Journal of Current Science and Technology, May-August 2023 Vol. 13 No. 2, pp. 296- 316
ISSN 2630-0656 (Online)

Cite this article: Maheshwar, K., & Veenadhari, S. (2023, May). HCPFRP: Heterogeneous cluster prediction and formation routing protocol for wireless sensor network. *Journal of Current Science and Technology*, *13*(3), 296- 316. https://doi.org/10.59796/jcst.V13N2.2023.1745

Journal of Current Science and Technology

Journal homepage: https://jcst.rsu.ac.th

HCPFRP: Heterogeneous cluster prediction and formation routing protocol for wireless sensor network

Kamini Maheshwar* and S Veenadhari

Department of CSE, Rabindranath Tagore University (RNTU), Bhopal (M.P), India, 462047

*Corresponding author; E-mail: kaminimaheshwar@gmail.com

Received 1 December 2021; 13 September2022; Accepted 23 September 2022;
Published online 15 July 2023

Abstract

Wireless sensor network (WSN) is composed of multiple sensors that are connected through a communication channel and communicate with each other. As these sensor nodes are battery-operated, therefore, as a consequence, battery life or energy is always an issue of concern. Therefore, researchers focus their work on optimizing the routing strategies to save energy wastage in WSNs. Among all routing strategies, cluster-based techniques proved to be quite able to successfully manage propagation from sender to receiver. Because it must gather all data and send it to the base station, each cluster's elected head is responsible for bearing the complete load. A cluster-based routing mechanism is established under this paper and termed a Heterogeneous Cluster Prediction and Formation Routing Protocol (HCPFR) in which the algorithm first creates the cluster and predicts the energy utilization or network lifetime, and then provides energy-efficient optimized clustering. In this method, the proposed HCPFR model is compared with different methods; LEACH PSO, LEACH-GWO, LEACH-EEGWO, and FZR, and the performance is compared with different parameters mainly First Dead Node (FDN), Network Longevity (NL) and throughput (THP) in term of packet delivered and residual energy. The result shows that the HCPFR model outperforms better over these approaches. The FDN, NL, and THP of the proposed HCPFR are nearly 8000,10000, and 30000. Also, the suggested model shows that as the number of rounds increases the residual energy drops to 0.1 from 3.8 as the rounds increases to 10000 from 2000.

Keywords: *cluster-based routing protocol; formation routing protocol; heterogeneous cluster prediction; lifetime prediction; optimization; wireless sensor network.*

1. Introduction

Nowadays, sensor-based systems that connect through the wireless medium are becoming increasingly popular because they can be used in a wider range of applications, including remote areas where public access is challenging. These sensors are compact devices equipped with components such as detectors, control electronics, communication devices, and a battery. These components enable them to detect, compute, and transmit data (Raj, 2020). The efficient use of electricity is critical in sensor networks since changing or replenishing batteries is time-consuming. As a result, energy-optimized routing must be devised to reduce power consumption while transporting information from the input data point to its desired target, without even any pauses or transcription errors triggered by fatigued sensors. Sensors sense and processes the modifications or demands of the internet-enabled actual environment and provide the appropriate cures so that it can be environmentally friendly in terms of energy consumption (Raj, & Basar, 2019). Wireless sensor networks (WSNs) are becoming more popular in defense, industrial, vulnerability scanning, commercial, medical, catastrophic events, and rescue teams due to their capacity to interface immediately with natural phenomena. Among the most significant limits of the sensor is their limited battery lifetime, which, notwithstanding this restriction, necessitates the effective use of power detectors (Raj, & Basar, 2019). Sensors rely on batteries' capacity to perform information-gathering processes. This causes a portion of the channel's data to be lost, so in most cases, owing to the large area of assessment and, in certain situations, the inability to change or recharge the sensor's batteries (Ramesh, & Smys, 2017; Smys, & Raj, 2019). Thus, saving energy is essential in WSN circumstances, and certain strategies are offered to reduce energy usage (Safara et al., 2020; Malar et al., 2020; Manfredi et al., 2012). Routing is a difficult problem to solve when constructing WSNs, hence much of the research that has been conducted in the field of routing algorithms has included WSNs in an attempt to minimize the energy of nodes and boost routing efficiency. Clustering can be defined as a fundamental strategy for extending the lifespan of WSNs by lowering energy usage (Rizk, Elhadidy, & Nassar, 2011; Khan et al., 2020). The data transfer length among cluster members is shortened in intra-cluster connections, and the cluster-member node may fall into a sleep state and preserve energy for a prolonged period (Shyjith, Maheswaran, & Reshma, 2020). Fast transmission, scaling, routing, and designing systems are all improved by clustering approaches (Panchal, & Singh, 2021; Thushara, & Raj, 2013; Mirjalili et al., 2016; Liao, Qi, & Li, 2013). The node in a cluster could choose a single cluster head (CH), or the network manager might have chosen one. CH may have the same resources and capabilities as other nodes, or they may be more powerful. The components of a cluster might be permanent or changeable (Yu et al., 2014; Gaber et al., 2018). One CH node may plan cluster operations whereby each node goes to sleep at all moment excluding the period allotted to it and preserving its residual battery level (Xu et al., 2017).

The information passes from the sensor node to the destination node, where it may be accessed via the internet by individuals. By separating the sensor system into tiny, controllable clusters, cluster-based routing methods offer an effective solution. The methods provide a flexible multi-hop routing route that improves cluster-to-BS communications. As a consequence, by combining information taken from the very same cluster, reduced power usage is accomplished. Cluster load balancing ultimately extends the network's lifetime. The energy-efficient routing technique is suggested in this paper which results in the energy efficiency of the designed model.

1.1 Related work

There are some parameters like Fault Tolerance (Mohapatra, & Mohapatra, 2019), Power Consumption (Ebrahimi, & Tabatabaei, 2020), Data Aggregation (Babu et al., 2020), Quality of Service (Yagouta, Jabberi, & Gouissem, 2018), Data Latency (Hidoussi et al., 2017), Load Balancing, execution time (Edla, Kongara, & Cheruku, 2019) and Node Deployment (El Khediri et al., 2020) with different techniques like Fuzzy Logic (Saadaldeen, Osman, & Ahmed, 2018), K-means++ and Fuzzy Logic (Wen et al., 2019), and also Hybrid Clustering (Malshetty, & Mathapati, 2019) that must be considered while implementing the clustering protocols. At 800 nodes, energy consumption is 40%; for 600 nodes, it is 30%. End-to-end time delay, route length, and several failed nodes are also discussed along with energy consumption. Goswami et al., (2021) proposed a novel approach for WSN based on the Ant colony algorithm (AOC) and the k-means clustering algorithm, that facilitates very reliable transmission with a power standpoint, while also being reliable and even with limited times, in Sensing devices of every dimension, easing the deployment of WSNs and widening the range of potential uses. Cui, Ma, & Ma (2019) proposed an adaptive filter-dependent prediction method. A node cluster approach is developed based on the prediction model, that works well in the energy recovery and efficiency WSN, alleviating the problem of DEEC adjustment problems in EH-WSN. Live nodes increase by 17.1%. The error of the given algorithm is greatly reduced to 13.5%. Outperformed LMS algorithm as well. For dynamic CH selection, Stephan et al., (2020) used a region-based clustered with a fuzzy-logic method. Its goal is to tackle the issue of imbalanced power dissipation in the channel's CHs. The suggested protocol surpasses current methods to have maximum network longevity, according to the findings of the experiments. SEP achieves almost 46.8% worse off than FZC, while ZSEP and DEEC perform approximately 50.5 percent and 45.1 percent worse off than FZC in terms of deferring the overall total number of sensor nodes from becoming dead over the number of cycles in operations, respectively Sujith, Dorai, & Kamalesh (2021) used a fuzzy-based method to construct clusters in the suggested study. This reduces node power consumption even more and extends network lifespan. The suggested method has the following benefits: efficient energy use, increased packet delivery rate, and increasing system lifespan. Pratha, Asanambigai, & Mugunthan (2021) proposed an integrated Grey Wolf Optimization (GWO) based Game Theoretical Approach (GWOGA), which assists clustering in finding solutions for grouping point selection that leads to the nodes maximizing their batteries/lifetime. The proposed model is better than EEGBR by 19%, MCFL by 34%, and LEACH by 79%. Effective usage of energy improves packet supply rate. Masoud et al., (2019) proposed a hybrid clustering algorithm that was designed for a reduction in network power consumption and an increase in the network lifetime by 30%. The number of received packets, number of failed nodes, and alive nodes were also discussed. Zivkovic et al., (2020) proposed a grey wolf optimization-based clustering with 50% efficiency. The given algorithm is 15% better than the ERNR algorithm. Rajeswari et al., (2021a) proposed a trusted energy-efficient fuzzy logic model for WSN clustering. This model integrated the security aspect with energy enhancement for clustering. The fuzzy logic considers the cluster density, distance, and residual energy of the nodes present in the network. Santhosh Kumar et al., (2021) proposed a secure environment for a cluster-based wireless sensor network. For security, cryptography was adopted. In this research, k-mean clustering was used for unequal clustering to support a dynamic environment. Ganapathy et al., (2021) also proposed a trust-based secure environment with cluster-based WSN. In this work, the author presented a clustering and filtering algorithm and achieved a good packet delivery ratio. Sangeetha et al., (2019) applied fuzzy rules for cluster decisions in WSN (Sangeetha et al., 2019). El Alami, & Najid (2016b) suggested an enhancement to the LEACH protocol termed the Energy efficient Fuzzy Logic Cluster Head (EEFL-CH). This method uses three fuzzy parameters to reduce energy consumption while extending the network lifespan. These factors are proximity to the base station, predicted efficiency, and residual energy. According to the findings of the simulation, the EEFL-CH strategy outperforms the LEACH and LEACH-ERE routing protocols. Lee, &Teng (2017) suggested a better low-energy adaptable clustering hierarchical protocol for MSNs is put forward to increase network lifespan while decreasing packet loss via the use of fuzzy inference algorithms. Simulation findings show that the suggested strategy is superior to the other one currently in use. Consequently, the method described in this paper could be modified further to investigate highly MSNs. Compared to other techniques, the LEACH-MF approach can save up to 17.2 percent and 34.2 percent of energy. El Alami, & Najid (2019) suggested proposed enhanced clustering hierarchy (ECH) method that uses sleeping-waking mechanisms for neighboring and overlapping nodes has been proposed to improve energy efficiency in WSNs. As a result, network lifetime is maximized while data redundancy is minimized. The simulation's outcomes demonstrate its efficacy. In the stability period, DEEC-ECH exhibits growth of 13.34% and 27.56%. El Alami, & Najid (2016a) suggested a new routing protocol for WSNs, (SET) smart energy management, and throughput maximization. The results demonstrate that the cluster heads use less energy, increasing network lifetime. Some of the research contributions and their merit and demerits are presented in table 1.

1.2 Challenges

A WAN is composed of several low-power, transient, multifunctional nodes with less/reduced memory. The battery's lifespan of these nodes is minimal, this is regarded as a difficult task. Saving energy is thus a major WSN concern (Ghorbani Dehkordi, & Barati, 2022). For a lengthy lifespan of WSNs, the actual situation is dynamic and involves diverse nodes (particularly concerning energy). Consequently, there is a requirement for an energy-efficient routing mechanism. (Hajipour, & Barati, 2021). Energy effectiveness deteriorates the whole network issue as WSN experiences heterogeneity-related concerns. The primary problem that has to be addressed is lowering the overhead for routine route updates, which consumes energy as well. Hence, the primary objective of this study is to reduce node energy loss by using heterogeneous WSN to decrease overhead, assess energy efficiency in a dynamic environment, and use model cost optimization based on factors like remaining energy, throughput, etc.

Table 1 Achievements, merit, and demerits of existing research contributions

Ref	Achievements	Merit	Demerits
Stephan et al., (2021)	Applied Fuzzy logic-based cluster head selection process.	Effective usage of energy improves packet delivery rate.	Not designed for heterogeneous environment
Goswami et al., (2021)	Hybrid Clustering	Reduction in network power consumption and an increase of the network lifetime by 30%.	Cannot handle dynamic network scenarios.
Zivkovic et al., (2020)	Improved efficiency by 15% in terms of	It is good in solving clustering problems	Not designed for heterogeneous environment
Rajeswari et al., (2021b)	Included security features with clustering. The trustworthiness of the cluster head was evaluated for secure transmission.	Achieved a good security level.	Network longevity was approx. 900 rounds. Doesn't support a dynamic heterogeneous environment of the network.
Santosh et al., (2021)	Included security features in cluster based WSN for malicious node identification and evaluation of the trust score of nodes.	Achieved a good packet delivery ratio.	With the increased percentage of malicious nodes, the residual energy decreases.
Ganapathy et al., (2021)	Included security features with clustering.	Achieved a good packet delivery ratio.	Throughput was approx. 80% that needs to improve.
Sangeetha et al., (2019)	Proposed clustering-based algorithm with congestion control mechanism using fuzzy logic.	Achieved a good packet delivery ratio and reduced the packet drop ratio.	Localization information for cluster head selection was not considered. Network longevity was average.

For reducing energy requirements, cluster-based routing protocols were designed (Papi, & Barati, 2022). But for cluster-based routing protocols, the main issue is to create clusters and select cluster heads to minimize the energy required for regular updation (Shahbaz, Barati, & Barati, 2021; Sharifi, & Barati, 2021; Yousefpoor, Barati, & Barati, 2021). Ahmad, & Dang (2015) proposed a density-based clustering algorithm that can create arbitrary shape clusters dynamically. This protocol was robust, but a major issue arises with such an algorithm failing to create a robust cluster as the density of nodes increases. Therefore, this paper is looking forward to designing an unequal cluster-based routing protocol using optimization features such that the increased density of nodes doesn't fail to identify the optimal cluster for them. Another major contribution, presented by Feng et al., (2018) is to data-fusion-based approach for unequal clustering for transmitting multiple tasks at the same time and reducing the transmission delay, especially for IoT applications. But the major issue with this approach is that there is no prior estimation of the energy of nodes. Apart from this, the model used the fusion tree to maintain a record of transmitted packets. Therefore, there is also an overhead to regular updates of the fusion tree. And if during transmission energy of the CH gets exhausted then packet delivery is failed. Therefore, to reduce these issues, the proposed algorithm has adopted a prediction strategy to predict the lifetime of clusters, and this will reduce such retransmission overhead.

1.3 Objectives

The purpose of this work is to create and execute a cluster-based routing protocol for WSN that is energy-efficient while utilizing the benefits of machine learning approaches as well as bioinspired optimization algorithms. Further, we have proposed a methodology with the integration of machine learning and modified particle swarm optimization with ANFIS. The objective of this methodology is to use the advantage of machine learning for predicting the lifetime of a cluster and optimize the network to make it energy efficient for homogeneous as well as heterogeneous environments also.

1.4 Motivation and innovation

The main issue with WSNs (Wireless Sensor Networks) that researchers are facing is battery life (energy of a node). As a result, the cluster this low-energy node formed will die early, consuming the resources of the whole network. The LEACH protocol requires the regular creation of new clusters since the cluster head (CH) is chosen in each round or iteration. Due to routing overhead, this may result in enormous energy consumption that might not be suitable for any mobile device. To avoid using additional energy for cluster creation and the transfer of advertising messages to cluster members, an effective CH replacement approach has been used. This research work's primary objective is to reduce node energy loss by minimizing the overhead using an uneven heterogeneous cluster based WSN. This work proposes to predict cluster lifetime and the formation of suitable clusters using appropriate machine learning algorithms. This research work also proposes a cluster head node selection using modified PSO-ANFIS based on multiple factors such as distance, transmission range, and residual energy to reduce energy loss during data transmission.

1.5 Paper organization

The paper is organized into four sections. Section 2 describes the methodology adopted in this paper. The further sub-sections describe the network model, energy consumption model, and description of the designed model. Section 3 shows the result analysis of the implemented model. Along with the results, a comparative state-of-art is also presented in this section. Finally, in section 4, the conclusion and future work is presented.

2. Methodology

This section, therefore, proposed cluster-based HWSN with the application of machine learning termed Heterogeneous Cluster Prediction and Formation Routing Protocol (HCPFR) using Machine Learning that provides application-specific assurance for QoS.

2.1 Network model

The model-based assumption used in this investigation is as follows:

- A sensing zone of size A= N*N is distributed randomly with N sensor nodes. Both the base stations and the SN are positioned randomly.
- Each node within the network has the same initial energy and a distinct ID identification. The Base Station has unlimited energy, but the Nodes have a finite quantity.
- The link is symmetrical. The node can determine the distance between the transmitter and itself based on the obtained signal strength.
- Each node may receive or send just one data packet and its associated control packet during each primetime that it needs to establish a connection with its parent node.
- Depending on the interaction distance, the node's transmit power may be changed.

2.2 Energy consumption model

The energy used by sensor nodes is consumed during data exchange. In this study, we just take into account the cost of energy used for data transmission and data merging. The equations below formalize the energy consumption of receiving and sending information:

$$E_{tx}(dl,s)= \begin{cases} dlE_{selects} + dl\varepsilon_{fs}s^2, & s<s_0 \\ dlE_{selects} + dl\varepsilon_{amp}s^4 & s\geq s_0 \end{cases} \quad (1)$$

$$E_{rx}(m)= dlE_{selects} \quad (2)$$

Where, dl = data length, s = data transmission distance or span, $E_{selects}$ = energy usage during transmitting and receiving of unit length data, ε_{fs} and ε_{amp} = amplifier energy usage of free space model and multiple path attenuation models, E_{tx} = transmitting energy, E_{rx} = receiving energy.

When the distance s between the sending and receiving nodes is less than the energy use model cutoff S_0 and the transmitted range is attenuated as s^2, the free space model is used. Rather, s^4 is used as the transmission signal while the multi-path attenuation architecture is used. The following equation determines how much energy is required for nodes to combine dl-length data.

$$E_u(dl) = dlE_{da} \tag{3}$$

Where E_{da} = The amount of energy it takes to merge a unit length of information.

In this paper, the energy consumption model is used to estimate the real-time demand energy requirement for cluster formation, head node selection, and data transmission. Therefore, for the evaluation of network longevity, it is needed to a proposed energy consumption model.

2.3 Overview of HCPFR

Cluster routing techniques work in cycles, with each cycle consisting of two stages: Data transfer and cluster generation This flowchart of the suggested technique is presented in Figure 1.

2.3.1 Cluster formation

Determination of optimal cluster number

In Wireless Sensor Networks, the reasonable estimation of the cluster number is generally associated with energy efficiency considerations. If there are enough clusters, there will be too much clustering expense; if there are too few clusters, there will be enough nodes inside every cluster, and several cluster heads will expire too quickly. Therefore, a sufficient quantity of clusters can not only enhance the system link's effectiveness but also balance node wasted energy and lengthen the network's lifespan.

The multi-hop routing mode is used in this study for inter-cluster interaction. S is the interval between the base station and the farthest cluster head. This distance is broken down into several hops. The linearly equidistant model is used for informational purposes. The energy usage in the multi-hop transmitting paradigm is stated as:

$$E_{multihop} = E_{tx} + E_{rx} + E_{da} \tag{4}$$

The compression algorithms ratio is denoted by the letter C, or the information fusion ratio (i.e., the data amount before compaction is split by the data quantity after contraction or compaction) if $s < s_0$. Then,

$$\begin{aligned} E_{multihop} &= (E_{select} \cdot L + \varepsilon_{fs} \cdot L \cdot s^2)_1 \\ &+ (E_{select} \cdot L + E_{da} \cdot L + E_{select} \cdot C \cdot L + \varepsilon_{fs} \cdot C \cdot L \cdot s^2)_2 \\ &+ \dots\dots + (E_{select} \cdot C^{m-2} \cdot L + E_{da} \cdot C^{m-2} \cdot L \\ &+ E_{select} \cdot C^{m-1} \cdot L + \varepsilon_{fs} \cdot C^{m-1} \cdot L \cdot s^2{}_m \end{aligned} \tag{5}$$

When, C = 1

$$E_{multihop} = E_{select} \cdot L \cdot (2m-1) + E_{da} \cdot L \cdot (m-1) + \varepsilon_{fs} \cdot L \cdot s^2 \cdot m \tag{6}$$

Where, L = length of data, m = clusters

The overall energy required by multi-hop transmissions, $E_{overall}$, can be calculated by adding the energy usage costs of the clusters, $E_{clusters}$, and the energy usage costs of the *n* nodes, $E_{incluster}$, in each cluster which can be written as:

$$E_{overall} = E_{clusters} + n \cdot E_{incluster} \tag{7}$$

Inside the cluster, energy usage can be calculated as demonstrated by the free-attenuating channel model arranged by:

$$E_{incluster} = \left(\frac{n}{m} - 1\right) \cdot L \cdot E_{select} + \left(\frac{n}{m} - 1\right) \cdot L \cdot \varepsilon_{fs} \cdot s^2_{to\,CH} \tag{8}$$

Assuming, that m circular cluster areas completely cover the system region.

$$M^2 = \pi \cdot r^2 \cdot m \tag{9}$$

The interval among clusters can be calculated as

$$s = 2r = \frac{2M}{\sqrt{\pi m}} \tag{10}$$

Now $E_{overall}$ can be calculated as:

$$\begin{aligned} E_{overall} = E_{select} \cdot L \cdot (2m-1) + E_{da} \cdot L \cdot (m-1) + 4\,M^2 \cdot \varepsilon_{fs} \cdot \frac{1}{\pi} + \\ N \cdot L \cdot E_{select} + N \cdot L \cdot \varepsilon_{fs} \cdot \frac{M^2}{2\pi m} \end{aligned} \tag{11}$$

We compute the derivatives of $E_{overall}$ with m and adjust the derivative to 0 (zero) to generate the number of clustering groups that is ideal m_{opt} to reduce the overall energy utilization of the network to determine the K-value that reduces energy usage.

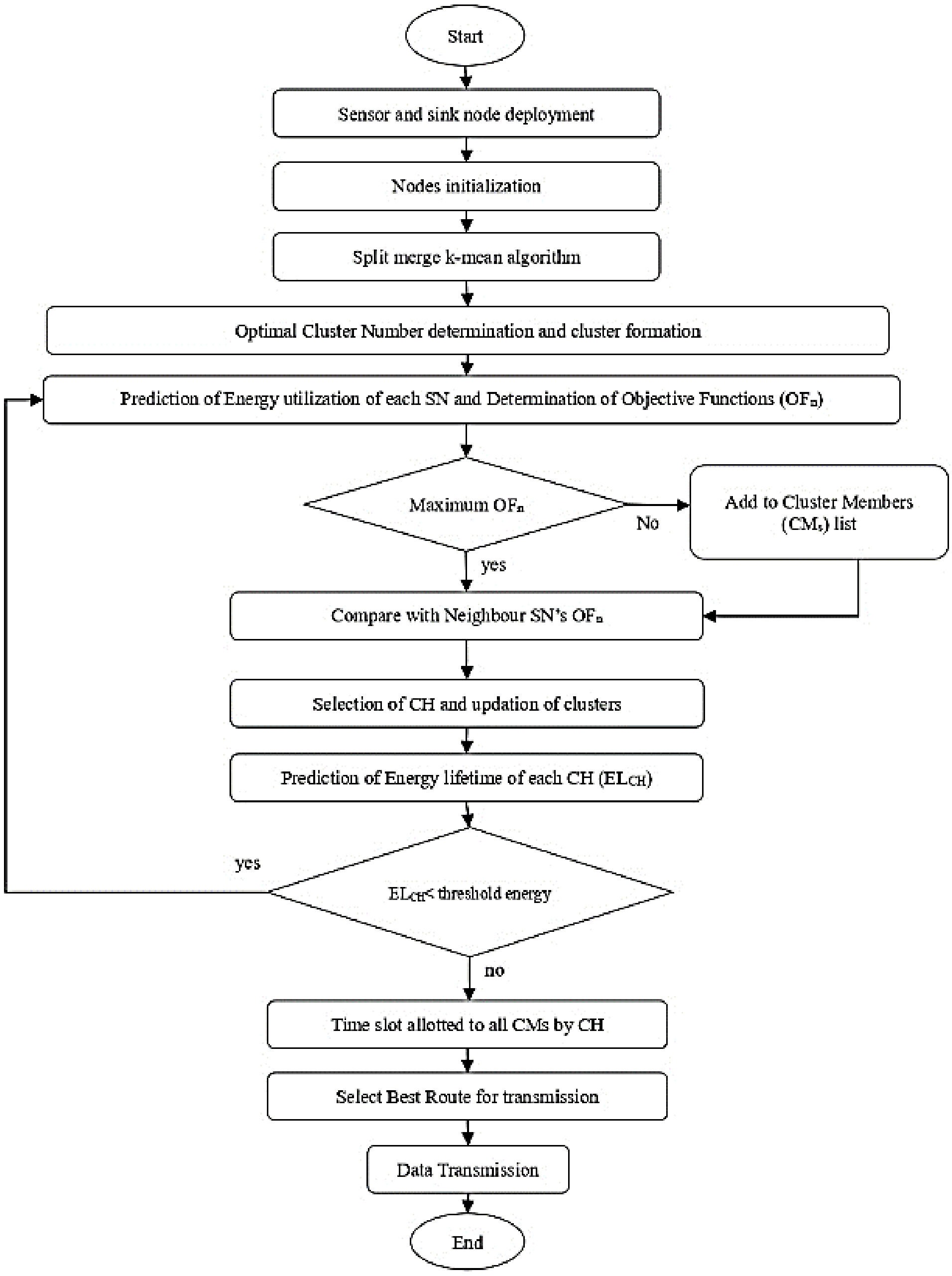

Figure 1 Proposed framework

2.3.2 The phase of developing clusters

Whenever employing the K-means technique to clustered information, the preliminary cluster midpoint selected has a direct effect on the clustering result and may have a significant effect on clustering efficiency. The algorithm's outcome is determined by the framework's initial state, i.e., the choosing of the preliminary cluster middle-point and the technique can only ensure merging to a stable point, not the objective function's minimal point. The following are the main concept and techniques of the cluster center point determination described in this work. The centroid of the nodes (x_i,y_i) in the definite region $G_k=(\bar{x};\bar{y})$ is investigated to demonstrate the dispersal of nodes in a region.

$$\bar{x}=\frac{\sum_{i=0}^{n}x_i}{n},\ \bar{y}=\frac{\sum_{i=0}^{n}y_i}{n} \tag{12}$$

Where n denotes the number of nodes in the network. Check the number of nodes across each area and make the first cluster center h_1 the centroid of the region with the most sensing nodes. Compute the difference here among the centroid of the further region W_B and the initial cluster midpoint h_1 one at a time and choose the point with the greatest distance from the first cluster midpoint as the next cluster midpoint, i.e., h_2. Continue to calculate the distances (i.e., s (W_B; h_1) and s (W_B; h_2) between the centroids of the other areas and the cluster centers. As the third cluster center, choose the centroid of the area with max [s (W_B; h_1) + s (W_B; h_2)], and so on. The kth cluster, h_k, with radii s could then be generated.

$$h_k=max\left(\sum_{i=1}^{k-1} s(W_B,\ h_i)\right) \tag{13}$$

The steps for definite clustering are given below:

Initial Step: select k-cluster midpoints.

Step 2: Find the distances between the n nodes and the k-cluster center points. Every node chooses the cluster with the least distance among them.

Step 3: As an innovative cluster middle point, in every cluster, the geometric mean of the given nodes is evaluated.

Step 4: Evaluate whether the error conditions have been met using the error square sum criterion. If not, go back to Step 2 and continue from there. Instead, the clustering process is completed, and the outcome is k categories.

$$F=\sum_{i=1}^{k}\sum_{x\in V_i}\left\|\left(x-\mu_i\right)\right\|^2 \tag{14}$$

2.3.3 Cluster structure optimization

The many-to-one streaming data transmission in a WSN causes the cluster heads closest to the base station to transport a larger data volume, causing the cluster heads to use more energy. The competitiveness of radius is defined in this study as the connection among several nodes in a cluster and their space from the Base Station. It's written like this:

$$r_i=\left(1-\tau\cdot\frac{s_{max}-s_{(t_i,bs)}}{s_{max}-s_{min}}\right)\cdot r_0 \tag{15}$$

The starting competitive radius is the competitive radius of the node specified, where τ is the variable that alters the span of the competitive radius and specifies the consequence of range on the competitive radius. The higher the tau, the more distance affects the competing radius. The highest competitive radius is r_0. The higher and lower lengths from all nodes to the base station are s_{max} and s_{min}, respectively. When tau rises, the range of variability of r_i value reduces; inversely, when tau falls, the variability of r_i value rises, and r_0 has a direct effect on the value of r_i. We may deduce that the cluster's competitive radius is directly proportionate to the space between the cluster and the BS (base station). The cluster's competitive radius is permanently in the middle of r_0 and $(1-\tau)r_0$. The competitive radius shrinks when a cluster gets nearer to the BS base station. The narrower the competitive radius, the less energy is spent to maintain the cluster's participants, allowing it to focus on data forwarding throughout multi-hop transmitting connections.

Supposing that the nodes are unsystematically dispersed inside the 2D level and have an unvarying dispersion, the possibility density of the nodes can be calculated, and the r (radius) of the cluster can be calculated by adding the values of r_i to get a reasonable value for the number of nodes in each cluster. Its meaning can be summed up as follows:

$$N_i=\pi\cdot r_i^2\cdot\rho \qquad (i=1,2,3\ldots.k) \tag{16}$$

2.3.4 Splitting and merging

The clustering impact of the K-means clustering algorithm is represented in the grouping of nodes near to one another into one cluster, as per the main concept of the algorithm. The structure of the cluster dimension is non-uniform and will induce the issue of an “energy hole”, i.e., clusters near the base station have many nodes, consuming a huge amount of data and consuming more energy. Because of the large distances, the clusters will have unequal energy usage, which will damage the overall WSN's function. To alter the cluster area obtained by the K-means algorithm, this work presents a split-and-merge procedure depending on the energy balancing. It does not divide and merge data in a repetitive manner, which would maintain the K-means algorithm's best clustering impact. When deciding which clusters to alter, a weighted evaluation function is presented, using the following expression:

$$w(i)=\alpha\cdot\frac{S_i-S_c}{S_{max}-S_{min}}+\beta.f(i) \tag{17}$$

$$f(i)=\begin{cases}\frac{(1+c)\cdot N_i-n_i}{n_i-N_i}\ (n_i>(1+c)\cdot N_i)\\ \frac{(1-c)\cdot N_i-n_i}{N_i-n_i}\ (n_i<(1-c)\cdot N_i)\end{cases} \quad (18)$$

The weight function in the aforementioned equation takes into account the cluster's distance from the base station as well as the number of nodes in the cluster. S_i represents the distance between cluster t_i and the base station in the equation. S_c is the mean interval between the center points of all clusters and the primary station, whereas S_{max} and S_{min} are the maximal and utmost lengths between the center points of all clusters and the base station, respectively. S_{max}-S_{min} is the bottom of the equation. The value of the first portion can be made within a range of 0 to 1, thus acting as a normalizer, thanks to the denominator. The impact of the number of nodes in the cluster on the examines the perception is denoted by $f(i)$. The impact of the mass of the space element and the number of sensor nodes on the assessment value is denoted by α and β.

N_i gives the number of optimum cluster nodes. Further k-means clustering, n_i is the absolute number of nodes in the cluster, and c was the frequency of nodes in the cluster. If the value of ni is between $[(1-c)\cdot N_i$ and $(1+c)\cdot N_i]$, the cluster is considered to have a suitable quantity of nodes and should not be divided or combined. The following are the precise algorithms for dividing and combining operations:

The first step is to split the data. Select the appropriate cluster whose real node count $n_i>(1+c)\cdot N_i$by traversing all clusters.

Then, using both of the aforementioned equations, compute the mass assessment standards $w(i)$ and category $w(i)$. Starting low to high $w(i)$, choose $w(i)$ out of the clusters those have $w(i)$ is smaller than 0.

Standard deviation is a measure of the nodes that need to be separated in the cluster. Remove the actual center and divide the cluster mean into two cluster blocks with c_i^+ *and* c_i^- centers. Let k = k+1. c_i^+ *and* c_i^- are computed as Given v value as $0<v\leq 1$, $c_i^+ = C_i+v\sigma_i$, $c_i^- = C_i-v\sigma_i$ here the value of v was selected so that the interval between t_i and c_i^+ *and* c_i^- is distinct, and it is also important to verify that the prior sample of t_i is even in the 2 additional sets.

Step 3: Perform a merge operation. Determine the weighted evaluation values w by traversing all of the clusters S_i and using equations (i). After that sorting w(i) and choose the clusters with w(i) > 0 from the biggest to the tiniest w(i).

Step 4: Determine the S_{ij} (interval) from the central point. The number of clusters t_i this must be integrated with all further cluster midpoints is P_i. Combine the clusters t_j and t_i that have the smallest S_{ij} in common. After combining, the cluster center is expressed as:

$$P_L=\frac{N_i\cdot P_i+N_j\cdot P_j}{N_i+N_j} \quad (19)$$

The actual centers P_i and P_j are then discarded, yielding to the center P_L. The quantity of cluster centers becomes $k = k-1$ as a result.

2.3.4 Cluster head selection

In this work, a modified PSO-ANFIS algorithm is used for cluster head selection of different objective functions, as illustrated in Algorithm 1. The PSO-ANFIS is integrated into the proposed model for CH selection and its lifetime prediction. For optimal selection, CH's ANFIS-based Particle swarm optimization (PSO) technique is used in this paper which will reduce the energy consumption of the entire network because it removes the burden of regular updation for CH selection. Each sensor node estimates the expected overall energy consumption of the system of chosen SN based on their condition during the initialization phase while choosing the best cluster head for uneven clusters. The system's transmission, reception, and processing of data lead to predictions about how much energy each cluster member will use (CMs). In this level, each SN in the network visualizes itself as a CH of the relevant group, following which it predicts the total estimated lost energy of every cluster member in the cluster. The definition of various operations that drain cluster members' energy is given by:

$$E_{CM}(i)=\sum_{j=1}^{n}\{E_{amplifier}\times k\times M\times L(i,j)^i+E_{tx}\times M\} \quad (20)$$

Wherever,

Total energy losses among member nodes of cluster are predicted is denoted by E_{CM}

E_{tx}, $E_{amplifier}$ is denoted for the amount of energy needed by an SN to transfer and to be amplified, expressed in Joule/bit.

Size of the bit can be represented as M

Nodes i and j have the distance $L(i, j)$

Number of SNs present in the system are denoted by n. k is represented for number of clusters.

Algorithm 1. Cluster formation and CH selection	
1:	Begin
2:	SN= Sensor Nodes
3:	S_kN= Sink Node
4:	For i=1: SN
5:	SN initialization
6:	Clusters←SMk-Mean (SN)
7:	Optimal_CH←MPSO-ANFIS(Clusters)
8:	Select Optimal_CH
9:	Predict lifetime of CH using ML
10:	Update
11:	If $EL_{CH} < E_{thd}$
12:	Time slot allotted to all CMs by CH
13:	Data transmission through best route
14:	End if
15:	End

2.3.5 Modified PSO-ANFIS

The PSO analytical creates a series of elements that are rationally distributed in the objective function's space. Then it iterates through generations to get the best of all conceivable outcomes. Two locations and velocity values are assigned to each particle relying on the two most fitness parameters: P_{best} and G_{best}. G_{best} is the global optimum result achieved by every single particle in the community tracked by Particle Swarm Optimization, however, P_{best} is the particle's best fitness remedy satisfied far-off. Overall particles upgrade their celerity and locations till the optimum solution can be found. PSO is convenient and applies an optimization strategy. It is computationally intensive and preserves the swarm's variety.

Suppose the positions $p_i^t = p_{i1}^t, p_{i2,}^t p_{i3\ldots\ldots}^t p_{in}^t$ and the velocity is $v_i^t = v_{i1}^t, v_{i2,}^t v_{i3\ldots\ldots}^t v_{in}^t$ of i^th^ particle in the t^th^ replication, the (t + 1)th iteration, the particle utilizes expression to optimize its placement.

$$v_i^{t+1} = W \cdot v_i^t + a_1 \cdot r_1 \cdot \left(l_i^t - p_i^t\right) + a_2 \cdot r_2 \cdot \left(s^t - p_i^t\right) \quad (21)$$

With $-v_{max} \leq v_i^{t+1} \leq v_{max}$

$$p_i^{t+1} = (p_i^t + v_i^{t+1}) \quad (22)$$

Here, l_i^t is the best site of the particle i^th^ iteration and s^t is the global best site up to the t^th^ renewal, W is represented as the inertia mass in which $1 \geq W \geq 0$, and variables a_1 & a_2 are the velocity rate and societal value, approximately r_1 and r_2 are random values in the range [0, 1], The rate of the acceleration from the preceding phase to the acceleration at the following step is substantially influenced by the inertia weight W. The following is a traditional method for raising inertia weight:

$$W = W_{final} + \left(W_{initial} - W_{final}\right)\left(1 - \frac{T}{B_{max}}\right) \text{ if } \quad s^t \neq p_i^t \quad (23)$$

$$W = W_{final} \quad \text{if} \quad s^t = p_i^t$$

Where, $T \in [0; B_{max}]$; B_{max} is the maximal quantity of replication; $W_{initial}$ is the commencing inertia mass; and W_{final} is the advancement value at the highest iteration. PSO particles may become caught in local optima instead of reaching global optima due to the enormous dimensionality of the feature vector. Hence, to ensure the best convergence:

$$v_i^{t+1} = K[v_i^t + a_1 \cdot r_1 \cdot \left(l_i^t - p_i^t\right) + a_2 \cdot r_2 \cdot \left(s^t - p_i^t\right)] \quad (24)$$

The constriction factor has to be a convex operation in early iterations to eliminate early convergence to a local minimum, and a curved inward operation in later iterations to vary slowly until attaining a global optimal. The constriction element, K utilizing this rule:

$$K = \frac{\cos\left(\left(\pi / B_{max}\right) \times T\right) + 2.5}{4} \quad (25)$$

Stopping criteria are the conditions that must be met for the iterative search method to be terminated where there was no discernible progress throughout the number of iterations. Termination criteria, as is customary, involve the intended rate of precision and the highest quantity of repetitions.

This work offers a modified PSO-ANFIS model to accurately predict. During training, the state upgraded PSO aids in tuning and achieving the optimal values of ANFIS variables in this hybrid model, as shown in algorithm 2.

The approach used by the modified PSO-ANFIS model is as follows. All datasets, which included the operational shield variables and the appropriate advancement rate, are reconstructed for the training model at first. The initial ANFIS method was developed using post-processed data, with all variables arbitrarily configured. A sufficient number of clusters must back the ANFIS model to achieve reliable prediction. The original ANFIS method optimizes the output by deriving a system of regulations that models the dataset and creates the FIS using the FCM clustering strategy. To construct a vector, the appropriate parameters for each MF are retrieved sequentially. The variables in this vector are the variables that PSO will optimize; thus, the span of each particle in Particle Swarm Optimization can be computed. The first population is formed after the PSO parameters have been specified. Following the initialization of entire particles, the modified PSO-ANFIS every particle in the swarm's velocity and location are updated until convergence is reached, resulting in the best possible values for the parameters. Each particle's goal function is calculated, and the best new values are modified automatically. The final phase allocates these optimal values to the concluding ANFIS version as a precursor and appropriate numbers.

Algorithm 2. Modified PSO-ANFIS	
1:	Begin
2:	Load Data
3:	Create ANFIS model
4:	Initialize parameters
5:	For i=1: Max_iterations
6:	Train and optimize ANFIS with MPSO
7:	Select Best Output as cluster head
8:	End
9:	End

2.3.6 Determination of objective functions

The best node in the group is chosen by the Cluster Head selection algorithm based on several variables, such as distance, computing complexities, residual power, and transmitting power. The network's nodes require energy for data consolidation, transfer, and receiving. In regard to energy, it is necessary to use a more economical CH selection procedure. In this work, a multi-objective methodology for CH selection has been suggested.

Objective 1: Distance among nodes

The method primarily measures the separation between adjacent nodes to assess their closeness. $N_{closeness}$.

$$N_{closeness} = \frac{1}{N_t}\sum_{i}^{1\text{-}N_t} l(n,i) \qquad (27)$$

Where,

The total number of nodes present in the system are denoted by N_t;

The space between nodes is represented by $l(n,i)$;

Consequently, the formula establishes the first objective function, OF_1 as:

$$Minimize\ OF_1 = \frac{1}{N_t}\sum_{i=1}^{N} N_{closeness}(N_i) \qquad (28)$$

Objective 2: Adjacency cost

The cost of interacting, c_{intr}, with the adjacent node is calculated as:

$$c_{intr} = \frac{l_{avg}^2}{l_0^2} \qquad (29)$$

Where,

l^2_{avg} = The mean separation among nodes and their neighboring nodes

l^2_0 = The half of the diameter of the nodes.

Thus, the 2nd objective function, OF_2 is represented as:

$$Minimize\ OF_2 = \frac{1}{N_t}\sum_{i=1}^{N} C_{intr}\ (N_i) \qquad (30)$$

Objective 3: Residual energy

After evaluating the utilized energy of every member of the cluster, the SN evaluates its own applied energy, which results from detecting, receiving, collecting, and transmission of the data. During the CH selection process, yet another energy use is measured. The total residual energy is the sum of the SN's collected energy and residual energy.

$$E_{TRE}(i) = E_{Rem}(i) + E_{Gathered}(i) + E_{Rec}(i) + E_{agg}(i) \quad (31)$$

Where, E_{TRE} = Total residual energy, E_{Rem}= Residual energy of node, $E_{Gathered}$= Re-energized energy of node, E_{Rec} represents the energy used in reception of the data, E_{agg} represents the energy used in accumulating data. Therefore, the 3rd objective function is now, OF_3, is presented as:

$$Maximize\ OF_3 = \frac{1}{N_t}\sum_{i=1}^{N} E_{Rem}\ (N)_i \qquad (32)$$

Objective 4: Transmission power

Another crucial factor for energy-efficient communication is transmission power. The network's coverage area, N_{range} is defined as:

$$N_{range}=r(N_i) \tag{33}$$

wherein r is the node's ½ of diameter. this objective function follows., OF_4, is defined as:

$$Maximize\ OF_4 = \frac{1}{N_t}\sum_{i-1}^{N} N_{Range} * \frac{E_T(i)-E_{TRE}(i)}{E_{TRE}(i)} \tag{34}$$

Where, E_T is the total energy of the entire network. These objective functions have been used to develop the fitness function (OFn). for choosing the best head node the node that satisfies all of the objectives will be chosen as a Cluster Head. This suggests that the node nearest to the user, with the Minimum possible cost for energy as well as range, will be chosen. Every cluster's CH is selected, and data are then gathered for transmission.

3. Results and discussions

We conducted simulations of the situation on the MATLAB program under various situations and with various parameter values to assess the effectiveness of the suggested model. Below, these factors are covered.

Residual energy: The sum of the residual energy of all sensor nodes in the network is considered residual energy.

$$Residual\_Energy = \sum_{i=1}^{n} TE_{nodes} - \sum_{i=1}^{n} UE_{nodes} \tag{35}$$

Where, TE_{nodes}= Total energy of all nodes, n
UE_{nodes}= Utilized energy of all nodes, n

Throughput: The throughput is determined by how efficiently data packets are delivered to the sink link at a given time.

$$Throughput = \sum_{i=1}^{n} D_{packet} / Total\_time \tag{36}$$

Where, D_{packet}= Delivered Packet

Network longevity: It was evaluated by calculating the active and dead nodes through every cycle or subsequently a particular period.

$$Network\_Longevity = \sum_{t=1}^{T} T_{SN} - D_{SN} \tag{37}$$

Where, T_{SN}= Total sensor nodes, D_{SN}= Dead sensor nodes, T= Simulation time

Convergence analysis

Before considering or selecting the best cluster head selection method, we must first calculate its converging curve. So, Figure 2 to Figure 6 below represents the comparative analysis of the suggested modified PSO ANFIS model with the conventional PSO optimization algorithm. For optimization parameters used for evaluating the convergence curve are illustrated in Table 2.

Table 2 Simulation factors for PSO-ANFIS

Simulating Factors	Values
Search Agents	30
Max Iteration	500
Weightmax	0.9
Weightmin	0.2
C1, C2	1

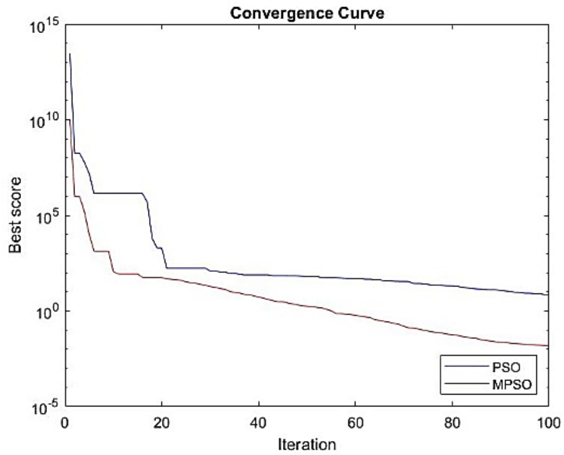

Figure 2 Convergence curve analysis at iteration 100

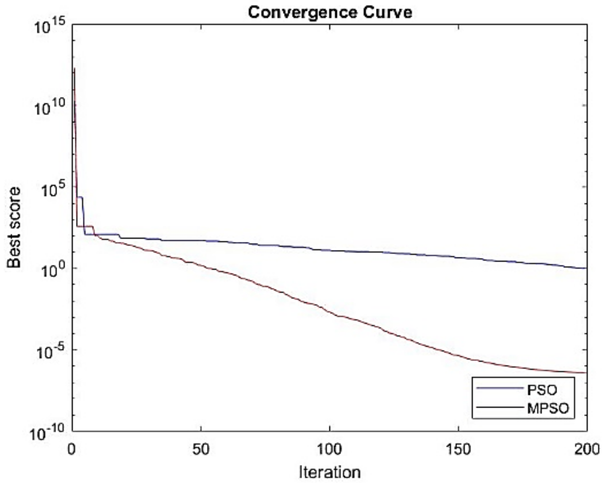

Figure 3 Convergence curve analysis at iteration 200

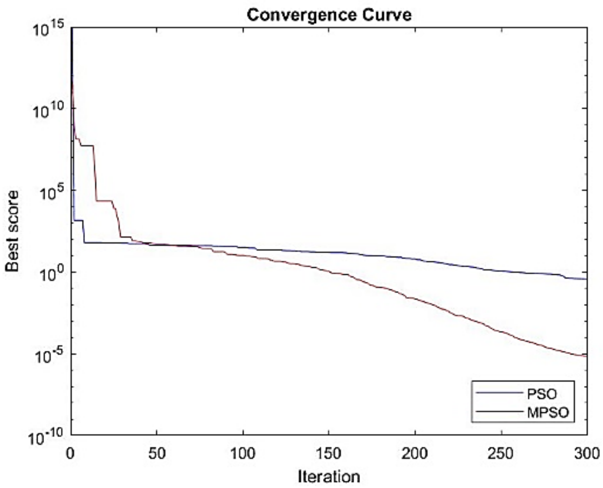

Figure 4 Convergence curve analysis at iteration 300

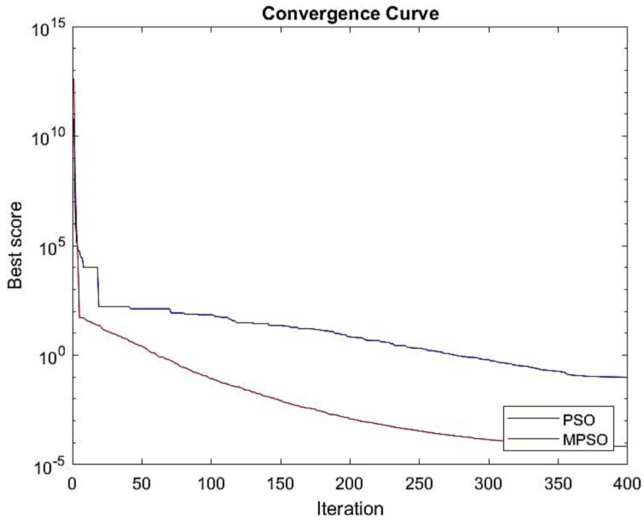

Figure 5. Convergence curve analysis at iteration 400

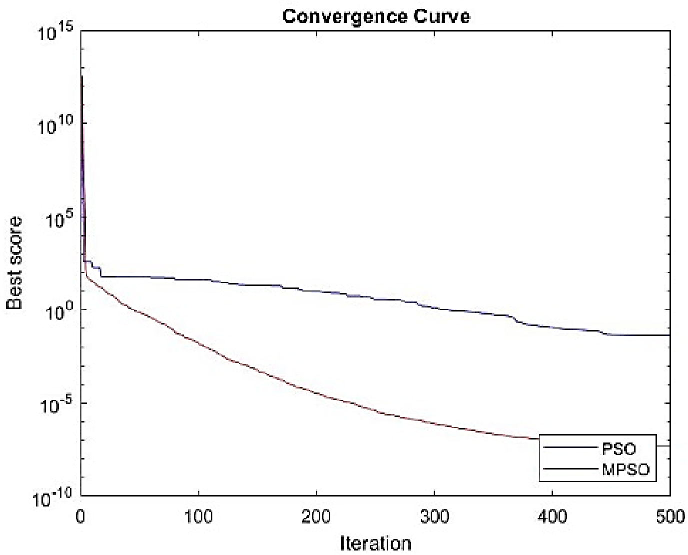

Figure 6 Convergence curve analysis at iteration 500

Table 3 Simulation factors for homogeneous WSN

Simulating Factors	Values
Region	100m*100m
Sensing nodes	100
Commencing energy of every network	0.5 J
Dissipated Energy during transmitting bits	50 nJ/bit
Dissipated Energy while reception of bits	50 nJ/bit
Energy Losses Throughout Power Amplification	0.01J/bits/ m^4
Packet size	4000

Table 4 Residual energy and time complexity of proposed HCPFR

Rounds	Residual Energy (in J)	Time Complexity (in Sec)
2000 round	~30.8	213
4000 rounds	~20.9	443
6000 rounds	~20	887
8000 rounds	~10.5	1295
10000 rounds	~1	1869

For homogenous WSNs in a certain region, WSN regions are simulated. While sensor nodes are deployed with variable energy levels and restricted energy, sink nodes are randomly deployed at different levels. The suggested HCPFR model is compared with a different method; LEACH PSO, LEACH-GWO, LEACH-EEGWO, FZR, and the performance is compared with different parameters mainly First Dead Node, Network Longevity, and throughput (in terms of packet delivered). The simulation scenarios for homogeneous WSNs are shown in Table 3.

The enduring energy of the nodes in the recommended HCPFR varied with no rounds. As the number of rounds varied from 2000 to 10000 rounds the Residual energy changed from nearly 3.8 to 0.1. The result in Table 4 and Figure 7 shows that as the quantity of rounds rises the Residual Energy of the Proposed HCPFR decreases, and both are inversely proportional. Table 4 also shows time complexity analysis with rounds

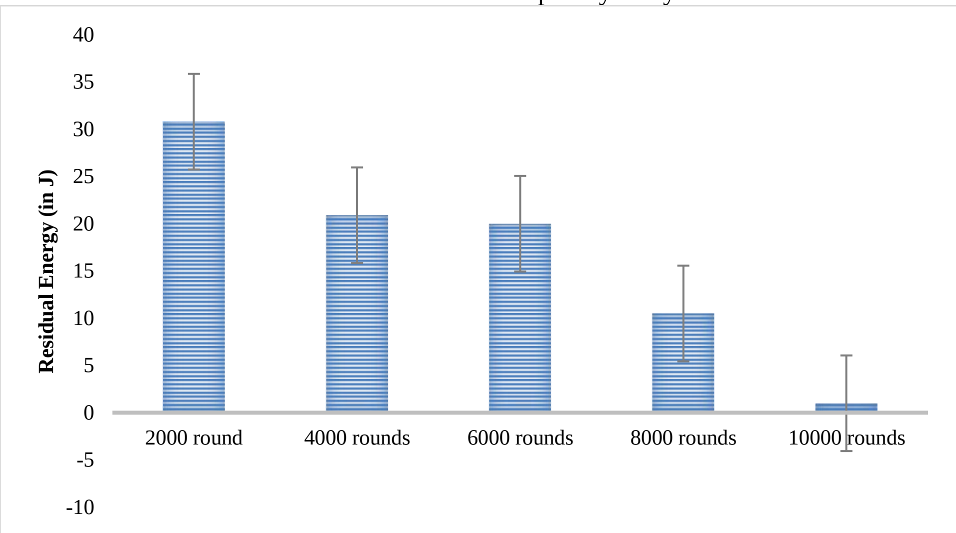

Figure 7 Number of rounds vs residual energy

Table 5 Comparative performance evaluation

Parameters	LEACH-PSO (Zivkovic et al., 2020)	LEACH-GWO (Zivkovic et al., 2020)	LEACH-EEGWO (Zivkovic et al., 2020)	FZC (Stephan et al., 2020)	HCPFR
First Dead Node	1,150	1,130	1,180	1293	~8000
Network Longevity	3,880	1,700	3900	8000	~10000
Throughput (in terms of packet delivered)	20,000	14,200	21000	-	~30000

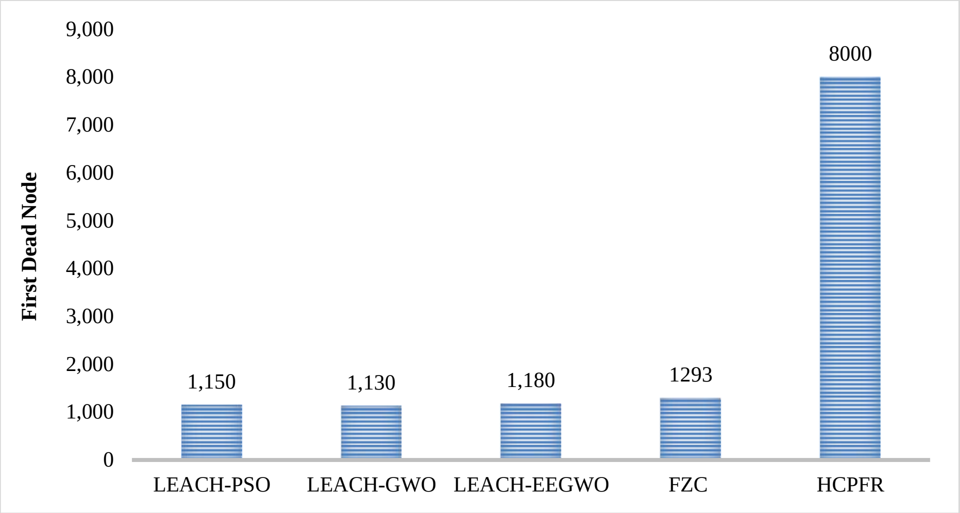

Figure 8 Comparative performance evaluation considering FDN

Figure 8 displays the comparison of the different models with the established model. The FDN of the proposed work is around 8000, which is the highest among the LEACH-PSO, LEACH-GWO, LEACH-EEGWO (Zivkovic et al., 2020), and FZC (Stephan et al., 2020). The values suggested that the proposed model HCPFR outperform the traditional models in term of FDN. Figure 9 shows a comparison of several models to the suggested model in terms of network longevity. The suggested work has network longevity (NL) of about 10000, which is the highest among the LEACH-PSO, LEACH-GWO, LEACH-EEGWO (Zivkovic et al., 2020) and FZC (Zivkovic et al., 2020; Stephan et al., 2020). In respect of NL, the recommended model HCPFR outperformed the different models, according to the results.

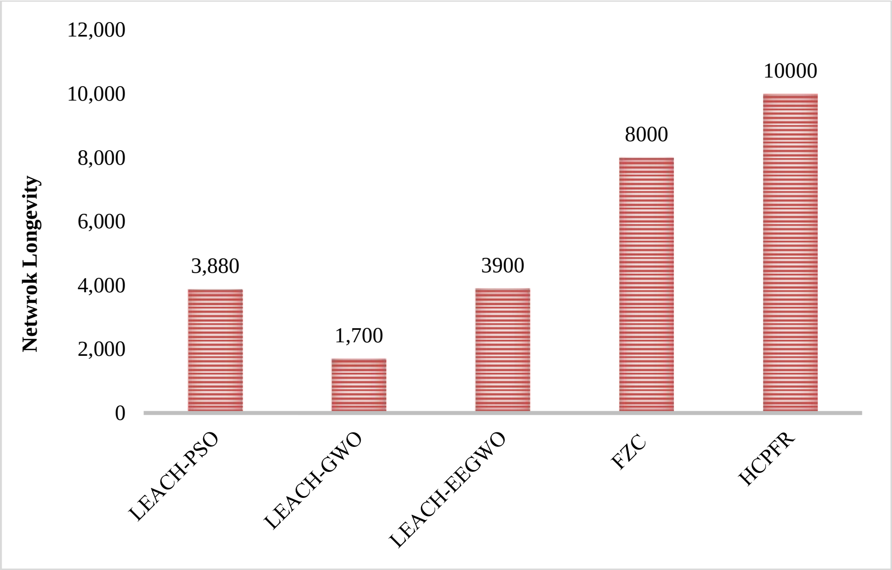

Figure 9 Comparative performance evaluation considering network longevity

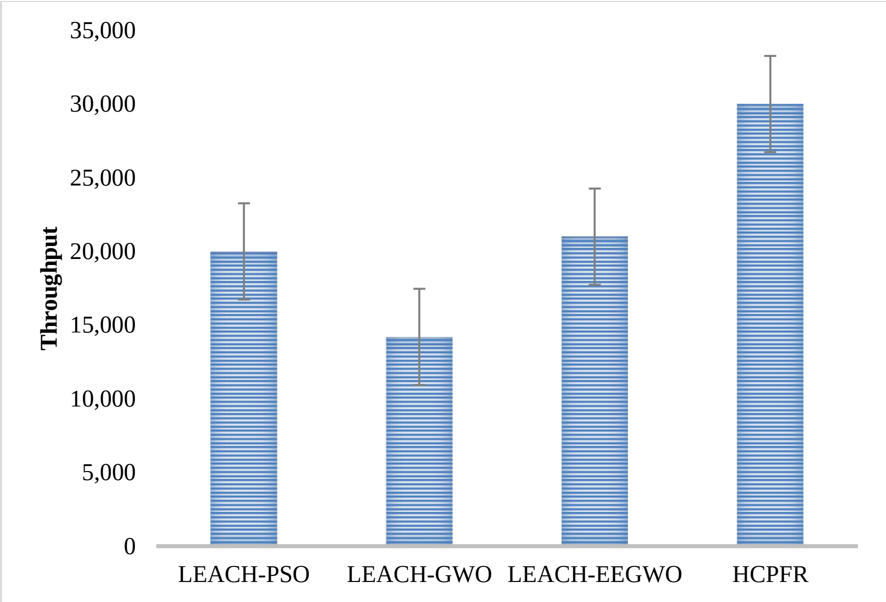

Figure 10 Comparative performance evaluation considering throughput

Figure 10 shows a comparison of several models to the suggested model in terms of throughput. The data packets every second collected at the endpoint is measured by end-to-end network throughput. The difference between the overall data packets received at the endpoint and the total number of data packets sent by the origin. The suggested work has a throughput of about 30000, which is the highest among the LEACH-PSO, LEACH-GWO, LEACH-EEGWO (Zivkovic et al., 2020), and FZC (Zivkovic et al., 2020; Stephan et al., 2020). In respect of throughput, the recommended model HCPFR outperformed the standard models, according to the results. The enhancement of the result is due to network longevity prediction and the multi-objective optimization algorithm used in the proposed HCPFR algorithm. As the algorithm considered multiple factors to decide CH. After CH selection, its prediction of CH lifetime results is optimal updation of CH when required. Unnecessary regular checking and updating are not required in HCPFR which preserves the energy life of nodes and ultimately increases the lifetime of the entire network.

4. Conclusions

A machine learning-based protocol is presented in this work termed HCPFR that can appropriately design the gateway that permits connection formation utilizing basic fuzzy rule-based-NN combined with clustering to have a suitable utilization of energy while avoiding the waste caused by the selection of the head and cluster patterning. The repeated computations depending on the set of data enable a reliable route creation during the communication. The improved method makes it possible for cluster patterns and routing to decide what nodes to deliver information to more efficiently, resulting in a speedier transmission network that is much more energy-efficient and less prone to errors. The suggested system's performance assessment in comparison to the previous techniques demonstrates that it is quite capable in terms of residual energy and FDN, THP, and NL. In terms of packet delivered and residual energy, the suggested HCPFR model is contrasted with LEACH PSO, LEACH-GWO, LEACH-EEGWO, and FZR methods, and the performance is compared to different parameters such as First Dead Node (FDN), Network Longevity (NL), and throughput (THP). The proposed HCPFR's FDN, NL, and THP are about 8000, 10000, and 30000, respectively. This shows approx. 40% improvement in throughput. Furthermore, the proposed model reveals that when the number of rounds grows from 2000 to 10,000, the residual energy declines to 1 from 30.8. The designed algorithm shows improvement in energy utilization but still, there is some limitation in the current system. The major limitation of this work was that the computational time is being increased with the increase in the number of rounds that needed to be resolved in future work.

Conflict of interests

The authors declare no conflict of interest.

5. References

Asqui, O. P., Marrone, L. A., Chaw, E. E., Asqui, O. P., Marrone, L. A., & Chaw, E. E. (2021). Multihop Deterministic Energy Efficient Routing Protocol for Wireless Sensor Networks MDR. *International Journal of Communications, Network and System Sciences*, *14*(3), 31–45. https://doi.org/10.4236/IJCNS.2021.143003

Babu, M. V., Alzubi, J. A., Sekaran, R., Patan, R., Ramachandran, M., & Gupta, D. (2020). An Improved IDAF-FIT Clustering Based ASLPP-RR Routing with Secure Data Aggregation in Wireless Sensor Network. *Mobile Networks and Applications*, *26*(3), 1059–1067. https://doi.org/10.1007/S11036-020-01664-7

Cui, X., Ma, D., & Ma, L. (2019, June 12-15). *An EH-WSN clustering algorithm based on energy prediction* [Conference presentation]. 2019 IEEE 11th International Conference on Communication Software and Networks, ICCSN, Canada, US. https://doi.org/10.1109/ICCSN.2019.8905383

Ahmad, H. P., & Dang, S. (2015). Performance Evaluation of Clustering Algorithm Using different dataset. *Journal of Information Engineering and Applications*, *5*(1), 39-47.

Ghorbani Dehkordi, E., & Barati, H. (2023). Cluster based routing method using mobile sinks in wireless sensor network. *International Journal of Electronics*, *110*(2), 360-372. https://doi.org/10.1080/00207217.2021.2025451

El Alami, H., & Najid, A. (2016a). (SET) smart energy management and throughput maximization: A new routing protocol for WSNs. *Security Management in Mobile Cloud Computing*, 1–28. https://doi.org/10.4018/978-1-5225-0602-7.CH001

El Alami, H., & Najid, A. (2019). ECH: An Enhanced Clustering Hierarchy Approach to Maximize Lifetime of Wireless Sensor Networks. *IEEE Access*, *7*, 107142–107153. https://doi.org/10.1109/ACCESS.2019.2933052

El Alami, H., & Najid, A. (2016b, March 30 – April 1). *Energy-efficient fuzzy logic cluster head selection in wireless sensor networks* [Conference presentation]. International Conference on Information Technology for Organizations Development (IT4OD). IEEE, Fez, Morocco. https://doi.org/10.1109/IT4OD.2016.7479300

Ebrahimi, S., & Tabatabaei, S. (2020). Using Clustering via Soccer League Competition Algorithm for Optimizing Power Consumption in WSNs (Wireless Sensor Networks). *Wireless Personal Communications*, *113*(4), 2387–2402. https://doi.org/10.1007/S11277-020-07332-Z

Edla, D. R., Kongara, M. C., & Cheruku, R. (2019). SCE-PSO based clustering approach for load balancing of gateways in wireless sensor networks. *Wireless Networks*, *25*(3), 1067–1081. https://doi.org/10.1007/S11276-018-1679-2

El Khediri, S., Fakhet, W., Moulahi, T., Khan, R., Thaljaoui, A., & Kachouri, A. (2020). Improved node localization using K-means clustering for Wireless Sensor Networks. *Computer Science Review*, *37*, Article 100284. https://doi.org/10.1016/J.COSREV.2020.100284

Feng, X., Zhang, J., Ren, C., & Guan, T. (2018). An Unequal Clustering Algorithm Concerned with Time-Delay for Internet of Things. *IEEE Access*, *6*, 33895–33909. https://doi.org/10.1109/ACCESS.2018.2847036

Gaber, T., Abdelwahab, S., Elhoseny, M., & Hassanien, A. E. (2018). Trust-based secure clustering in WSN-based intelligent transportation systems. *Computer Networks*, *146*, 151–158. https://doi.org/10.1016/J.COMNET.2018.09.015

Goswami, P., Mukherjee, A., Hazra, R., Yang, L., Ghosh, U., Qi, Y., & Wang, H. (2021). AI based energy efficient routing protocol for intelligent transportation system. *IEEE Transactions on Intelligent Transportation Systems*, *23*(2), 1670-1679. https://doi.org/10.1109/TITS.2021.3107527

Hajipour, Z., & Barati, H. (2021). EELRP: energy efficient layered routing protocol in wireless sensor networks. *Computing*, *103*(12), 2789-2809. https://doi.org/10.1007/s00607-021-00996-w

Hidoussi, F., Toral-Cruz, H., Boubiche, D. E., Martínez-Peláez, R., Velarde-Alvarado, P., Barbosa, R., & Chan, F. (2017). PEAL: Power Efficient and Adaptive Latency Hierarchical Routing Protocol for Cluster-Based WSN. *Wireless Personal Communications*, *96*(4), 4929–4945. https://doi.org/10.1007/S11277-017-4963-Z

Khan, I. U., Qureshi, I. M., Aziz, M. A., Cheema, T. A., & Shah, S. B. H. (2020). Smart IoT control-based nature inspired energy efficient routing protocol for Flying Ad Hoc Network (FANET). *IEEE Access*, *8*, 56371–56378. https://doi.org/10.1109/ACCESS.2020.2981531

Lee, J. S., & Teng, C. L. (2017). An Enhanced Hierarchical Clustering Approach for Mobile Sensor Networks Using Fuzzy Inference Systems. *IEEE Internet of Things Journal*, *4*(4), 1095–1103. https://doi.org/10.1109/JIOT.2017.2711248

Liao, Y., Qi, H., & Li, W. (2013). Load-balanced clustering algorithm with distributed self-organization for wireless sensor networks. *IEEE Sensors Journal*, *13*(5), 1498–1506. https://doi.org/10.1109/JSEN.2012.2227704

Malar, A. C. J., Kowsigan, M., Krishnamoorthy, N., Karthick, S., Prabhu, E., & Venkatachalam, K. (2020). Multi constraints applied energy efficient routing technique based on ant colony optimization used for disaster resilient location detection in mobile ad-hoc network. *Journal of Ambient Intelligence and Humanized Computing*, *12*(3), 4007–4017. https://doi.org/10.1007/S12652-020-01767-9

Malshetty, G., & Mathapati, B. (2019, April 23-25). *Efficient clustering in WSN-Cloud using LBSO (Load Based Self-Organized) technique* [Conference presentation]. 2019 3rd International Conference on Trends in Electronics and Informatics (ICOEI), Canada, US. https://doi.org/10.1109/ICOEI.2019.8862584

Manfredi, S. (2012). Reliable and energy-efficient cooperative routing algorithm for wireless monitoring systems. *IET Wireless Sensor Systems*, *2*(2), 128–135. https://doi.org/10.1049/IET-WSS.2011.0103

Masoud, M. Z., Jaradat, Y., Zaidan, D., & Jannoud, I. (2019). *To Cluster or Not to Cluster: A Hybrid Clustering Protocol for WSN* [Conference presentation]. 2019 IEEE Jordan International Joint Conference on Electrical Engineering and Information Technology (JEEIT), Canada, US. https://doi.org/10.1109/JEEIT.2019.8717524

Mirjalili, S., Saremi, S., Mirjalili, S. M., & Coelho, L. D. S. (2016). Multi-objective grey wolf optimizer: A novel algorithm for multi-criterion optimization. *Expert Systems with Applications*, *47*, 106–119. https://doi.org/10.1016/J.ESWA.2015.10.039

Mi, J., Wen, X., Sun, C., Lu, Z., & Jing, W. (2019). *Energy-efficient and low package loss clustering in UAV-assisted WSN using kmeans++ and fuzzy logic* [Conference preseatation]. 2019 IEEE/CIC International Conference on Communications Workshops in China (ICCC Workshops), Canada, US. https://doi.org/10.1109/ICCCHINAW.2019.8849956

Mohapatra, H., & Rath, A. K. (2019). Fault Tolerance Through Energy Balanced

Cluster Formation (EBCF) in WSN. *Advances in Intelligent Systems and Computing*, *851*, 313–321. https://doi.org/10.1007/978-981-13-2414-7_29

Panchal, A., & Singh, R. K. (2021). EHCR-FCM: Energy Efficient Hierarchical Clustering and Routing using Fuzzy C-Means for Wireless Sensor Networks. *Telecommunication Systems: Modelling, Analysis, Design and Management*, *76*(2), 251–263. https://doi.org/10.1007/S11235-020-00712-7

Papi, F., & Barati, H. (2022). HDRM: A hole detection and recovery method in wireless sensor network. *International Journal of Communication Systems*, *35*(8). https://doi.org/10.1002/dac.5120

Pratha, S. J., Asanambigai, V., & Mugunthan, S. R. (2021). Grey wolf optimization-based energy efficiency management system for wireless sensor networks. Retrieved https://assets.researchsquare.com/files/rs-397273/v1_covered.pdf?c=1631873220

Raj, J. S. (2020). Machine learning based resourceful clustering with load optimization for wireless sensor networks. *Journal of Ubiquitous Computing and Communication Technologies (UCCT)*, *2*(01), 29-38. https://doi.org/10.36548/jucct.2020.1.004

Rajeswari, A. R., Kulothungan, K., Ganapathy, S., & Kannan, A. (2021a). Trusted energy aware cluster-based routing using fuzzy logic for WSN in IoT. *Journal of Intelligent & Fuzzy Systems*, *40*(5), 9197–9211. https://doi.org/10.3233/JIFS-201633

Rajeswari, A. R., Ganapathy, S., Kulothungan, K., & Kannan, A. (2021b). An efficient trust-based secure energy-aware clustering to mitigate trust distortion attack in mobile ad-hoc network. *Concurrency and Computation: Practice and Experience, 33(13),* e6223. https://doi.org/10.1002/CPE.6223

Ramesh, S., & Smys, S. (2017). A software-based heuristic clustered (SBHC) architecture for the performance improvement in manet. *Wireless Personal Communications*, *97*, 6343-6355. https://doi.org/10.1007/s11277-017-4841-8

Rizk, R., Elhadidy, H., & Nassar, H. (2011). Optimized mobile radio aware routing algorithm for wireless sensor networks. *IET Wireless Sensor Systems*, *1*(4), 206–217. https://doi.org/10.1049/IET-WSS.2011.0047

Saadaldeen, R. S. M., Osman, A. A., & Ahmed, Y. E. E. (2018, August 12-14). *Clustering for Energy Efficient and Redundancy Optimization in WSN using Fuzzy Logic and Genetic Methodologies a Review* [Conference presentation]. 2018 International Conference on Computer, Control, Electrical, and Electronics Engineering (ICCCEEE), Canada, US. https://doi.org/10.1109/ICCCEEE.2018.8515880

Safara, F., Souri, A., Baker, T., Al Ridhawi, I., & Aloqaily, M. (2020). PriNergy: a priority-based energy-efficient routing method for IoT systems. *The Journal of Supercomputing*, *76*(11), 8609-8626. https://doi.org/10.1007/S11227-020-03147-8

Sangeetha, G., Vijayalakshmi, M., Ganapathy, S., & Kannan, A. (2019). An improved congestion-aware routing mechanism in sensor networks using fuzzy rule sets. *Peer-to-Peer Networking and Applications*, *13*(3), 890–904. https://doi.org/10.1007/S12083-019-00821-4

Santhosh Kumar, S. V. N., Palanichamy, Y., Selvi, M., Ganapathy, S., Kannan, A., & Perumal, S. P. (2021). Energy efficient secured K means based unequal fuzzy clustering algorithm for efficient reprogramming in wireless sensor networks. *Wireless Networks*, *27*(6), 3873–3894. https://doi.org/10.1007/S11276-021-02660-9

Raj, J. S., & Basar, A. (2019). QoS optimization of energy efficient routing in IoT wireless sensor networks. *Journal of ISMAC, 1(01),* 12-23. https://doi.org/10.36548/jismac.2019.1.002

Smys, S., & Raj, J. S. (2019). Performance optimization of wireless adhoc networks with authentication. *Journal of Ubiquitous Computing and Communication Technologies (UCCT*), *1*(2), 64-75. https://doi.org/10.36548/JUCCT.2019.2.001

Smys, S. (2019). Energy-aware security routing protocol for WSN in big-data applications. *Journal of ISMAC*, *1*(1), 38-55. https://doi.org/10.36548/JISMAC.2019.1.004

Shahbaz, A. N., Barati, H., & Barati, A. (2021). Multipath routing through the firefly algorithm and fuzzy logic in wireless sensor networks. *Peer-to-Peer Networking and Applications, 14*(2), 541–558. https://doi.org/10.1007/s12083-020-01004-2

Sharifi, S. S., & Barati, H. (2021). A method for routing and data aggregating in cluster-based wireless sensor networks. *International Journal of Communication Systems*, *34*(7), 1–17. https://doi.org/10.1002/dac.4754

Shyjith, M. B., Maheswaran, C. P., & Reshma, V. K. (2020). Optimized and Dynamic Selection of Cluster Head Using Energy Efficient Routing Protocol in WSN. *Wireless Personal Communications, 116*(1), 577–599. https://doi.org/10.1007/S11277-020-07729-W

Stephan, T., Sharma, K., Shankar, A., Punitha, S., Varadarajan, V., & Liu, P. (2020). Fuzzy-Logic-Inspired Zone-Based Clustering Algorithm for Wireless Sensor Networks. *International Journal of Fuzzy Systems*, *23*(2), 506–517. https://doi.org/10.1007/S40815-020-00929-3

Sujith, A., Dorai, D. R., & Kamalesh, V. N. (2021). Energy efficient zone-based clustering algorithm using fuzzy inference system for wireless sensor networks. *Engineering Reports*, *3*(4), Article e12310. https://doi.org/10.1002/ENG2.12310

Thushara, K., & Raj, J. S. (2013). Dynamic Clustering and Prioritization in Vehicular Ad-hoc Networks: Zone Based approach. *International Journal of Innovation and Applied Studies*, *3*(2), 535–540. http://www.issr-journals.org/ijias/

Xu, L., Collier, R., & O'Hare, G. M. P. (2017). A Survey of Clustering Techniques in WSNs and Consideration of the Challenges of Applying Such to 5G IoT Scenarios. *IEEE Internet of Things Journal*, *4*(5), 1229–1249. https://doi.org/10.1109/JIOT.2017.2726014

Yagouta, A. B., Jabberi, M., & Gouissem, B. B. (2018, October 30, 2017 - November 3, 2017). *Impact of sink mobility on quality-of-service performance and energy consumption in wireless sensor network with cluster based routing protocols* [Conference presentation]. 2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA), Canada, US. https://doi.org/10.1109/AICCSA.2017.198

Yousefpoor, E., Barati, H., & 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), 1917–1942. https://doi.org/10.1007/s12083-021-01116-3

Yu, J., Feng, L., Jia, L., Gu, X., & Yu, D. (2014). A Local Energy Consumption Prediction-Based Clustering Protocol for Wireless Sensor Networks. *Sensors*, *14*(12), 23017–23040. https://doi.org/10.3390/S141223017

Zivkovic, M., Bacanin, N., Zivkovic, T., Strumberger, I., Tuba, E., & Tuba, M. (2020, May 26-27). *Enhanced Grey Wolf Algorithm for Energy Efficient Wireless Sensor Networks* [conference presentation]. 2020 Zooming Innovation in Consumer Technologies Conference, ZINC 2020, Canada, US. https://doi.org/10.1109/ZINC50678.2020.9161788