International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

Fuzzy Election based Optimization Algorithm (FEBOA) And Energy Harvesting Possibilistic FUZZYC-Means (EHFPCM) Clustering for EH-WSN

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

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

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

Abstract: Wireless Sensor Network (WSN) includes of many nodes by restricted energy resources. Energy efficiency and harvested energy are major important issues in the WSN. Studies recently conducted have demonstrated that clustering is an effective way to increase energy efficiency. Energy Harvesting- Wireless Sensor Network (EH-WSN) is a flexible strategy for even clustering and Cluster Head (CH) selection is helpful to maximize network constancy and energy efficiency. In this paper, Energy Harvesting Possibilistic Fuzzy C-Means (EHFPCM) clustering is introduced to improve harvested energy usage by maintaining the consistency, connectivity, and balancing of harvested energy consumption in EH-WSN. It is based on Data Transmission (DT) and Cluster Establishment (CE). During CE, PFCM clustering is introduced for cluster formation. PFCM clustering divides the network into clusters. Each area forms a group and chooses one or more CH based on the multi-criteria like energy, distance to neighbors, distance to the Base Station (BS), and network load. In a cluster, the Fuzzy Election Based Optimization Algorithm (FEBOA) selects the CH according to the multi-criteria. It desires to receive packets from Cluster Member (CM), aggregate the received packets, and subsequently forward it to DT. DT, every CM wakes up during its designated working time and transmits the data it has gathered to the CH in the cluster. Lastly, measures such as Residual Energy (RE), Packet Delivery Ratio (PDR), Packet Loss Ratio (PLR), energy consumption, and average delay for transmission are used to measure the results of routing protocols.

Keywords: Clustering, Cluster Head Selection (CHS), Energy Harvesting Possibilistic Fuzzy C-Means (EHFPCM), Fuzzy Election Based Optimization Algorithm (FEBOA), and data transmission.

1. INTRODUCTION

Wireless Sensor Network (WSN) is the essential data acquisition mechanism of the internet of things [1], [2]. In WSN, sensor nodes are usually battery-powered. Energy efficiency has emerged as a crucial concern for WSN because of the limited amount of energy that batteries are able to store and the difficulty associated with replacing them [3]. Cluster-based routing schemes have been focused to extend the lifetime of WSN [4]. A sink node and a specific number of clusters are the typical components of a Clustered Wireless Sensor Network (CWSN) [5-6]. A CH and CM nodes are present in every cluster. Data from the CM must be received by the CH, who must then aggregate it before sending it to the sink. As a result, CM utilizes a smaller amount of energy than CH. CH in a cluster is chosen at random in order to maintain stability in the energy utilization of the nodes. Nonetheless, sensor battery energy exhaustion is probable as long as the battery capacity is limited.

In order to reduce energy constraints, EH technology was recently introduced into WSN [7]. EH is the method of effectively obtaining energy from external renewable energy sources and storing it for use in a variety of application systems such as wearable electronic WSN systems. Nodes in an EH-WSN don't fail for lack of energy as extensive energy consumption is lower than harvested energy [8]. However, because of the uneven and unpredictable amount of energy that can be gathered from the ambient settings, EH-WSN still face diverse additional design issues even though they operate by collecting energy from sensor nodes and are theoretically unaffected to network lifetime limitations. The idea of EH leads to reducing regular cost drastically, since once the infrastructure has been established, it is able to generate electricity by negligible cost from open obtainable renewable sources. EH is an unmanageable and dynamic external source. Many cluster-based protocols have been developed recently for EH-WSN [9, 10]. Nevertheless, in these protocols, the DT techniques are designed without taking into account the gathered energy usage efficiency. Additionally, a new CH selection approach is used in EH-WSN performance by consuming a significant amount of energy. Figure 1 shows the process of EH in WSN.

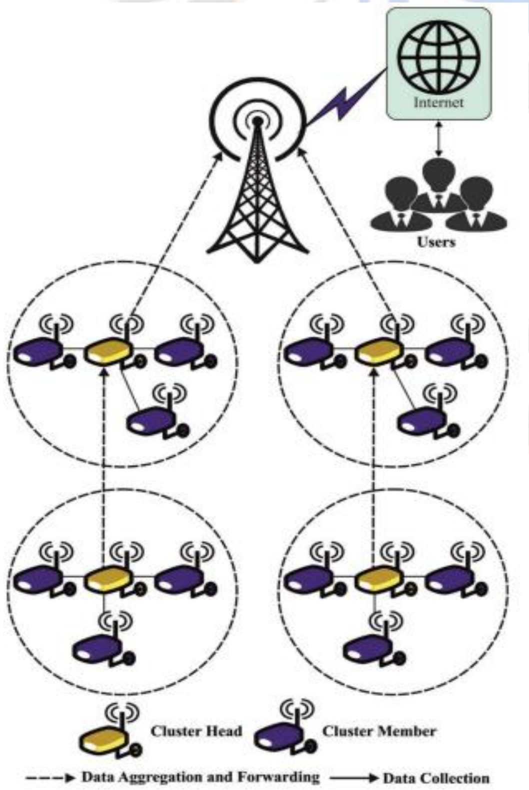


FIGURE 1. ENERGY HARVESTING IN WSN

However cluster-based routing protocols with a focus on swarm intelligence and nature inspired has greater potential for preserving the energy stability of sensor nodes across longer network lifetime [11]. On the other hand, analyzing the theoretical logic and mathematical computation related to the clustering-based routing method turned out to be a Nondeterministic Polynomial time (NP) hard optimization problem. Furthermore, swarm-intelligence algorithms' capacity to identify an optimal or nearly optimal solution opened the way for the development of prospective routing algorithms that choose the best CH in a network by remarkable a better balance between exploration and utilization of the network space. During the CH selection process, these swarm-intelligent routing algorithms include the factors like node density, node location, and RE of sensor nodes for balancing the energy consumption in the network. But these routing algorithms execute well in each exploration/exploitation. Many NP-hard problems have been successfully solved with metaheuristic algorithms.

For maintaining energy consistency and enhancing the lifespan of network durability, this study proposes the Energy Harvesting Possibilistic Fuzzy C-Means (EHFPCM) clustering, and Fuzzy Election Based Optimization Algorithm (FEBOA). Steps like CH selection and clustering process has been focused by this study. Particularly, from the deployed collection of sensor nodes in the network, FEBOA chooses an ideal CH by optimizing the energy, distance to neighbors, distance to the BS, and network load. The evaluation metrics of RE, PDR, PLR, Energy Utilization, and average transmission delay under CH selection and network clustering are used to measure the experiments. It is confirmed its effectiveness when compared to other schemes for experimentation analysis.

2. LITERATURE REVIEW

Haq et al. [12] suggested an innovative protocol that addresses communication reliability and energy efficiency. It is called the energy-efficient multi-attribute-based clustering technique (E^2-MACH). It employs selection criteria for a trustworthy CH that are based on a weighted function specified by several characteristics, including neighbourhood density, link statistics, current RE, and node energy harvesting rate. When choosing a CH, taking these factors into account helps to ensure that data is sent over links with a higher signal-to-noise ratio, which minimises packet loss and preserves node energy consumption. IoT applications, the reduced PLR helps to improve network throughput, energy utilization, and network lifetime.

Arjunan and Sujatha [13] suggested a hybrid routing scheme called FUCARH, which combines ant colony optimisation with fuzzy logic to increase network longevity. Ant Colony Optimisation methods from CH to BS and Fuzzy Logic (FL) for CH selection carry out the inter-cluster routing operation. 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 balanced load distribution.

Sah and Amgoth [14] proposed a Novel Energy Harvesting Clustering Protocol (NEHCP). It makes advantage of solar EH is the foundation of the NEHCP. Information gathered from the sensor nodes are transmitted over the CH to the BS. The first phase, setup phase, and data transmission phase are the three divisions of the NEHCP algorithm. Furthermore, EH-WSN different aspect ability is used to produce more effective network lifespan results. EH-WSN network efficiency is increased and its ability to balance energy usage is demonstrated by the results.

Hao et al. [15] proposed an energy evaluation model that determines the energy state of a node by taking into account all relevant energy harvesting, energy consumption, and energy classification parameters. A system for adjusting the reception significance is devised by combining these two models. It modifies the data reception state of nodes by considering the Medium Access Control (MAC) layer protocol and buffer occupancy. Analyse the introduced algorithm accuracy and computational complexity as well. Lastly, simulation experiments are carried out to demonstrate that the proposed algorithm achieves acceptable performance in energy variance and optimal performance in energy efficiency, PDR, average hop count, and end-to-end (E2E) delay.

Mansura et al. [16] proposed the EH-WSN uses the Energy Balanced and Nodes Aware (EBNA) routing protocol. When choosing the CH, which increases throughput, it takes into account the amount of energy that has been harvested as well as the amount of energy is still available. The weightages of the energy are also examined. The Objective Modular NEtworkTestbed (OMNET) network simulator GreenCastalia is used to assess EBNA. The effectiveness is contrasted with the Clustering Routing Algorithm of Self-energized (CRAS) for EH-WSN and Energy-Aware Distributed Clustering (EADC). EBNA works better than other methods in terms of throughput, the number of CH, and delay.

Roberts and Ramasamy [17] proposed by overcoming obstacles in the CH selection process, the Golden Eagle Optimisation Algorithm (GEOA) and Improved Grasshopper Optimisation Algorithm (IGHOA), which are based on the energy-efficient cluster-based routing protocol, may retain energy stability and increase network lifetime longevity. Specifically, GEOA chooses an ideal CH from the deployed group of sensor nodes in the network by optimising the centrality of node, degree of node, distance to the BS& neighbours, and RE. In addition, IGHOA is used to evaluate factors in order to find a dependable and ideal path among the CH & BS. GEIGOA may effectively increase the likelihood of keeping the worst nodes from being selected as CH while by a varied number of sensor nodes.

Han et al. [18] proposed a distributed modification of the data transmission based adaptive Hierarchical-Clustering routing protocol for EH-WSN (HCEH-UC) to ensure continuous coverage of the target region. First, HC routing protocol is introduced to the stability among energy consumption of nodes. The number of nodes in the EH mode is then adaptively controlled through a distributed rotation of working modes, which may result in constant target coverage. HCEH-UC protocol can provide uninterrupted target coverage and increased network lifetime coverage when compared to the other methods.

Wan and Chen [19] proposed a sensible technique for relay selection in energy collection wireless sensor networks. The relay nodes taking part in cooperative transmission are then regulated to conserve cooperative transmission energy in the system, and the cooperation probability is optimised by the interruption probability threshold portion as the constraint. A multi-criteria relay selection technique is used to choose the best node based on the several criteria like solar energy status, network energy stability, Signal-to-Noise Ratio (SNR), and outage likelihood of the relay node. The sensible technique works better than the other methods.

Han et al. [20] proposed Clustering Protocol for Energy Harvesting (CPEH) protocol. When forming clusters and facilitating intercluster communication, CPEH takes into account the variety of sensors capacities for energy collection. Ant Colony Optimisation (ACO) is used to find an extremely effective intercluster routing between the CH and the BS. Cluster Head Relay (CHR) technique is presented to enable the appropriate cluster member to perform the CH in energy depletion. In addition to successfully resolving the cluster dormancy issue, CPEH may effectively increase the network performance and PDR

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

when compared to other methods. CHR approach can effectively keep the cluster operating regularly.

Huamei et al. [21] proposed an Improved Shuffled Frog Leaping Algorithm (ISFLA)-based Energy-Efficient Non-Uniform Clustering Routing (E2NUCR) protocol. The CH node nearer the sink uses significantly less energy, while the network's overall energy consumption is constant. The protocol iterates node performance and chooses the best CH by using the fitness function and sub-cluster elite individual updating technique. It is employed to extend network lifetime, minimise energy gaps, and balance the energy of network nodes. The E2NUCR protocol is used to simplify the algorithm and speed up its rate of convergence.

3. PROPOSED METHODOLOGY

In this paper, Energy Harvesting Possibilistic Fuzzy C-Means (EHFPCM) clustering protocol is proposed by two steps like cluster formation and DT. Initially, sensor nodes are clustered during cluster formation stage, and then data is transmitted from source to destination using data transmission. Clusters are formed by Possibilistic Fuzzy C-Means (PFCM). Then CH is elected between the clusters using Fuzzy Election Based Optimization Algorithm (FEBOA). Once the CH is selected then data is collected from each cluster node, and then it forwards the aggregated data to the BS during data transmission. Finally the results of the routing protocols are evaluated using evaluation metrics.

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 subsequently 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 $\mathrm{ID_i}(1 \leq \mathrm{i} \leq \mathrm{N})$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 depending on distance involving the receiver and transmitter 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 $\mathrm{En_{cap}}$ are the same for all of them. Node i remaining energy is denoted by the symbol $\mathrm{En_i}$. $\mathrm{En_0}$ 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 & j is indicated as$\mathrm{dis_{ij}}$. The energy used to transport k-bit data from node i to j is as follows,

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

$\mathrm{En_{elec}}$ 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 $\mathrm{En_{tx}}$and $\mathrm{En_{rx}}$. It is described as follows,

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

where the propagation loss coefficients are $\varepsilon_{\mathrm{fs}}$ and $\varepsilon_{\mathrm{mf}}$.The transmission distance $\mathrm{dis_{ij}}$ and a predetermined threshold, $\mathrm{dis_0} = \sqrt{\frac{\varepsilon_{\mathrm{fs}}}{\varepsilon_{\mathrm{mf}}}}$, n=2 if $\mathrm{dis_{ij}} < dis_0$ and n=4 determine the value of n, with n=2 if $\mathrm{dis_{ij}}\mathrm{dis_0}$and n=4 in all other cases [14]. Expected value of the node i harvested energy at time slot t+1($\mathrm{EH_i^{exp}}(\mathrm{t}+1)$) . It is described as follows,

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

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

$$\mathrm{EH_i^{pre}}(\mathrm{t}+1) = \varphi_\mathrm{i}(\mathrm{t}) \times \mathrm{EH_i^{exp}}(\mathrm{t}+1) \tag{4}$$

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

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

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 EHFPCM, CM utilizes various sample rates due to the unsteady and unevenly gathered energy. Some related methods determine the CM sampling rate [13]. The CH continues to work in this stage by listening and receiving data. CH aggregates the received data and subsequently it sends the data towards 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.

3.4. Cluster Establishment (CE) by Possibilistic Fuzzy C-Means Clustering Algorithm (PFCM)

CE is used to choose first cluster at this stage. Its major role is to choose a first CH for every cluster after splitting the EH-WSN into several irregular clusters. When every node has been deployed, the sink sends a message to all of them for clustering, called Partion_Cluster (dis_{max}, dis_{min}). Subsequently, node i uses the $RSSI_i$ signal to calculate its distance from the sink. Node i then transmits a message for Cluster $\left(i, dis_{is}, En_i, Ra_i^C\right)$, Ra_i^C competitive radius for node i by the equation (6),

$$Ra_i^C = \left(1 - \beta \frac{dis_{max} - dis_{is}}{dis_{max} - dis_{min}}\right) Ra^C \tag{6}$$

where Ra^C is is the predetermined maximum competition range of each and every one the nodes, and $\beta \in (0,1)$ is a constant coefficient. The entire observed region is then divided into numerous uneven clusters using the recently described approach [22]. Node i can learn the desired node density (des_i) in its area. Signal-to-Noise Ratio (SNR_i) is described as follows [23],

$$SNR_i = 10 \log_{10} \left(\frac{Pow_i^{signal}}{Pow_i^{noise}} \right) \tag{7}$$

where, Pow_i^{signal} and Pow_i^{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 WTC_i^m by cluster m is calculated by equation (8),

$$WTC_i^m = a_1 \times \frac{En_i}{En_{cap}} + a_2 \times \frac{EH_i^{Pre}(t+1)}{\max(EH_i^{Pre})} + a_3 \times \frac{dis_{is}}{dis_{max}} + a_4 \times \frac{des_i}{\max(des)} + a_5 \times \frac{SNR_i}{\max(SNR)} \tag{8}$$

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. After receiving WTC_i^m and initiating the timer, Node i runs in the listening mode and waits for its wait time to end. 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 $CH_{Win}(i,m)$. After receiving the CH win message, each CM node i creates its sampling rate using the process [23]. It then transmits the sampling rate message Sam_Rat (i,j,m) to the CH node j in the cluster. Additionally, based on its RE, storage capacity, and the cluster's CM sampling rate, each CH chooses its data forwarding cycle.

Possibilistic Fuzzy C-Means Clustering Algorithm (PFCM) is used to form number of clusters in the WSN model. PFCM is worked based on 2 types of memberships: 1) A possibilistic membership which computes the complete degree of typicality of a node in every cluster, and 2) a fuzzy membership which computes the relative degree of sharing of a node between the clusters. PFCM is built as follows,

$$J_{m,\eta}(U,T,V,X,\beta) = \sum_{i=1}^{c} \sum_{k=1}^{n} (\mu_{ik}^m + \tau_{ik}^\eta) ||v_i - x_k||^2 + \sum_{i=1}^{c} \beta_i \sum_{k=1}^{n} (1 - \tau_{ik})^\eta \tag{9}$$

Subject to the constraints,

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

$$m > 1, \eta > 1;\ 0 \leq \mu_{ik}, \tau_{ik} \leq 1; \sum_{i=1}^{c} \mu_{ik} = 1; \sum_{k=1}^{n} \tau_{ik} = 1 \tag{10}$$

where n is denoted as no. of nodes in a given EH-WSN model, c is denoted as the no. of clusters, X is denoted as the parameter to read the value of nodes presented in the EH-WSN model, V is denoted the CH of the clusters, U is a fuzzy partition matrix, T is a typicality partition matrix, $m\&\eta$ is the weighting parameter for U and T, β_i is user defined constants. $J_{m,\eta}$ is used to define the relative value of $U\&T$. The matching CH of the clusters and membership degree to every respective node for cluster creation is specified by equations (11-13), which give an iterative process. It is used to get better a series of fuzzy clusters until no further development in $J_{m,\eta}$ be able to be attained.

$$v_i = \frac{\sum_{k=1}^{n}(\mu_{ik}^{m} + \tau_{ik}^{n})x_i}{\sum_{k=1}^{n}(\mu_{ik}^{m} + \tau_{ik}^{n})} \tag{11}$$

$$\mu_{ik} = 1 / \sum_{j=1}^{c} \left(\frac{||v_i - x_k||}{|v_j - x_k||} \right)^{2/(m-1)} \tag{12}$$

$$\tau_{ik} = 1 / \left(1 + (\frac{1}{\beta_i} ||v_i - x_k||)^{1/(\eta-1)} \right) \tag{13}$$

Equations (11-13) are an iterative optimization procedure for CE in WSN model until no further improvement in $J_{m,\eta}$ can be made. PFCM based CE algorithm in algorithm 1 consists of the subsequent steps,

ALGORITHM 1: PFCM BASED CE ALGORITHM

1. Start
2. Given a preselected no. of clusters c and $m\&\eta$ values are chosen
3. Initialize U and T by constraint in 2
4. Choose CH of the fuzzy cluster, v_i for $i = 1, 2, \dots, c$ using equation (11)
5. Equation (12) is used to update U matrix
6. Equation (13) is used to update T matrix
7. if $Max(|\mu_{ik}^{(t+1)} - \mu_{ik}^{(t)}|)$ is lower than a definite threshold (ϵ)
8. Stop;
9. Otherwise go to step 3
10. End

3.5. Cluster Head Selection (CHS) by Fuzzy Election Based Optimization Algorithm (FEBOA)

Fuzzy Election-Based Optimization Algorithm (FEBOA) is proposed for CHS. CH is selected based on the factors like energy, distance to neighbours, distance to BS, node density, and SNR.

Inspiration: The members of a cluster choose a CH from between the nodes is called an election. All nodes in the EH-WSN model (society) are impacted by the CH chosen as leader, even those who did not vote for him. The ability of the nodes in the EH-WSN to select and vote for the superior candidate will increase with their level of awareness. The FEBOA design incorporates these expressed ideas regarding elections and voting.

Initialization: The nodes of the population-based metaheuristic algorithm FEBOA are members of the community. Each individual in the population represents a potential CH election result in the FEBOA. Equation (14), that represents a population matrix in the population of FEBOA.

$$X = \begin{bmatrix} X_1 \\ \vdots \\ X_i \\ \vdots \\ X_N \end{bmatrix} = \begin{bmatrix} x_{1.1} \dots x_{1,j} \dots x_{1,m} \\ \vdots \ \ddots \ \vdots \ \iddots \ \vdots \\ x_{i.1} \cdots x_{i,j} \cdots x_{i,m} \\ \vdots \ \iddots \ \vdots \ \ddots \ \vdots \\ x_{N.1} \cdots x_{N,j} \cdots x_{N,m} \end{bmatrix}_{N \times m} \tag{14}$$

where X is denoted as the population matrix, X_i is denoted as the i^th^ FEBOA member, $x_{i,j}$ is represented as the value of the j^{th} preferred CH individual by the i^th^ node(member), N is denoted as the population size of FEBOA i.e.no. of nodes in the WSN model, and m is denoted as the no. of selected CH in the EH-WSN. The initial position of nodes is randomly selected by equation (15)in the search space,

$$x_{i,j=lb_j} + r.\left(ub_j - lb_j\right), i = 1,2,\dots,N, j = 1,2,\dots,m \tag{15}$$

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

where lb_j and ub_j is represented as the lower bound and upper bound of the j^{th} CH correspondingly, and $r \in [0,1]$ is represented as a random number using the fuzzy function. FEBOA, member for the CH selection, fitness value has been evaluated using the objective function. It has been generated as vector (OF) using equation (16),

$$OF = \begin{bmatrix} OF_1 \\ \vdots \\ OF_I \\ \vdots \\ OF_N \end{bmatrix}_{N\times 1} = \begin{bmatrix} OF(X_1) \\ \vdots \\ OF(X_i) \\ \vdots \\ OF(X_N) \end{bmatrix}_{N\times 1} \quad (16)$$

where the vector of the objective function in the population is indicated by OF, and OF_i refers to the attained objective function for the i^{th} FEBOA member (node). Based on parameters like energy, distance to neighbors, distance to BS, node density, and SNR, the best value of the OF identifies the best node is selected as CH, and the worst significance of the OF identifies the nodes are not selected as CH. The method that updates population members and refines suggested solutions with each iteration is the primary distinction amongst metaheuristic approaches. The two stages of exploration and exploitation that make up the FEBOA algorithm population update process are discussed below.

Phase 1: Voting process and holding elections (exploration)

FEBOA members cast their votes for one of the candidates (nodes) in the election based on their level of awareness. Equation (17) is used to replicate CH awareness in the EH-WSN. The best CH in the EH-WSN throughout this awareness simulation procedure is those with higher OF values.

$$A_i = \begin{cases} \dfrac{OF_i - OF_{worst}}{OF_{best} - OF_{worst}}, & OF_{best} \neq OF_{worst}; \\ 1, & else, \end{cases} \quad (17)$$

where A_i is denoted as the awareness of the i^{th} member, OF_{best} and OF_{worst} are the best and worst values. OF_{best} is associated to the lowest value of the OF for energy, distance, and SNR and OF_{worst} is related to the worst with lower node density. Among the members, approximately 10% of the individuals are considered as CH election candidates. Voting is based on each node awareness level in relation to a random number r, A node can vote for the best CH (C_1) if its awareness level is greater than r.Else, it is considered as CM. Voting procedure is modeled by equation (18),

$$V_i = \begin{cases} C_1, & A_i > r; \\ C_k, & else, \end{cases} \quad (18)$$

where V_i is denoted as the vote of the i^{th} node in the EH-WSN, and C_k is denoted as the k^{th} candidate, where k isa randomly chosen from the set $\{2,3,\ldots,N_C\}$. When the voting process reaches its conclusion, the node with the most number of votes is chosen as the winner and it is known to as the CH. Every EH-WSN node, including those who did not vote for him, is impacted by CH. The chosen CH has control over and guidance over the updating of node positions in the EBOA. In the clustering process, this CH directs the algorithm population toward various members and improves the global search exploration capability. The CH monitors the procedure of updating the FEBOA population that generates a new node position for every member. This update procedure in the EBOA is formulated by equations (19-20),

$$x_{i,j}^{new,P1} = \begin{cases} x_{i,j} + r.\left(L_j - I.x_{i,j}\right), & OF_L < OF_i; \\ x_{i,j} + r.\left(x_{i,j} - L_j\right), & else, \end{cases} \quad (19)$$

$$X_i = \begin{cases} X_i^{new.P1}, & OF_i^{new,P1} < OF_i \\ X_i, & else \end{cases} \quad (20)$$

where $X_i^{new.P1}$ is denoted as the new position for the i^{th} EBOA member, $x_{i,j}^{new,P1}$ is its j^{th} dimension, $OF_i^{new,P1}$ is its value of the OF, I is an integer randomly chosen from the 1 or 2, L is denoted as the selected leader, L_j is denoted as the j^{th} CH, and OF_L is its objective function.

Phase 2: Public movement to raise awareness (exploitation)

From a mathematical perspective, a local search next to CH solution might reveal a superior solution. As a result, nodes efforts to become more aware in the EH-WSN model enhance their capacity to leverage FEBOA in local searches and locate better CH. In order to repeat this local search process, a random node position is taken into consideration near each member in the search space of CH. In order to determine whether this new leader is superior to the cluster current leader, Based on this new leader, the OF for CH selection is then evaluated. If there is a better value for the aim function at the new node position, the local search is successful and the suitable member node position is updated. A higher objective function value will raise that node awareness of the need for better CH in the upcoming election. The FEBOA model is derived from equations (21–22).

$$x_{i,j}^{new,P2} = x_{i,j} + (1-2r).R.\left(1-\frac{t}{T}\right).x_{i,j} \quad (21)$$

$$X_i = \begin{cases} X_i^{new,P2}, OF_i^{new,P2} < OF_i; \\ X_i, else, \end{cases} \quad (22)$$

where $X_i^{new,P2}$ refers to a new generated position for the i[th] FEBOA member, $X_{i,j}^{new,P2}$ is its j[th] dimension, $OF_i^{new,P2}$ is its value of the OF, R=0.02is the constant, t is referred to iteration contour, and T is denoted as the maximum no. of iterations.

ALGORITHM 2. FEBOA ALGORITHM

Start

Define the energy, distance to neighbours, distance to BS, node density, and SNR

Set FEBOA with population size (N) as no.of nodes in the EH-WSN, and iterations (T)

Create the primary node population matrix as randomly

Evaluate the fitness function

For t = 1 to T

Greatest and worst members are updated based on OF

Phase 1:

A is computed using equation (17)

Best CH candidates are computed based on fitness function

Replicate holding selection and voting by equation (18)

Count the votes and decide the selection (CH) as leader

For i = 1 to N

$x_{i,j}^{new,P1}$ is computed using equation (19)

X_i is updated using equation (20)

Phase 2:

$x_{i,j}^{new,P2}$ is calculated using equation (21)

X_i is updated using equation (22)

End for

Save best selected CH so far

end

Output best CH solution attained by the FEBOA

End

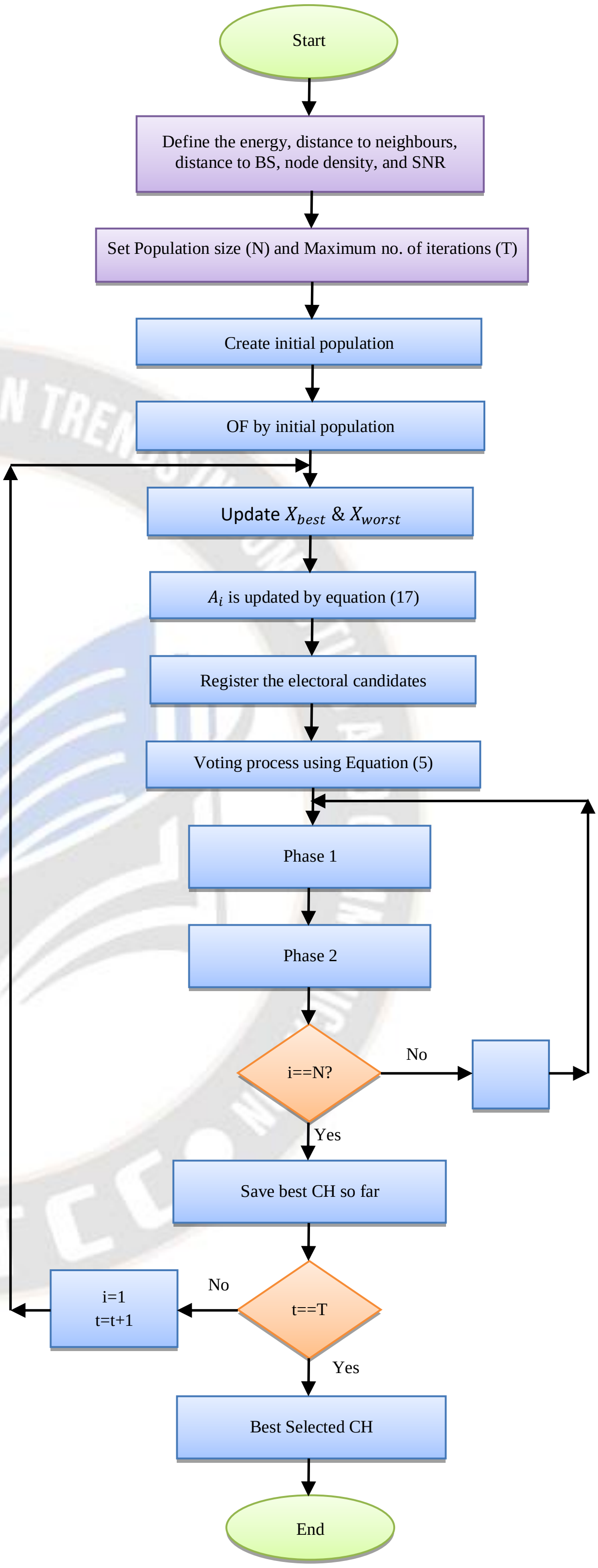


FIGURE 2. FUZZY ELECTION BASED OPTIMIZATION ALGORITHM (FEBOA)

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

3.6. Data Collection (DC)

Data Transmission (DT) and CH selection (CHS) are the two parts of this stage. When the assigned working time slot comes, each CM in DT wakes up and gives the CH in the related cluster the information it has gathered. If the RE of the current CH is below the predefined threshold, the CHS stage is started to prefer a new CH. At this point, every cluster adheres to the same protocol. 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 used 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 HMBCR, NEHCP, EEHC, and EHFPCM. Table 1 describe the simulation parameters which have been used for implementation procedure [13]. The clustering methods are assessed using performance evaluation metrics like RE, PDR, PLR, Network Lifetime, and average delay.

TABLE 1. 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 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,

$$\text{Packet Delivery Ratio (PDR)} = \frac{\sum \text{No. of packets Received by all destination node}}{\sum \text{Total Packets Send by all source node}} \quad (23)$$

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,

$$\text{Packet Loss Ratio (PLR)} = \frac{\sum \text{No. of packets lost}}{\sum \text{Total Packets Send by all source node}} \quad (24)$$

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.

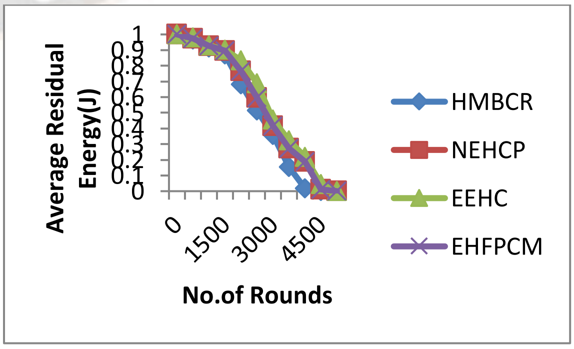


FIGURE 3.AVERAGE RESIDUAL ENERGY COMPARISON VS. CLUSTERING METHODS

Figure 3 shows the average residual energy comparison of clustering methods by varying number of rounds. In 1000 no.of rounds, proposed system achieved higher results of 0.9857J, other methods like HMBCR, NEHCP, and EEHC methods have achieved reduced results of 0.9171J, 0.9254J, and 0.9811J. EHFPCM system attains an increased average RE of 0.3986J (Refer Table 2). Since the CH is selected using FEBOA and clustering is formed by the FPCM algorithm with multi-hop communication.

TABLE 2.ARE ANALYSIS OF CLUSTERING ROUTINGMETHODS

No.of Rounds	Average Residual Energy (ARE) (J)			
	HMBCR	NEHCP	EEHC	EHFPCM
0	1.0000	1.0000	1.0000	1.0000
500	0.9682	0.9728	0.9811	0.9857
1000	0.9171	0.9254	0.9317	0.9492
1500	0.8719	0.8965	0.9039	0.9376
2000	0.6825	0.7659	0.8348	0.8954
2500	0.5166	0.5972	0.6894	0.7568
3000	0.3584	0.4147	0.4571	0.5641
3500	0.1545	0.2719	0.3257	0.4895
4000	0.0181	0.1878	0.2181	0.3986
4500	0.0000	0.0115	0.0457	0.0687

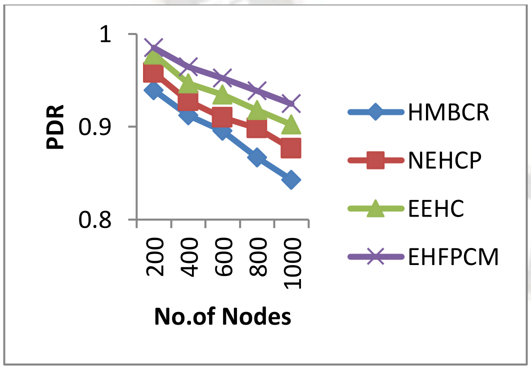


FIGURE 4.PDR COMPARISON VS. CLUSTERING METHODS

PDR comparison of the proposed system and existing clustering methods are illustrated in Table 3 and Figure 4. Highest PDR is achieved by changing the no. of nodes. In 200 nodes, a higher PDR of 98.51% is achieved by the proposed system, whereas the HMBCR, NEHCP, and EEHC have produced a lower PDR of 93.95%, 95.83%, and 97.78% respectively. In 1000 nodes, the proposed system has attained an increased PDR of 92.47%, other methods like HMBCR, NEHCP, and EEHC give lower results of 84.29%, 87.65%, and 90.23% correspondingly (Refer Table 3).

TABLE 3. PDR COMPARISON OF CLUSTERING ROUTINGMETHODS

No.of Nodes	PDR			
	HMBCR	NEHCP	EEHC	EHFPCM
200	0.9395	0.9583	0.9778	0.9851
400	0.9122	0.9277	0.9465	0.9645
600	0.8955	0.9098	0.9344	0.9523
800	0.8668	0.8985	0.9182	0.9384
1000	0.8429	0.8766	0.9023	0.9247

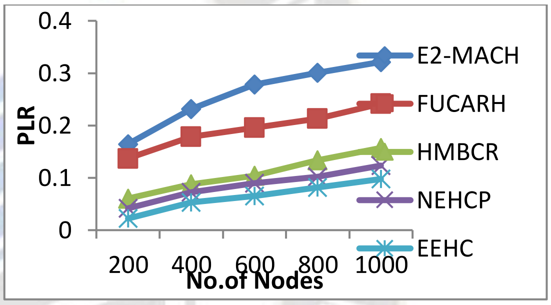


FIGURE 5.PLR COMPARISON VS. CLUSTERING METHODS

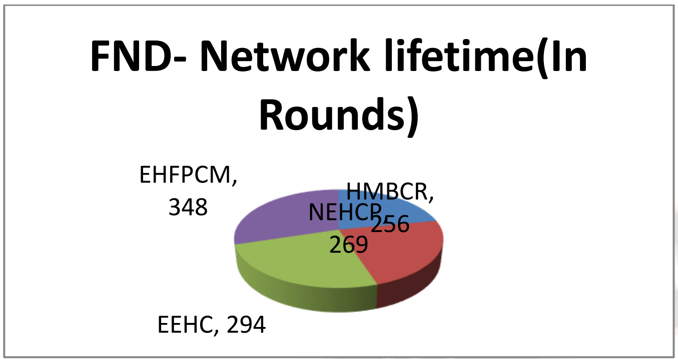
Table 4 shows the performance comparison of PLR among clustering protocols. PLR results are measured by changing no.of nodes from 200 to 1000. PLR results attained by the EHFPCM system are1.49%, whereas HMBCR, NEHCP, and EEHC methods have highest PLR results of 6.05%, 4.17%, and 2.22% (200 nodes). For 1000 no.of nodes, a minimum PLR of 7.53% is achieved by the proposed model, higher PLR of 15.71%,12.34%, and 9.77% is produced by the HMBCR, NEHCP, and EEHC methods (Refer Table 4).

TABLE 4. PLR COMPARISON OF CLUSTERING ROUTING METHODS

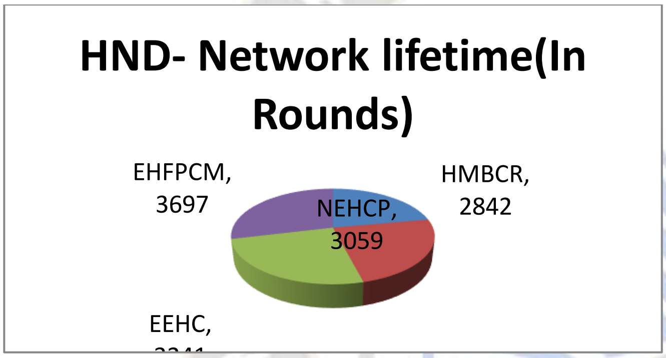
No.of Nodes	PLR			
	HMBCR	NEHCP	EEHC	EHFPCM
200	0.0605	0.0417	0.0222	0.0149
400	0.0878	0.0723	0.0535	0.0355
600	0.1045	0.0902	0.0656	0.0477

International Journal on Recent and Innovation Trends in Computing and Communication
ISSN: 2321-8169 Volume: 11 Issue: 9
***Article Received:** 25 July 2023 **Revised:** 12 September 2023 **Accepted:** 30 September 2023*

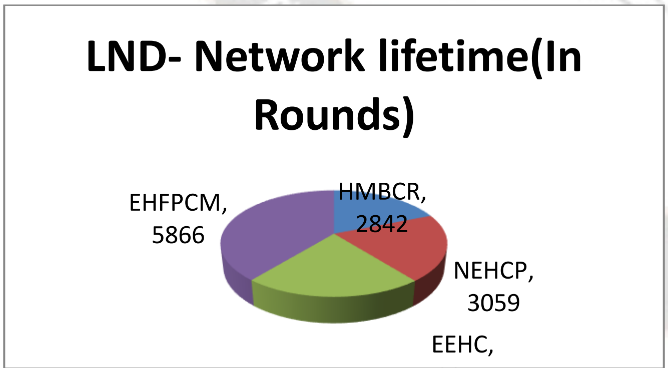
800	0.1332	0.1015	0.0818	0.0616
1000	0.1571	0.1234	0.0977	0.0753



(A) **FND comparison vs. cluster based routing methods**



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



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

FIGURE 5.NETWORK LIFETIME VS. CLUSTERING METHODS

Figure 5 shows the network lifetime comparison of the clustering methods by FND, HND, and LND. Network lifetime attained by the proposed system is 294 rounds, whereas the HMBCR, NEHCP, and EEHC have produced lower FND of 256, 269, and 294 rounds respectively. HND results attained by the proposed system is 3697 rounds, HMBCR, NEHCP, and EEHC methods had lower rounds of 2842, 3059, and 3241 respectively (Refer Table 5).

TABLE 5. NETWORK LIFETIME COMPARISON OF CLUSTERING ROUTING METHODS

Measures	Network lifetime(rounds)			
	HMBCR	NEHCP	EEHC	EHFPCM
FND	256	269	294	348
HND	2842	3059	3241	3697
LND	4928	5147	5369	5866

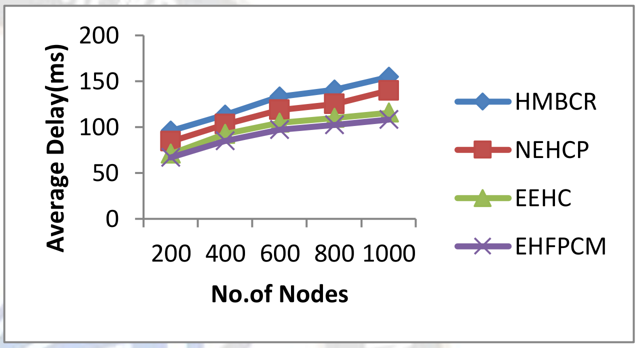


FIGURE 6.AVERAGE DELAY VS. CLUSTERING METHODS

Figure 6 shows the average delay comparison of the clustering routing methods. Proposed system has lesser minimum average delay of 66.92 ms, higher delay of 145.81 ms, 132.55 ms, 95.84 ms, and 84.25 ms is produced by HMBCR, NEHCP, and EEHC for 200 no.of nodes. For 1000 nodes, the least average delay of 108.17 ms is required by the proposed model, higher delay of 246.74 ms, 227.88 ms, 154.57 ms, and 139.85 ms is required by the HMBCR, NEHCP, and EEHC methods (Refer Table 6).

TABLE 6. AVERAGE DELAY COMPARISON OF CLUSTERING ROUTING METHODS

No.of Nodes	Average Delay (ms)			
	HMBCR	NEHCP	EEHC	EHFPCM
200	95.84	84.25	70.74	66.92
400	113.50	102.71	92.18	85.11
600	133.12	118.47	104.45	96.89
800	140.82	124.94	109.72	102.54
1000	154.57	139.85	115.55	108.17

5. CONCLUSION AND FUTURE WORK

In this paper, Energy Harvesting Possibilistic Fuzzy C-Means (EHFPCM) Clustering is introduced in

Energy Harvesting- Wireless Sensor Network (EH-WSN). EHFPCM clustering uses cluster-establishment and data transmission through the introduction of an energy efficiency and RE in order to achieve better energy utilization. It is achieved between the energy consumption and energy harvesting ability by each sensor node in the EH-WSN. Fuzzy Election Based Optimization Algorithm (FEBOA) has been presentedfor the best CH. By using EHFPCM, less energy is used for CH selection and saves more energy during DT. EHFPCM also uses a dynamic transmission power adjustment system for DT throughout the data gathering process to further progress the harvested energy consumption. FEBOA every member in the population represents a potential result for the CH election. A local and global search may be used to find best CH in FEBOA. Additionally, the EHFPCMmethod may successfully assure proper cluster formation and CH selection. The results demonstrate that EHFPCM can consistently get the highest levels of performance in average delay, network lifetime, PDR, PLR, and RE. Furthermore, this study does not take fault tolerance into account, particularly for the CH. When a CH fails for unknown factors, the associated clusters are unable to function appropriately. Consequently, the future task will be to develop an EH-WSN fault-tolerant cluster-based routing system.

REFERENCES

1. Lee S. K., M. Bae, and H. Kim, ``Future of IoT networks: A survey," Appl.Sci., vol. 7, no. 10, pp. 1-25, 2017.
2. Shah S. H. and I. Yaqoob, ``A survey: Internet of Things (IoT) technologies, applications and challenges," in Proc. IEEE Smart Energy Grid Eng. (SEGE), Aug. 2016, pp. 381-385.
3. Zhang X., Y. Ding, G. Yao, and K. Hao, ``An adaptive clustering routing algorithm for energy harvesting-wireless sensor networks," in Proc. IEEE Congr. Evol. Comput. (CEC), Vancouver, BC, Canada, Jul. 2016, pp. 4699-4704.
4. Singh J., R. Kaur, and D. Singh, ``A survey and taxonomy on energy management schemes in wireless sensor networks," J. Syst. Archit., vol. 111, Dec. 2020, Art. no. 101782, pp.1-22.
5. Merabtine N., D. Djenouri, and D.-E. Zegour, Towards energy efficient clustering in wireless sensor networks: A comprehensive review, IEEEAccess, vol. 9, pp. 92688-92705, 2021.
6. Sambo D.W., B. Yenke, A. Förster, and P. Dayang, Optimized clustering algorithms for large wireless sensor networks: A review, Sensors, vol. 19,no. 2, pp. 1-27, Jan. 2019.
7. Sanislav T., G. D. Mois, S. Zeadally, and S. C. Folea, ``Energy harvesting techniques for Internet of Things (IoT)," IEEE Access, vol. 9, pp. 39530-39549, 2021.
8. Adu-Manu, K.S., Adam, N., Tapparello, C., Ayatollahi, H. and Heinzelman, W., 2018. Energy-harvesting wireless sensor networks (EH-WSNs) A review. ACM Transactions on Sensor Networks (TOSN), 14(2), pp.1-50.
9. Bahbahani M. S. and E. A. Alsusa, ``A cooperative clustering protocol with duty cycling for energy harvesting enabled wireless sensor networks," IEEE Trans. Wireless Commun., vol. 17, no. 1, pp. 101-111, Jan. 2018.
10. Sah D. K. and T. Amgoth, ``Renewable energy harvesting schemes in wireless sensor networks: A survey," Inf. Fusion, vol. 63, pp. 223-247, Nov. 2020.
11. Yousefpoor, E., Barati, H. and Barati, A., 2021. A hierarchical secure data aggregation method using the dragonfly algorithm in wireless sensor networks. Peer-to-Peer Networking and Applications, 14(4), pp.1917-1942.
12. Haq, I.U., Javaid, Q., Ullah, Z., Zaheer, Z., Raza, M., Khalid, M., Ahmed, G. and Khan, S., 2020. E2-MACH: Energy efficient multi-attribute based clustering scheme for energy harvesting wireless sensor networks. International Journal of Distributed Sensor Networks, 16(10), pp.1-17.
13. Arjunan, S. and Sujatha, P., 2018. Lifetime maximization of wireless sensor network using fuzzy based unequal clustering and ACO based routing hybrid protocol. Applied Intelligence, 48, pp.2229-2246.
14. Sah, D.K. and Amgoth, T., 2020. A novel efficient clustering protocol for energy harvesting in wireless sensor networks. Wireless Networks, 26(6), pp.4723-4737.
15. Hao, S., Hong, Y. and He, Y., 2022. An energy-efficient routing algorithm based on greedy strategy for energy harvesting wireless sensor networks. Sensors, 22(4), pp.1-24.
16. Mansura, A., Drieberg, M., Aziz, A.A., Bassoo, V. and Sarang, S., 2022. An energy balanced and nodes aware routing protocol for energy harvesting wireless sensor networks. Peer-to-Peer Networking and Applications, 15(2), pp.1255-1280.

17. Roberts, M.K. and Ramasamy, P., 2022. Optimized hybrid routing protocol for energy-aware cluster head selection in wireless sensor networks. Digital Signal Processing, 130, p.103737.
18. Han, B., Ran, F., Li, J., Yan, L., Shen, H. and Li, A., 2022. A novel adaptive cluster based routing protocol for energy-harvesting wireless sensor networks. Sensors, 22(4), pp.1-16.
19. Wan, J. and Chen, J., 2022. AHP based relay selection strategy for energy harvesting wireless sensor networks. Future Generation Computer Systems, 128, pp.36-44.
20. Han Y., J. Su, G. Wen, Y. He and J. Li, "CPEH: A clustering protocol for the energy harvesting wireless sensor networks," Wireless Communications and Mobile Computing, vol. 2021, pp. 1–14, 2021.
21. Huamei, Q., Chubin, L., Yijiahe, G., Wangping, X. and Ying, J., 2021. An energy-efficient non-uniform clustering routing protocol based on improved shuffled frog leaping algorithm for wireless sensor networks. IET Communications, 15(3), pp.374-383.
22. Haseeb, K., Bakar, K.A., Abdullah, A.H. and Darwish, T., 2017. Adaptive energy aware cluster-based routing protocol for wireless sensor networks. Wireless Networks, 23, pp.1953-1966.
23. Peng S., T. Wang, and C. P. Low, ``Energy neutral clustering for energy harvesting wireless sensors networks," Ad Hoc Netw., vol. 28, pp. 1-16, May 2015.