{\mathrm{C}} = \left(1 - \beta \frac{\mathrm{dis}_{\max} - \mathrm{dis}_{\mathrm{is}}}{\mathrm{dis}_{\max} - \mathrm{dis}_{\min}}\right) \mathrm{Ra}^{\mathrm{C}} \tag{6}$$

where $\mathrm{Ra}^{\mathrm{C}}$is the predetermined maximum competition range of each and every one the nodes, and $\beta \in (0\ \mathrm{to} 1)$ is a constant coefficient. The entire observed region is then divided into numerous uneven clusters using the recently described approach [10]. Clusters which are closer the sink is smaller than ones that are farther away. CH which is nearer the sink uses lesser energy for intra-cluster and inter-cluster data transmission [21]. Node i can learn the desired node density (des_i) in its area. Signal-to-Noise Ratio (SNR_i) is described as follows,

$$\mathrm{SNR}_{\mathrm{i}} = 10 \log_{10}\left(\frac{\mathrm{Pow}_{\mathrm{i}}^{\mathrm{signal}}}{\mathrm{Pow}_{\mathrm{i}}^{\mathrm{noise}}}\right) \tag{7}$$

where, $\mathrm{Pow}_{\mathrm{i}}^{\mathrm{signal}}$and $\mathrm{Pow}_{\mathrm{i}}^{\mathrm{noise}}$ is denoted as the effective signal and noise powers respectively. In order to begin the CH selection $CH_{Select()}$, the sink sends a message to each and every one of nodes in the cluster. The wait time $\mathrm{WTC}_{\mathrm{i}}^{\mathrm{m}}$ by cluster m is calculated by equation (8),

$$\mathrm{WTC}_{\mathrm{i}}^{\mathrm{m}} = a_1 \times \frac{\mathrm{En}_{\mathrm{i}}}{\mathrm{En}_{\mathrm{cap}}} + a_2 \times \frac{\mathrm{EH}_{\mathrm{i}}^{\mathrm{Pre}}(t+1)}{\max(\mathrm{EH}_{\mathrm{i}}^{\mathrm{Pre}})} + a_3 \times \frac{\mathrm{dis}_{\mathrm{is}}}{\mathrm{dis}_{\max}} + a_4 \times \frac{\mathrm{des}_{\mathrm{i}}}{\max(\mathrm{des})} + a_5 \times \frac{\mathrm{SNR}_{\mathrm{i}}}{\max(\mathrm{SNR})} \tag{8}$$

where a_1, a_2, a_3, a_4 and $a_5$and $a_1 + a_2 + a_3 + a_4 + a_5 = 1$are constant coefficients between 0 and 1. As can be seen from equation (1), a parameter that influences energy usage in WSN is distance. Node i operates in the listening mode and awaits the conclusion of its wait time after obtaining $\mathrm{WTC}_{\mathrm{i}}^{\mathrm{m}}$and starting the timer. When a CH win message$CH_{Win}(j, m)$received from one of its cluster neighbours, node i pauses its wait timer and switches to the role of a CM. Otherwise, at the conclusion of its wait time, it declares itself to be a CH. Additionally, it communicates with its neighbours in cluster m via $\mathrm{CH}_{\mathrm{Win}}(\mathrm{i}, \mathrm{m})$hemessage. Each CM node i uses the procedure [21] to create its sampling rate following receiving the CH win message, and it subsequently sends the sampling rate message $\mathrm{Sam}_{\mathrm{Rat}}(\mathrm{i}, \mathrm{j}, \mathrm{m})$to the CH node j in the similar cluster. Each CH also selects its data forwarding cycle depending on its RE, storage capacity, and the sampling rate of CM in the similar cluster.

3.3.2. Cluster Head Selection (CHS) by Gaussian Harris Hawks Optimizer (GHHO)

The Harris Hawks Optimizer (HHO) is used to simulate the behaviour of hawk team hunting and the prey fleeing in order to find the optimal CH solutions. In HHO, the best CH location is represented by the prey, and the hawks chasing behaviours serve as the search agent. CH is selected based on the parameters like energy, distance to neighbours, distance to BS, node density, and SNR). The HHO structure was modelled after the hunting strategy, surprise pounce, and prey exploration of Harris hawks.

Phase of exploration: The location of the hawks throughout the exploration phase allows for the best choice of CH. It depends on two different tactics. According to equation (9), the first approach describes how hawks locate prey based on the CH positions of the real members (X_i,i=1,2,…., N) (N is the total no. of hawks). According to equation (9), the second technique describes how hawks find prey when they assemble on a random tree (X_{rand})[22],

$$X_i(t+1) = \begin{cases} X_{rand}(t) - r_1 |X_{rand}(t) - 2r_2 X(t)|, & q \geq 0.5 \\ (X_{prey}(t) - X_m(t) - Y), & q < 0.5 \end{cases} \tag{9}$$

where $\mathrm{X_i(t+1)}$ stands for the updated position of the hawks in the subsequent iteration, t, as determined by the CH choice. Hawks current location in the CH selection is given byt. $\mathrm{X_{rand}(t)}$, whereas $\mathrm{r_1, r_2, r_3, r_4}$ is denoted as the random values inside the range of (0, 1). It has been generated using the Gaussian distribution function. It is believed that any evaluation of criteria will follow a normal distribution with an equal number of evaluations by mean value, but the Gaussian distribution is a bell-shaped curve. Here, the average value is taken by lower energy consumption, shorter distances, higher node density, and lower SNR. The position of the prey for the optimal choice of CH is indicated by the symbol $\mathrm{X_{prey}(t)}$Equation (10) [22] is used to express the average of the hawks' positions as $\mathrm{X_m(t)}$,

$$\mathrm{X_m(t)} = \frac{\sum_{i=1}^{N} \mathrm{X_i(t)}}{\mathrm{N}} \tag{10}$$

The variation among the upper and lower ranges of criteria are represented by the expression $\mathrm{Y = r_3(LB + r_4(UB - LB))}$. The prey Escape Energy (EE) is expressed in equation (11) [22],

$$\mathrm{EE} = 2\mathrm{En_0}\left(1 - \frac{\mathrm{t}}{\mathrm{T}}\right) \tag{11}$$

$\mathrm{En_0} \in (-1,1)$ is the initial energy of the prey [22].

Phase of exploitation: The main steps involve the hawks chasing tactics and the prey evasion techniques. It attempts to mimic the hawk surprise pounce behaviour (seven kills) on the investigated prey. Changing between chasing methods in HHO based on two criteria [22],

TABLE 1. PARAMETER DESCRIPTION OF GHHO ALGORITHM

Escaping energy (EE)	$\lvert EE \rvert \geq 0.5$ prey having sufficient energy $\lvert EE \rvert < 0.5$ prey not having sufficient energy
Chance of Escape r	$r \geq 0.5$. prey not effectively on the run (soft besiege) $r < 0.5$prey effectively on the run (hard besiege)

The proposed strategies are described in the sections,

Strategy 1(Soft Besiege)- In this strategy $|EE| \geq 0.5$ and $r \geq 0.5$. Because the energy of the prey is depleted while attempting to flee from the hawks, successful escape attempts are impossible. The model for this behaviour is presented in equations (12-13) [22],

$$X_i(t+1) = \Delta X(t) - EE|JX_{prey}(t) - X(t)| \tag{12}$$

$$\Delta X(t) = X_{prey}(t) - X(t) \tag{13}$$

where $\Delta X(t)$denotes the deviation between the rabbit CH position vector and the current location during iteration t. The prey fleeing method used by $J = 2(1 - r_5)$varied at random throughout each iteration. Inside of (0, 1), r_5 is denoted as a random number.

Strategy 2(Hard Besiege): In this strategy, 2 hard besieges occur $if\ |EE| < 0.5\ and\ r \geq 0.5$, indicating to the prey cannot effectively run away since it is exhausted. Equation (14) [22] provides the revised CH positions of hawks,

$$X(t+1) = X_{prey}(t) - EE|\Delta X(t)| \tag{14}$$

Strategy 3 (Soft Besiege By Progressive Rapid Dives): In updates hawks locations (CH) when the prey still have the strength to effectively run away $|EE| \geq 0.5$ and the hawks are still building a soft besiege $r < 0.5$. Levy flight (LF) is used to improve the development ability by equation (16) [22].

$$Y = X_{prey}(t) - EE|JX_{prey}(t) - X(t)| \tag{15}$$

$$Z = Y + S \times LF(D) \tag{16}$$

where D stands for the CH selection problem dimension. S is a random vector of length $1 \times D$. Levy flight is represented by LF in equation (17),

$$LF(X) = \frac{u \times \sigma}{|v|^{\frac{1}{\beta}}}, \sigma = \left(\frac{\Gamma(1+\beta) \times sin\left(\frac{\pi\beta}{2}\right)}{\Gamma\left(\frac{1+\beta}{2}\right) \times \beta \times 2^{\left(\frac{\beta-1}{2}\right)}}\right) \tag{17}$$

where random values between (0,1) are represented by $u\ and\ v$. B stands for a constant with the value 1.5. As a result, equation (18) updates the CH positions of hawks using a progressive rapid dive approach,

$$X(t+1) = \begin{cases} Y if F(Y) < F(X(t)) \\ Z if F(Z) < F(X(t)) \end{cases} \tag{18}$$

Equation (8) computes a fitness function called F for CH selection. Equations (15–16) are used in the calculation of $Y\ and\ Z$.

Strategy 4 (Hard Besiege by Progressive Rapid Dives): This tactic involves hawks building a strong besiege $r < 0.5$ and prey not having enough energy to escape $|EE| < 0.5$. Hawks are used to decrease average distance among their present location and the prey for optimal CH selection. According to the harsh besiege by equation (19),

$$X(t+1) = \begin{cases} Y if F(Y') < F\big(X(t)\big) \\ Z if F(Z') < F\big(X(t)\big) \end{cases} \tag{19}$$

Equation (20) is used to get Y′.

$$Y' = X_{prey}(t) - EE|JX_{prey}(t) - X_m(t)| \tag{20}$$

Equation (20) yields X_m(t)equation (21), yields Z′and so on.

$$Z' = Y' + S \times LF(D) \tag{21}$$

Algorithm 1 presents the overall steps of the GHHO algorithm.

ALGORITHM 1. PSEUDO-CODE OF GHHO ALGORITHM

INPUT: Number o nodes in the network N, t is the number of iteration, T is the maximum number of iterations
OUTPUT: Prey Location and its fitness value
Initialize ($\boldsymbol{X_i, i = 1, 2, \ldots, N}$)
While (t<T) **do**
Compute the fitness value of hawks by equation (8)
Set X_{prey} as the location of prey (best location)
FOR (each hawk (X_i)) do
    Update the initial energy En_0 and jump strength J
    $\boldsymbol{En_0} = 2rand() - 1, J = 2(1.rand())$
    Update the EE using equation (11)
if ($|EE| \geq 1$)**then**
    Location vector is updated by equation (9)
if ($|EE| < 1$)**then**
if ($r \geq 0.5$) and $|EE| \geq 0.5$) **then**
    Location vector is updated by equation (12)
else if ($r \geq 0.5$) and $|EE| < 0.5$) **then**
    Location vector is updated by equation (14)
else if ($r < 0.5$) and $|EE| \geq 0.5$) **then**
    Location vector is updated by equation (18)
else if ($r < 0.5$) and $|EE| < 0.5$) **then**
    Location vector is updated by equation (19)
RETURN $\boldsymbol{X_{prey}}$

GHHO algorithm is population-based method which has a number of benefits. Firstly, HHO is a technique that benefits from the time-varying elements. Secondly, HHO has an extendable exploration phase with the purpose of also reflects the average location of hawks for best CH selection in the inspiration part. Thirdly, different jump configurations with levy-triggered patterns throughout the exploitation phase (local search). Fourthly, expansion of the stochastically assisted search is expressed in the progressive selection scheme. To avoid local optima avoidance, the randomized jump strength is intelligently developed to increase the harmony of the global and local search. Gaussian distribution function has been used to tackle the problem since the worst CH selection could result from the use of random numbers.

3.3.3. Data Collection (DC)

Data Transmission (DT) and CH selection (CHS) are the two parts of this stage. Each CM in DT awakens during its designated working time slot and delivers the data it has gathered to the CH in the similar cluster. The CHS stage is activated to choose a new CH for this cluster if RE of the present CH is lesser than the predetermined threshold. In this stage, each cluster follows the same procedure. The CM sends the CH the data it has gathered during the DT phase. CH must continue to operate in a listening state to receive data from CM. Additionally CH accumulates the data it receives before periodically sending it to the sink. Multi-hop routing is used in cluster-based WSN to conserve energy for CH. For both CM and CH, a dynamic transmission power adjustment method is introduced to extend the effectiveness of the energy utilization. Energy usage of each CM i node is assured after data transmission between nodes.

4. RESULTS AND DISCUSSION

The MATLAB tool is used to implement the performance of the E^2-MACH, FUCHAR, HMBCR, NEHCP, and planned EEHC system. Table 2 describe the simulation parameters which have been used for implementation procedure [20]. The clustering methods are assessed using performance evaluation metrics like RE, PDR, PLR, Network Lifetime, and average delay

TABLE 2. PARAMETER SETTINGS OF WSN MODEL

Parameter	Values
Target Area	1000*1000 m^2
Location of BS	500*500 m^2
Number of nodes	1000
Initial Energy(En_o)	1J
Electronic circuit energy (En_{elec})	50 nJ/bit
ε_{fs}&ε_{mf}	100 pJ/bit/m^2
Bandwidth	25 kbps
Packet Size	4500 bits
Node deployment	Random
Antenna Direction	Omnidirectional

Residual Energy: At the conclusion of an experiment, the active set of nodes remaining energy is referred to as residual energy (RE).

Packet Delivery Ratio (PDR): PDR is described as the proportion of total packets delivered to total packets sent from source nodes to destination nodes. It has been expressed as follows,

$$\text{Packet Delivery Ratio (PDR)} = \frac{\sum \text{No. of packets Received by all destination node}}{\sum \text{Total Packets Send by all source node}} \tag{22}$$

Packet Loss Ratio (PLR): PLR is described as the proportion of total packets delivered to packets lost (not received at receiving node, such as a sink node or a CH node). It has been expressed as follows,

$$\text{Packet Loss Ratio (PLR)} = \frac{\sum \text{No. of packets lost}}{\sum \text{Total Packets Send by all source node}} \tag{23}$$

Network Lifetime (NL): The period of time until the first node in a network runs out of energy is referred to as the network lifetime. First Node Die (FND), Half Node Die (HND), and Last Node Die (LND) have been used to quantify network lifespan study.

First Node Die (FND): FND is referred to as the interval of time between the start of the network process and the death of the first node. It is also called as stability period. If node density is below 5, the region that was covered by the first node may stay exposed; however, if node density is high that area may be covered by a number of other nodes.

Half Node Die (HND): It is denoted as the time interval among the start of network process and death of 50% of the nodes of the network. Less no.of hops are accessible for communication up to sink node, less area purpose be enclosed and network performance causes rigorously.

Last Node Die (LND): When 10% of the nodes are still alive, the LND is said to have been reached. Since at this point, the network is unable to work correctly and the information exchange cannot be considered complete.

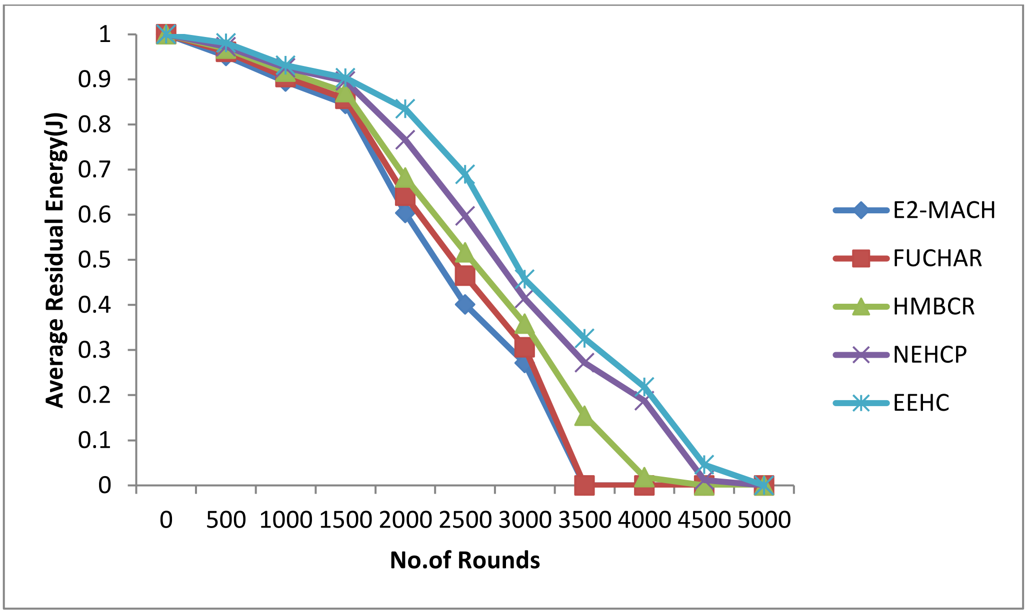

FIGURE 2. AVERAGE RESIDUAL ENERGY ANALYSIS VS. CLUSTERING METHODS

Figure 2 and Table 3 show the average residual energy comparison of clustering methods. From the results it shows that the proposed system has higher results achieved when compared to other methods. In 1000 no.of rounds, proposed system achieved higher results of 0.9317J, other methods like E2-MACH, FUCHAR, HMBCR, and NEHCP models have achieved reduced results of 0.8955J, 0.9048J, 0.9171J, and 0.9254J. Under 4000 no.of rounds, the proposed method attains an increased average RE of 0.2181J. Since the CH is selected using GHHO algorithm and makes use of multi-hop communication.

TABLE 3. RESIDUAL ENERGY ANALYSIS OF CLUSTER BASED ROUTING METHODS

No.of Rounds	Average Residual Energy (ARE) (J)				
	E^2-MACH	FUCHAR	HMBCR	NEHCP	EEHC
0	1.0000	1.0000	1.0000	1.0000	1.0000
500	0.9521	0.9615	0.9682	0.9728	0.9811
1000	0.8955	0.9048	0.9171	0.9254	0.9317
1500	0.8458	0.8571	0.8719	0.8965	0.9039
2000	0.6041	0.6418	0.6825	0.7659	0.8348
2500	0.4012	0.4646	0.5166	0.5972	0.6894
3000	0.2711	0.3062	0.3584	0.4147	0.4571
3500	0.0000	0.0000	0.1545	0.2719	0.3257
4000	0.0000	0.0000	0.0181	0.1878	0.2181

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4500	0.0000	0.0000	0.0000	0.0115	0.0457
5000	0.0000	0.0000	0.0000	0.0000	0.0000

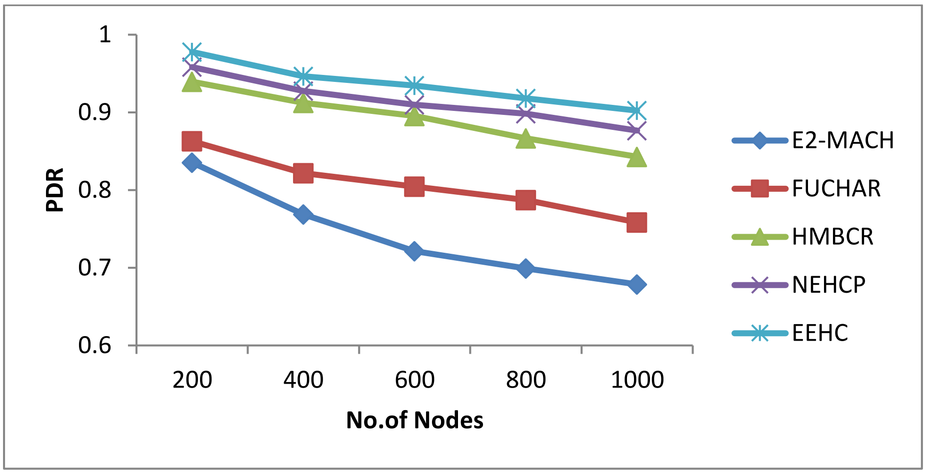


FIGURE 3. PDR COMPARISON ANALYSIS VS. CLUSTERING METHODS

PDR comparison of the proposed system and existing clustering methods are illustrated in Table 4 and Figure 3. It shows that the proposed system has higher PDR by changing the no. of nodes. In 200 nodes, the proposed system shows higher PDR of 0.9778, whereas the E^2-MACH, FUCHAR, HMBCR, and NEHCP methods have confirmed a lower PDR of 0.8355, 0.8629, 0.9395, and 0.9583, respectively. In 1000 nodes, the proposed system has attained increased PDR of 0.9023, other methods like E^2-MACH, FUCHAR, HMBCR, and NEHCP gives the lower results of 0.6786, 0.7584, 0.8429, and 0.8765 correspondingly.

TABLE 4. PDR COMPARISON OF CLUSTER BASED ROUTING METHODS

No.of Nodes	PDR				
	E^2-MACH	FUCHAR	HMBCR	NEHCP	EEHC
200	0.8355	0.8629	0.9395	0.9583	0.9778
400	0.7688	0.8219	0.9122	0.9277	0.9465
600	0.7214	0.8047	0.8955	0.9098	0.9344
800	0.6992	0.7871	0.8668	0.8985	0.9182
1000	0.6786	0.7584	0.8429	0.8766	0.9023

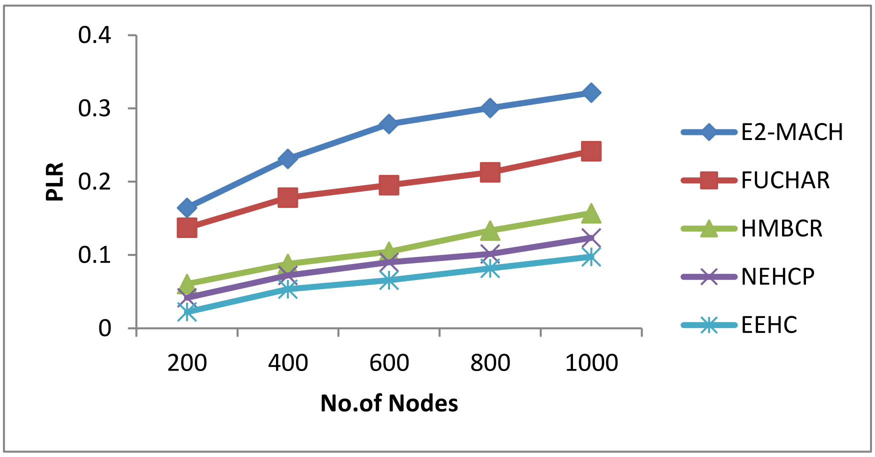
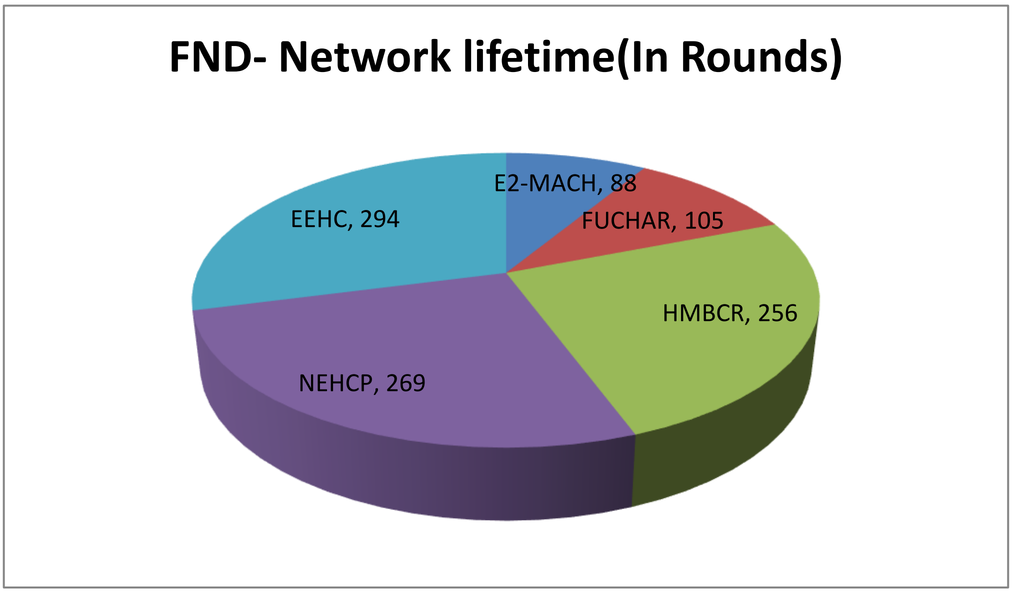


FIGURE 4. PLR COMPARISON VS. CLUSTERING METHODS

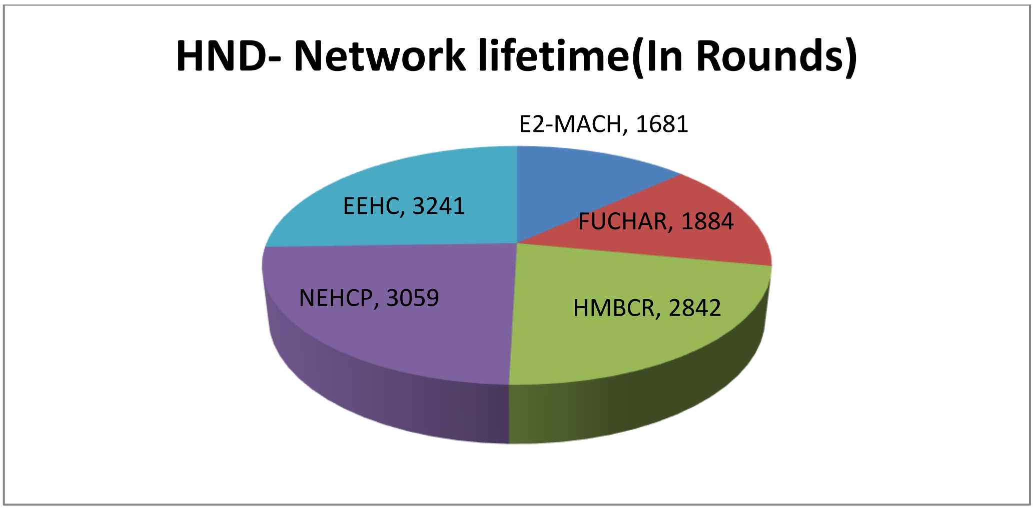
Table 5 shows the performance comparison of PLR among proposed system with existing methods. Figure 4 show that the proposed system has lesser PLR by the proposed technique by changing no.of nodes. For PLR achieved by the proposed system is 0.0222, whereas a PLR of 0.1645, 0.1371, 0.0605, and 0.0417 is achieved by the E^2-MACH, FUCHAR, HMBCR, and NEHCP methods (200 nodes). For 1000 no.of nodes, a minimum PLR of 0.0977 is achieved by the proposed model, higher PLR of 0.3214, 0.2416, 0.1571, and 0.1234 is produced by the E^2-MACH, FUCHAR, HMBCR, and NEHCP methods.

TABLE 5. PLR COMPARISON OF CLUSTER BASED ROUTING METHODS

No.of Nodes	PLR				
	E^2-MACH	FUCHAR	HMBCR	NEHCP	EEHC
200	0.1645	0.1371	0.0605	0.0417	0.0222
400	0.2312	0.1781	0.0878	0.0723	0.0535
600	0.2786	0.1953	0.1045	0.0902	0.0656
800	0.3008	0.2129	0.1332	0.1015	0.0818
1000	0.3214	0.2416	0.1571	0.1234	0.0977



(A) FND comparison vs. cluster based routing methods



(B) **HND comparison vs. cluster based routing methods**

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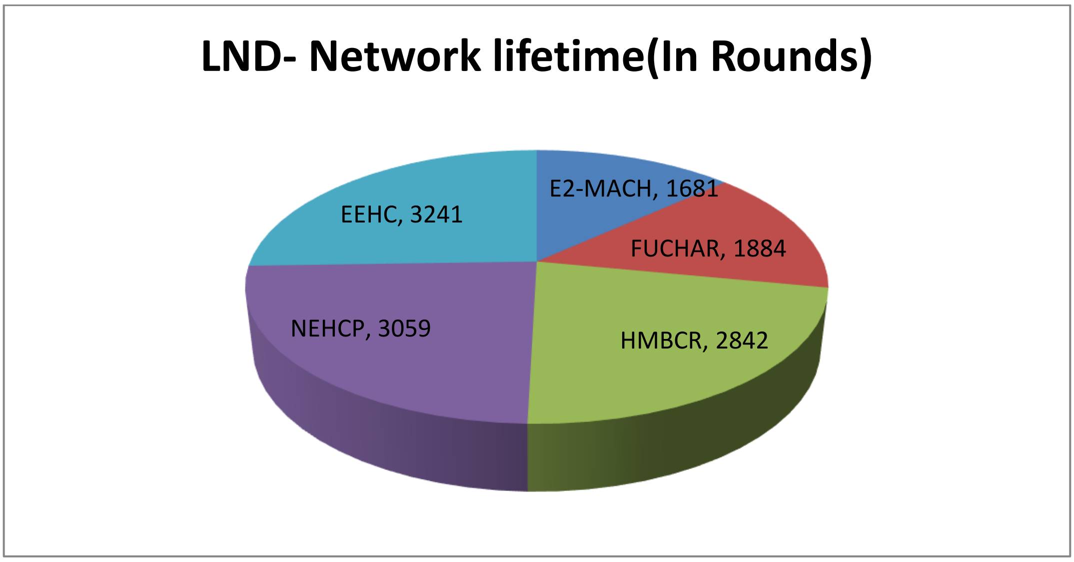

(C) **LND comparison vs. cluster based routing methods**

FIGURE 5. NETWORK LIFETIME COMPARISON VS. CLUSTERING METHODS

Table 6 and Figure 5 show the network lifetime comparison of the proposed system by FND, HND, and LND. Extended the network lifetime of 294 rounds is attained by proposed system, whereas the E^2-MACH, FUCHAR, HMBCR, and NEHCP methods have produced lesser FND of 88, 105, 256, and 269 rounds, respectively. In HND, the results obtained by the proposed system with 3241 rounds, E^2-MACH, FUCHAR, HMBCR, and NEHCP methods had lesser rounds of 1681, 1884, 2842, and 3059 respectively.

TABLE 6. NETWORK LIFETIME COMPARISON OF CLUSTER BASED ROUTING METHODS

Measures	Network lifetime(rounds)				
	E^2-MACH	FUCHAR	HMBCR	NEHCP	EEHC
FND	88	105	256	269	294
HND	1681	1884	2842	3059	3241
LND	3582	3158	4928	5147	5369

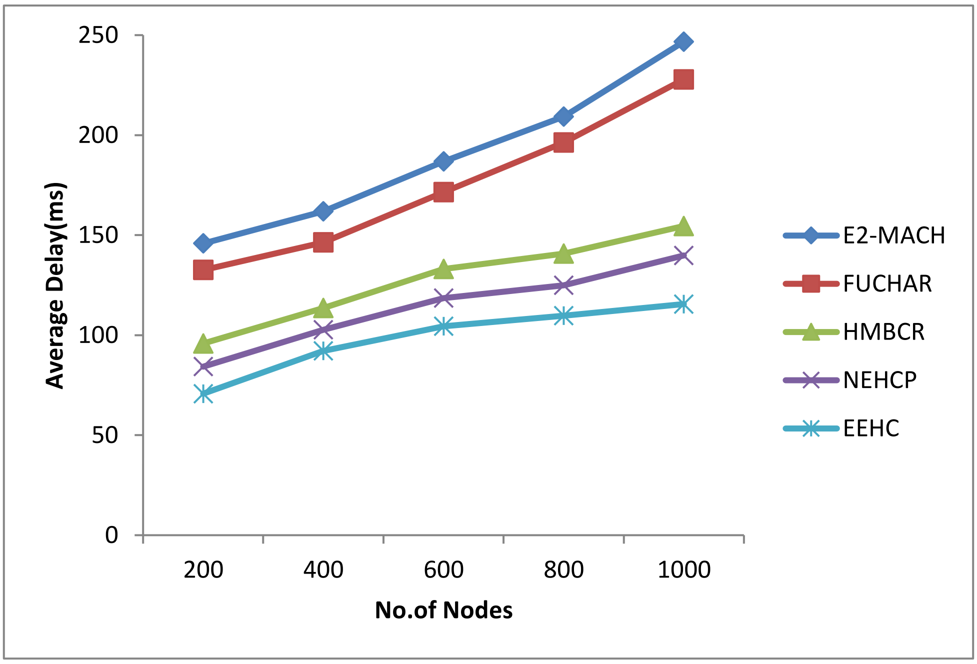

FIGURE 6. AVERAGE DELAY ANALYSIS VS. CLUSTERING METHODS

TABLE 7. AVERAGE DELAY COMPARISON OF CLUSTER BASED ROUTING METHODS

No.of Nodes	Average Delay (ms)				
	E^2-MACH	FUCHAR	HMBCR	NEHCP	EEHC
200	145.81	132.55	95.84	84.25	70.74
400	161.94	146.38	113.50	102.71	92.18
600	186.77	171.55	133.12	118.47	104.45
800	209.19	196.21	140.82	124.94	109.72
1000	246.74	227.88	154.57	139.85	115.55

Table 7 and Figure 6 show the average delay comparison of the proposed EEHC system with existing methods. Minimum average delay of 70.74 ms is required by the proposed system, whereas a higher average delay of 145.81 ms, 132.55 ms, 95.84 ms, and 84.25 ms is required by the E^2-MACH, FUCHAR, HMBCR, and NEHCP for 200 no.of nodes. For1000 nodes, the least average delay of 115.55 ms by the proposed model, while a increased average delay of 246.74 ms, 227.88 ms, 154.57 ms, and 139.85ms is required by the E^2-MACH, FUCHAR, HMBCR, and NEHCP methods.

5. CONCLUSION AND FUTURE WORK

In this paper, Enhanced Energy Harvesting Clustering (EEHC) system has been introduced for energy harvesting aware WSN. It offered balanced energy harvesting and distribution during the cluster creation and data transmission stages. CH is elected by the Gaussian Harris Hawks Optimizer (GHHO) during the cluster building phase. Hawks chasing behaviours serve as the search agent in the GHHO algorithm, while prey serves as the ideal CH position. Since the HHO algorithm random number generation could lead to poor CH selection, the problem has been resolved by employing the Gaussian distribution function. Data from each cluster node is collected by CHS, which then sends the aggregated data to the BS. Following CHS, linking CM to the appropriate CH for data transmission occurs. The CM sends the CH the data it has gathered during the DT phase. CH must continue to operate in a listening state to receive data from CM. Additionally, CH accumulates the data it receives before periodically sending it to the sink. The experimental results are measured in terms of RE, PDR, PLR, network lifetime, and average delay, it shows that the proposed system performs better when compared to other methods. HND, whereas the results from the proposed system were acquired after 3241 rounds, those from the E^2-MACH, FUCHAR, HMBCR, and NEHCP approaches were obtained after 1681, 1884, 2842, and 3059 rounds respectively. In order to save energy, data aggregation has been joined with the EEHC protocol in future development.

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