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# Enhancing the Lifetime of Wireless Sensor Networks Using Fuzzy Logic LEACH Technique-Based Particle Swarm Optimization

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**ABSTRACT** Wireless sensor networks (WSNs) have attracted significant attention because of their widespread use in health care, habitat tracking, disaster prevention, agriculture, monitoring areas, fire tracking, and other real-life applications. The lifetime of WSNs must be prolonged to increase their use for various applications. One of the most effective methods for improving the network's lifetime is clustering with the optimal cluster head (CH). This study proposes a fuzzy Logic (FL) low-energy adaptive clustering hierarchy (LEACH) technique-based particle swarm optimization (PSO). It employs hybrid PSO and a K-means clustering algorithm for cluster formation. It selects the primary CH (PCH) and secondary CH (SCH) using FL. Extensive simulations were conducted using a simulation program to validate the proposed protocol's performance. Furthermore, the proposed protocol was compared with traditional algorithms, such as fuzzy c-means (FCM) clustering and FLS-based CH selection to enhance the sustainability of WSNs for environmental monitoring applications, LEACH-Fuzzy clustering protocol, and LEACH based on energy consumption equilibrium. The results confirmed that the proposed protocol efficiently balances energy consumption to improve wireless sensor network performance and to maximize throughput. The simulated results indicated that network lifetime was improved by more than 46% and packet transmission by 17.6%.

**INDEX TERMS** Clustering, energy consumption, fuzzy logic, leach, particle swarm optimization, throughput.

## NOMENCLATURE

$BS$	Base station	$E_{RX}$	Receiver consumption energy
$(BS_X, BS_Y)$	Base station's coordinates	$FND$	First node die
$B$	B-bit data	$FIS$	Fuzzy inference system
$CoA$	Center of Area	$FL$	Fuzzy logic
$CH$	Cluster head	$g_i$	Global best position
$CM$	Cluster member	$HND$	Half node die
$ C_{ij} $	Number of sensor nodes in cluster $C_{ij}$	$LND$	Last node die
$d$	Distance	$M_f$	Membership function
$d_0$	Threshold value	$N$	Number of sensor nodes
$D$	Input Dimension	$N_c$	Number of clusters
$E_{fs}$	Free space parameter	$LEACH$	Low energy adaptive clustering hierarchy
$E_{amp}$	Multi-path parameter	$PCH$	Primary cluster head
$E_{elec}$	Electronic energy	$PSO$	Particle swarm optimization
$E_{DA}$	Data aggregation energy	$SCH$	Secondary cluster head
$E_{TX}$	Transmitter consumption energy	$VCH$	Vice cluster head
		$v_i$	$i^{th}$ Particle's current velocity
		$WSN$	Wireless sensor network
		$x_i$	$i^{th}$ Particle's current position
		$y_i$	Personal best position

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## I. INTRODUCTION

Wireless sensor networks (WSNs) consist of several sensors (a few tens to thousands), with characteristics such as self-organizing, low cost, and random deployment [1]–[3]. Sensors are tiny nodes randomly distributed throughout the network area. They detect environmental signals and then transfer sensed data to the base station (BS). They have mostly been used for habitat monitoring, disaster prevention, health care, agriculture, monitoring regions, and fire tracking [4].

Sensor nodes have tiny batteries that are costly to recharge or replace through complex environments. In real-world applications, each node in WSN must consume minimal energy as possible for data gathering and transmission to extend the WSN's lifespan.

Researchers have studied numerous energy-efficient WSN operation strategies using clustering. Clustering has been an effective approach for reducing energy utilization, increasing the stabilization of the network topology and the lifetime of the network. The lifetime can be specified as the round when the first node dies (FND), half of the nodes die (HND), or last node dies (LND) [5]–[7].

In WSNs, the routing protocol determines the path for sending data to the sink using the least amount of energy [8]–[10].

In clustering routing, WSNs are split into various clusters. The main processes are cluster formation, cluster head (CH) selection, and routing between nodes and BS [11]–[16]. Every cluster includes CH and cluster members (CMs). The clustering-routing protocol consumes less energy than the other routing protocols.

Low-energy adaptive clustering hierarchy (LEACH) [17], [18] is a popular clustering-routing protocol. It employs a distributed approach for the formation of clusters and CH selection. Although it is a simple algorithm, a random selection of CHs results in increasing energy usage and earlier death.

This study proposes a fuzzy Logic (FL) low energy adaptive hierarchy (LEACH) technique-based particle swarm optimization (PSO) that applies hybrid PSO and a K-means clustering algorithm to centralized approaches in cluster creation and FL for selecting CHs, namely, primary CH (PCH) and secondary CH (SCH). FL is used to transform an input space into an output space [2]. Communications among CMs, CHs, and BS follow the standard rules for the number of hops.

The contributions of this work using the proposed technique are summarized as follows:

- Cluster construction is performed using a hybrid particle swarm optimization (PSO) and K-means clustering algorithm as a centralized strategy.
- The WSN's lifespan and throughput are enhanced by employing three parameters to perform PCH selection—using FL, including energy level, distance to cluster's center, and distance to BS.
- To improve network stability, FL is used to select the SCH by employing two parameters: energy level and distance to PCH.

- Using simulation software, the proposed protocol is compared with conventional algorithms, such as FCM clustering and FLS-based CH selection, to enhance the sustainability of WSNs for environmental monitoring applications (Rajput and Kum) [19], LEACH-fuzzy clustering (LEACH-FC) protocol [2], and LEACH based on energy consumption equilibrium (Chen *et al.*) [20].

The remainder of the paper is organized as follows: Section 2 discusses related works and current problems. Section 3 presents the network system model. Section 4 presents our proposed technique, including the hybrid PSO and a K-means clustering algorithm and the CHs selection algorithms. Section 5 presents simulation experiments for the proposed technique and compares it with state-of-the-art methods. Finally, section 6 presents the conclusion.

## II. RELATED WORK

The technology for wireless sensor systems is growing quickly. Many protocols for the effective routing of WSNs have been developed. These protocols rely on energy conservation and network lifespan extension.

Heinzelmen *et al.* [17], [18] proposed the low-energy adaptive hierarchical clustering protocol (LEACH). It is among the most well-known hierarchical protocols. LEACH's primary functions are to randomly establish clusters and to transfer data between CMs and CHs, as well as between CHs and BS. It is a simple algorithm. However a random selection of CHs results in increased energy consumption and an earlier death.

Heinzelmen *et al.* [21] introduced a centered clustering protocol LEACH-centralized (LEACH-C). It calculates the average energy level of CMs at BS. It does not choose as CHs those that have an energy level below average. Centralized clusters are better than LEACH clusters, but this protocol does not offer larger networks scalability and robustness.

Mumtaz *et al.* [22] proposed the energy aware routing using improved LEACH protocol (E-LEACH). The number of CHs is estimated with a parameter equal to the square root of the total number of sensors by application of a minimum spanning mechanism. The lifespan of the protocol network is increased by maximising energy during the initialization stage, but still random selection of the specific number of CHs leads to more energy consumption and earlier death of these nodes.

Sharma *et al.* [23] presented a method for the determination of cluster heads, Distance-based Cluster Head (DBCH). Both energy level and distance from nodes to BS were used. Despite this, CH still had many tasks to be performed according to its energy level. It needed to use a vice cluster head (VCH) or a SCH to minimize its energy consumption by performing some tasks.

Loscrì *et al.* [24] introduced a two-levels hierarchy for low-energy adaptive clustering hierarchy protocol (TL-LEACH). It performed a two-tier transmission operation. Data were transferred to the SCH from CMs and then to PCH directly connected to BS. The selection of PCH and SCH is not

dependent both on energy level and distance measures. This results in greater energy efficiency.

Chen *et al.* [20] developed the LEACH algorithm based on the energy consumption equilibrium protocol. PCH selection is performed in such as a LEACH protocol. Two levels of the transmitting mechanism involve transforming data between the simple nodes and SCH. Then, transforming between the SCH and PCH. PCH communicates directly with BS. This protocol extends the network's life by optimizing energy during the setup stage. However, it may increase energy consumption and the earlier death of such nodes if the clusters are randomly created and the PCHs are selected randomly.

Abdulsalam and Kamel [25] proposed a centralized clustering protocol, the weighted low energy adaptive clustering hierarchy aggregation algorithm for data streams in WSNs (W-LEACH). This protocol was created with non-uniform WSNs in mind. Initially, all nodes were assumed to have the same energy. CH is chosen based on the weight value given to each sensor. Regardless of whether or not that node has previously been elected as CH. Despite this, CH still had many tasks to be performed according to its energy level and needed to use a VCH or a SCH to minimize its energy consumption by performing some tasks.

Kim *et al.* [26] introduced a CH election mechanism using FL in WSN (CHEF) protocol. Each sensor produces a random number among zero and one. If that number falls below a threshold, the sensor uses FL to determine the probability. CH is chosen as a node having higher chance. Two inputs are used by the fuzzy inference system (FIS): residual energy and the distance between nodes. This protocol improves energy use, but still presents the possibility that the random number of nodes chosen for CHs is a problem that leads to a number of suitable nodes not allowed in the selection phase.

Bagci and Yazici [27] introduced an energy-aware fuzzy approach to unequal clustering in WSNs (EAUCF) protocol. The network region is broken up into unequal clusters. Clusters are smaller than those nearer to BS. CHs are elected based on FL. The FIS takes two inputs: the remaining energy level and distance from the sensor to BS. All sensors can use the fuzzy inference method to measure the chance of winning in each round. It compares the output to a random number between 0 and 1. The Sensor is chosen as CH if the output is large. Repeating the entire process of selecting CH in each round leads to energy conservation. The CHEF method prevents a suitable node from being selected because of the comparison between the fuzzy output and the random number.

Baranidharan and Santhi [28] developed a distributed load balancing unequal clustering in WSNs using the FL approach (DUCAF) protocol. They used three inputs in FIS: energy level, node temperature and distance from the node to the BS. All sensors can use FIS to measure the chance of winning in each round. Although this approach has taken the best cluster node into account, the selection of CHs increases energy consumption as it is performed in each round.

Zhang *et al.* [29] proposed the energy-efficient distributed clustering algorithm for WSNs with nonuniform distribution (EEDCF) using FL. It is a completely distributed clustering technique. It analyzes whether each node fits into the CH compared to its neighbors using a TSK FIS. The input parameters were energy level, node degree, and neighboring node energies. Despite this, CH had many tasks to be performed based on its energy level. It must use a VCH or a SCH to minimize its energy consumption by performing some tasks.

Moh'd Alia [30] proposed the decentralized fuzzy c-means-based energy-efficient routing protocol for WSNs (DCFP). It is a fuzzy c-mean algorithm energy-efficient WSN routing protocol. The clusters are created using the fuzzy c-mean technique. The node closest to its cluster center is then picked as CH. The average energy level for all CMs per cluster is calculated using CH from the previous round. Then, the target function is executed to choose CH for the following round. The proposed protocol constructs clusters with less intracluster communication. However, it overloads the present CHs for all CMs to elect CHs for the following round with iterative computations. For the proposed protocol, CH works only in the present round.

Lata *et al.* [2] proposed a fuzzy clustering protocol (LEACH-FC) by selecting the optimal PCH is based on FL. The node with lower centrality than others and consuming less energy for transferring data is elected as CH. The results confirmed that the LEACH-FC algorithm performed better than the LEACH protocol. However, CH selection is not the best in several scenarios and must use a VCH or a SCH to minimize its energy consumption by performing some tasks.

Dohare and Singh [31] introduced the PSO-based deterministic energy-efficient clustering (PSODEC) in IoT. Based on the largest remaining energy, this method chooses the CH node among the CMs. The nodes are distributed at random throughout the network. The cluster is constructed using the K-means algorithm. After that, the PSODEC method is utilized for choosing PCH node in every cluster. Simulation is run, as well as the findings show that the PSODEC performed better than LEACH and DEC. But even so, because the CH's remote location from the BS, communication can be problematic in some scenarios.

Sert *et al.* [32] proposed a two-tier distributed fuzzy protocol (TTDFP). It is an energy-efficient protocol for data aggregation in multihop WSNs. In CH selection, it examines proportional node connectivity, node's remaining energy, and distance to BS. In selecting a route, it examines the average link remaining energy and proportional distance. It uses FL to handle the uncertainties that arise in these phases.

Sert *et al.* [33] introduced a multi-objective fuzzy clustering algorithm (MOFCA) for WSNs that is not only energy-efficient and distribution-independent. In calculating the CH competition radius, the suggested MOFCA algorithm evaluates the remaining energy levels, distance to BS, and density. It uses FL to handle the uncertainties that arise in these phases.

Sert and Adnan [34] proposed a modified energy-efficient clonal selection algorithm (CLONALG-M) for rule-based

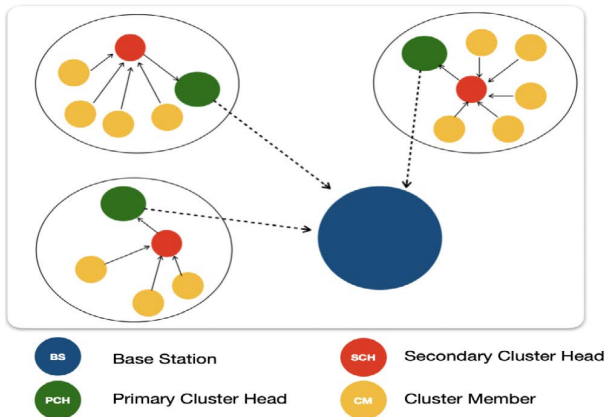


FIGURE 1. Proposed network model.

clustering algorithms. They extended the main ideas of the original CLONALG technique by incorporating fuzzy validity measures of the mutations and the production steps of possible solutions.

Wang et al. [35] developed a compressive sensing-based (CS-based) and clustering technique to handle load balancing in WSNs.

Lin et al. [36], introduced the game theory-based energy-efficient clustering-routing protocol (GEEC) to solve the load-balancing problem in WSNs using CHs.

Table 1 shows the comparison of several LEACH protocols in terms of CH selection criteria, number of clusters, clustering level, medium access, hop count, and time complexity.

### III. SYSTEM MODEL

Sensor nodes have been assumed in this section based on the network model. The energy consumption of the sensor nodes has been discussed based on a radio model (energy model).

#### A. NETWORK MODEL

Suppose that  $N$  sensors are randomly dispersed within a two-dimensional square area, and that sensors within that area collect information regularly. The sensed information must be received, aggregated, and transmitted to BS. PCH still has many tasks to be performed based on its energy level. It must use a SCH to minimize its energy consumption by performing some tasks, as shown in Fig.1. The SCH collects sensed data from all CMs through clusters and aggregates them. After aggregation, SCH transmits aggregated data to PCH through its cluster. The PCH receives and transmits the data to BS. Communications among CMs, CHs, and BS follow the standard rules for the number of hops.

The network model has the following characteristics:

- 1) The sensor network is in a fixed state. If the nodes have been deployed, they cannot be relocated.
- 2) After deployment, the BS's position is fixed and known to all CMs.
- 3) The BS's energy is unlimited.
- 4) Each CM has a GPS device that can save its location.

- 5) Data aggregation is performed by all SCHs, and information is sent to the BS by all PCHs.
- 6) Communications among CMs, CHs, and BS follow the standard rules for the number of hops [2], [18], [22].

#### B. RADIO MODEL (ENERGY MODEL)

The recommended technique is implemented on the radio model employed by the LEACH protocol [17], [18]. Each sensor node in WSN requires energy to perform clustering and transmission of data from other sensor nodes. Two distinct energy models are presented: free-space model and multipath fading channel models [21]. Power attenuation is caused by the distance  $d$  between the transmitter and the receiver. When this distance is less than the threshold value ( $d_0$ ), the algorithm uses the free-space model ( $d^2$  power loss). Otherwise, it uses the multipath fading channel model ( $d^4$  power loss), and the threshold  $d_0$  is given in (1) [37], [38]:

$$d_0 = \sqrt{\frac{E_{fs}}{E_{amp}}} \tag{1}$$

where,  $E_{fs}$  is the free-space parameter, and  $E_{amp}$  is the multipath parameter.

If the transmitter transmits  $B$ -bit data to the receiver across a  $d$  distance, the transmitter's energy consumption ( $E_{TX}$ ) can be computed as given in (2) [37], [38]:

$$E_{TX}(B, d) = \begin{cases} E_{elec} * B + E_{fs} * B * d^2, & d < d_0 \\ E_{elec} * B + E_{amp} * B * d^4, & d \geq d_0 \end{cases} \tag{2}$$

where,  $E_{elec}$  is the electronics energy dissipation for  $B$ -bit transmission or reception, and  $d$  is the distance between the transmitter and receiver. To receive  $B$ -bit data, sufficient energy ( $E_{RX}$ ) is obtained from (3) [37], [38]:

$$E_{RX} = B * E_{elec} \tag{3}$$

### IV. PROPOSED FUZZY LOGIC LEACH TECHNIQUE-BASED PSO

In this study, a FL LEACH Technique-based PSO is proposed for energy efficiency and for maximizing the number of bits transferred to BS. As Shown in Fig.(2), the proposed protocol is divided into setup and steady phases (three main steps).

The setup phase consists of cluster formation using a hybrid PSO and K-means clustering algorithm. The sensor network is in a fixed state. If the nodes have been deployed, they cannot be relocated. Because we are testing fixed nodes, there is no need to repeat cluster formation per round, as shown in Fig.(2).

The steady phase includes three main steps: PCH selection, SCH selection, and intracluster data communication. This phase is repeated in each round, as shown in Fig.(2), because the energy of CMs, PCHs, and SCHs changes during the rounds; thus, there is a need to repeat it.

First, cluster formation is performed depending on the hybrid PSO and K-means clustering algorithm. Input data, which are the locations of the ( $N$ ) sensors, are clustered into a specified number of clusters ( $N_c$ ).



TABLE 1. Comparison of different LEACH protocols.

Cluster Routing Protocol	Cluster Head Selection Criteria	Number of Clusters	Clustering Level	Medium Access	Hop Count	Time Complexity
LEACH [17], [18]	Probability and threshold	Dynamic	One-level	Distributed	Single	$\mathcal{O}(n)$
LEACH-C [21]	BS selects CH based on energy and distance from BS	Dynamic	One-level	Centralized	Single	$\mathcal{O}(n)$
E-LEACH [22]	BS selects CH based on energy and initial energy of node	Static	One-level	Distributed	Single	$\mathcal{O}(n)$
DBCH [23]	BS selects CH based on energy and distance from BS	Dynamic	One-level	Distributed	Single	$\mathcal{O}((n \times m) \times \frac{n}{2})$
TL-LEACH [24]	BS selects CH based on a threshold for the first selection, energy level for the second selection	Dynamic	Two-levels	Distributed	Multi	$\mathcal{O}(n^2)$
ECE-LEACH [20]	BS selects CH based on a threshold for the first selection, energy level and distance measure for the second selection	Dynamic	Two-levels	Distributed	Multi	$\mathcal{O}(n^2)$
W-LEACH [25]	BS selects CH based on its high weight	Dynamic	One-level	Centralized	Single	$\mathcal{O}(2n)$
CHEF [26]	BS selects CH based on a threshold and FL with two inputs: energy level and distance between nodes	Dynamic	One-level	Distributed	Single	$\mathcal{O}(n \times FL_r)$
EAUCF [27]	BS selects CH based on a threshold and FL with two inputs: energy level and distance to BS	Dynamic	One-level	Distributed	Single	$\mathcal{O}(n \times FL_r)$
DUCF [28]	BS selects CH based on a FL with three inputs: energy level, node temperature and distance to BS	Dynamic	One-level	Distributed	Single	$\mathcal{O}(n)$
EEDCF [29]	BS selects CH based on a FL	Dynamic	One-level	Centralized	Multi	$\mathcal{O}(n)$
DCFP [30]	FCM method with efficient energy	Static	One-level	Centralized	Single	$\mathcal{O}(n)$
LEACH-FC [2]	BS selects CH based on a FL with three inputs: node energy, centrality and concentration	Static	One-level	Centralized	Single	$\mathcal{O}(n \times FL_r)$
PSODEC [31]	The K-means technique is used to build the cluster. Then, the PSODEC method is used to select the CH node per cluster.	Static	One-level	Centralized	Single	$\mathcal{O}(n^2)$
TTDFP [32]	It examines proportional node connectivity, distance to BS, and remaining node energy for selecting CH average link remaining energy and proportional distance for selecting of a route.	Dynamic	One-level	Distributed	Multi	$\mathcal{O}(n^2)$
MOFCA [33]	It examines the remaining energy, distance to BS, and density for calculating CH competition radius while using FL to solve the uncertainties occurring in the WSN nature	Dynamic	One-level	Distributed	Multi	$\mathcal{O}(n^2)$
CLONALG-M [34]	It extended an energy-efficient clonal selection algorithm for rule-based clustering algorithms	Dynamic	One-level	Distributed	Multi	$\mathcal{O}(n^2) + \mathcal{O}(CL)$

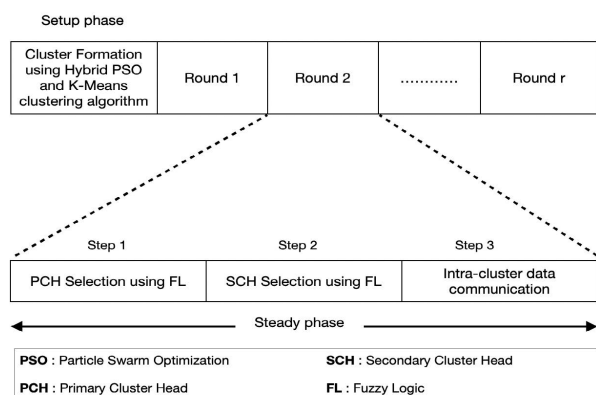


FIGURE 2. Phases of the proposed protocol.

$N_c$  should be obtained using Gap statistic clustering evaluation. The gap statistic compares the total within intracluster variation for various values of  $N_c$  to their predicted values under the data's null reference distribution. The value that maximizes the gap statistic will be used to determine the best clusters [39]. Distance metric (Euclidean distance) is used for to compute the criterion values. This indicates that the clustering structure differs significantly from a random uniform distribution of points.

Second, PCH is selected based on the node's residual energy, distance from the node to the cluster's center, and distance from the node to BS. Third, SCH is selected based on the node's energy level and distance from the node to PCH within its cluster. Furthermore, the BS runs the FL to select the entire PCH and SCH nodes in the network.

Finally, intracluster data communications, all CMs sense data and transfer them to SCH within the cluster. Each SCH acquires and aggregates the data from all CMs for transmission to PCH. Each PCH receives data from all SCHs and forwards them to the BS.

A. CLUSTER FORMATION

In the context of data clustering, the input data are divided into a given number of clusters depending on the similarity between data vectors. The output is the clusters with the associated data over each cluster, thus determining the cluster center [40]. The network clustering in our proposed technique is based on the hybrid PSO and K-means clustering algorithm.

1) K-MEANS CLUSTERING ALGORITHM

K-means clustering divides data vectors into a preset number of clusters using Euclidean distance as a similarity metric.

Data vectors inside a cluster have minimal Euclidean distances between them and are linked to a single centroid vector, representing the cluster’s “midpoint”. The centroid vector is calculated by taking the mean of the data vectors in the relevant cluster.

The number of cluster centers in K-means is obtained by applying Gap static clustering evaluation on input data (sensor nodes) to obtain the exact number of clusters. Then, define the outcome of the K-means clustering algorithm as one of the particles for the PSO algorithm to be used in the clustering process.

In this paper, the data vectors are the sensor nodes. The K-means algorithm will be described as follows:

- 1) Calculate the distance from each sensor node to each cluster center using the Euclidean distance [23], [41] from (4):

$$d(s, c) = \sqrt{((s_1 - c_1)^2 + (s_2 - c_2)^2)} \quad (4)$$

where, points  $s = (s_1, s_2)$  and  $c = (c_1, c_2)$  are the sensor node and cluster center coordinates, respectively.

- 2) Assign the sensor node to the cluster with the closest center.
- 3) After assignment for all sensors, recalculate the new cluster center ( $c$ ) using the mean [40] as given in (5):

$$c = 1/n_j \sum_{\forall S_p \in C_j} S_p \quad (5)$$

where,  $n_j$  denotes the number of sensor nodes in the cluster  $j$ , and  $S_p$  denotes the subset of sensors that forms the cluster  $C_j$ , until a stopping criterion is achieved.

In this paper, the stopping criterion is satisfied when a specified number of iterations have been exceeded [40].

## 2) PARTICLE SWARM OPTIMIZATION

PSO is a population-based stochastic search algorithm inspired by the social behaviour of flocks of birds’ [42], [43]. A swarm in the context of PSO, refers to a collection of possible solutions to the optimization problem, with each possible solution denoted by a particle. The PSO aims to discover the particle position that best assesses a given fitness (objective) function. Every particle provides a position in search space and is flown across it, updating its position toward the personal best position of the particle. During the flow, a particle position is updated using (6) and (7) [40]:

$$v_{i,D}(t + 1) = wv_{i,D}(t) + c_1r_{1,D}(t)(y_{i,D}(t) - x_{i,D}(t)) + c_2r_{2,D}(t)(g_i(t) - x_{i,D}(t)) \quad (6)$$

$$x_i(t + 1) = x_i(t) + v_i(t + 1) \quad (7)$$

where,  $w$  is the inertia weight,  $c_1$  and  $c_2$  are the acceleration coefficients,  $r_1$  and  $r_2$  are random numbers between 0 and 1, and  $D$  is the input dimension. The cognitive component

$$c_1r_{1,D}(t)(y_{i,D}(t) - x_{i,D}(t)) \quad (8)$$

is a function of the particle’s distance from its best personal position. The social component

$$c_2r_{2,D}(t)(g_i(t) - x_{i,D}(t)) \quad (9)$$

is a function of the particle’s distance from the global best position. The global position is the best particle in the neighborhood of the particle. In this paper, the PSO was stopped after a certain number of iterations were reached.

## 3) HYBRID PSO AND K-MEANS CLUSTERING ALGORITHM

In the proposed algorithm, a single particle denotes the  $N_c$  cluster center vectors structured as follows:

$$X = (c_1, c_2, \dots, c_{N_c})$$

A swarm represents a possible clustering for the sensor nodes. Using the hybrid PSO and K-means clustering algorithm, data vectors (sensor nodes) can be clustered as follows:

- 1) Defines the outcome of the K-means clustering algorithm as one of the particles.
- 2) Initializes the remaining swarm’s particles (cluster centers) randomly.
- 3) For  $t=1$  to  $t_{max}$  do:
  - a) For each particle  $i$  do
  - b) For each sensor node
    - i) Computes the Euclidean distance  $d(s,c)$  using (4).
    - ii) Assigns node to cluster  $c$  with closest cluster’s center.
    - iii) Calculates the fitness of particles as the quantization error  $J$  as given in (10):

$$J = \frac{\sum_{j=1}^{N_c} [ \sum_{\forall S_p \in C_{ij}} d(s, c_j) / |C_{ij}| ]}{N_c} \quad (10)$$

- c) Updates personal and global best positions.
- d) Updates the cluster centers using (6, 7).  
Where,  $t_{max}$  denotes the max number of iterations [40].

## B. PCH SELECTION USING FL

FL is used for decision-making, where the input conditions are considered to obtain the desired result as obtained from the “if-then” statement. Two fuzzy models are used: Mamdani [44] and Sugeno [45]. The Mamdani fuzzy model is widely used in various applications [19]. Thus, for our proposed protocol, the Mamdani method (one of the most widely used methods) is used as a fuzzy inference methodology.

In our proposed protocol, each sensor runs a FL every round to calculate its chance of becoming PCH. That PCH selection is based on three node parameters. Crisp input parameters for the FL were examined using three input variables, given as follows:

**Residual-energy:** available energy level in each node.

**Distance-to-cluster’s center:** distance between CM and its cluster’s center.

**Distance-to-BS:** distance between CM and BS.

To determine distance-to-cluster's center and distance-to-BS, we used the Euclidean distance given in (4). Consequently, CMs have easier access to the node, which is nearest to the cluster center point. It indicates that other nodes can spend less energy on data transmission through the node as PCH.

Each input function (fuzzy variable) contains three membership functions  $M_f$  with varying degrees of function. Three levels were used for the lingual representation of node energy, as shown in Fig.3: low, medium, and high. Here,  $M_f$  ranges from 0 to 0.5, as calculated form (11) [2].

Fig.4 shows that the node's distance-to-cluster's center has three levels for the lingual representation: near, adequate, and distant. Here,  $M_f$  ranges from 0 to 140, as calculated form (13) [2].

The node's distance-to-BS, as shown in Fig.5, has three levels for the lingual representation: near, adequate, and distant. Here,  $M_f$  ranges from 0 to 70, as calculated form (12) [2].

Nine membership functions have been established to indicate the decision of a node as a PCH selection chance: very weak, weak, little weak, little medium, medium, high medium, little strong, strong, and very strong as illustrated in Fig.6 an expert-defined fuzzy output function (Chance) [46], [47].

Nine membership functions were used instead of seven membership functions of previously proposed systems, because the differences in the relevance of the inputs might be represented more clearly in the experiments, yielding better outcomes [46], [47].

Triangular  $M_f$  was used to represent low, medium, high, and adequate fuzzy sets. Meanwhile, trapezoid  $M_f$  was used to represent near and distant fuzzy sets. Trapezoidal and triangular membership functions are suitable for real-time operations and their computations are not complex [48].

Equations (11), (12), and (13) are used to obtain the optimal values for our parameters:

$$Max\_Energy = InitialEnergy \tag{11}$$

$$Max\_distance\_to\_BS = \sqrt{(BS_x)^2 + (BS_y)^2} \tag{12}$$

$$Max\_distance\_to\_cluster's\_center = \sqrt{(X_m)^2 + (Y_m)^2} \tag{13}$$

Figs. 3, 4, and 5 show the graphical representation and associated linguistic states for the input established  $M_f$ : energy level, distance to cluster center, and distance to BS.

Expert-defined ( $3^3 = 27$ ) fuzzy rules are used to describe the interaction between variables in the fuzzy rule base [19], [49] for PCH selection based on the output chance value, as presented in Table 2 and are then examined using the Mamdani model. These rules are true for high-energy nodes, close distance-to-cluster's center, and close distance-to-BS.

Fig.6 shows the graphical representation and associated linguistic state for an expert-defined fuzzy output function  $M_f$  (chance value) for PCH selection.

Furthermore, the final crisp number, which is a chance value, was obtained using the centroid defuzzication

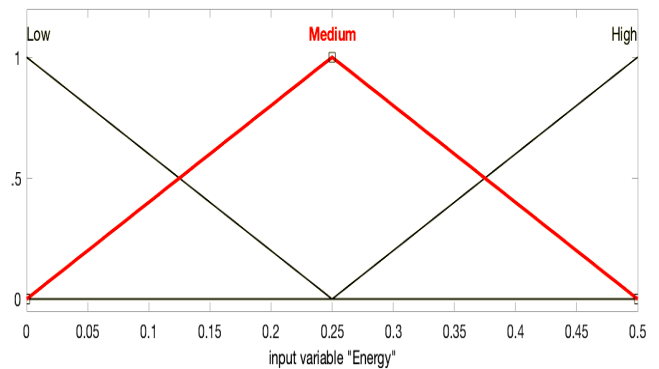


FIGURE 3. Residual energy.

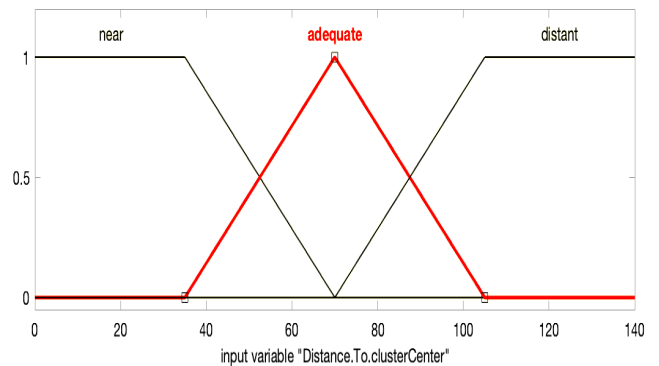


FIGURE 4. Distance to cluster's center.

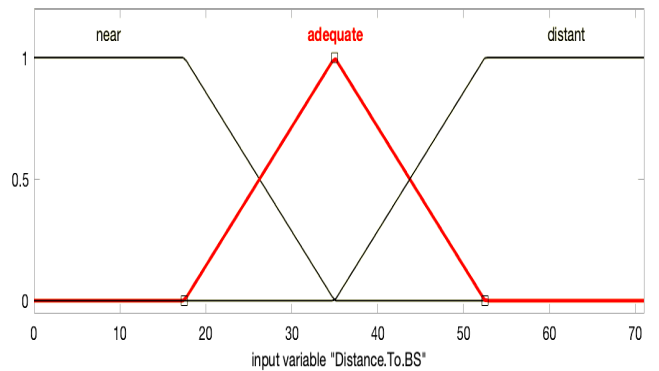


FIGURE 5. Distance to BS.

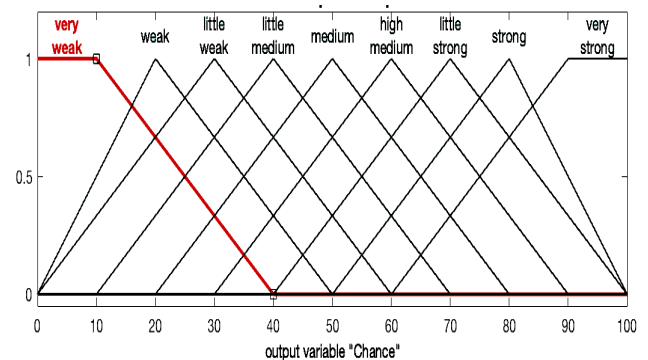


FIGURE 6. An expert-defined fuzzy output function: PCH Selection Chance.

procedure. Centroid defuzzication would include the center of area (CoA) method. The chance values of all nodes in

TABLE 2. If-then rules for a fuzzy inference scheme [19], [49].

	Energy Level	Distance To Cluster Center	Distance To BS	PCH Selection Chance
1	low	distant	distant	very weak
2	low	distant	adequate	weak
3	low	distant	near	little weak
4	low	adequate	distant	weak
5	low	adequate	adequate	little weak
6	low	adequate	near	little medium
7	low	near	distant	little weak
8	low	near	adequate	little medium
9	low	near	near	medium
10	medium	distant	distant	little weak
11	medium	distant	adequate	little medium
12	medium	distant	near	medium
13	medium	adequate	distant	little medium
14	medium	adequate	adequate	medium
15	medium	adequate	near	high medium
16	medium	near	distant	medium
17	medium	near	adequate	high medium
18	medium	near	near	little strong
19	high	distant	distant	medium
20	high	distant	adequate	high medium
21	high	distant	near	little strong
22	high	adequate	distant	high medium
23	high	adequate	adequate	little strong
24	high	adequate	near	strong
25	high	near	distant	little strong
26	high	near	adequate	strong
27	high	near	near	very strong

each cluster were compared, and PCH is chosen based on the node with the greatest chance value. PCH is chosen from the higher-energy node when two or more nodes have the same maximum chance value. It receives data from SCH and sends it to BS. The processes required for PCH selection are described in Algorithm 1.

**Algorithm 1** PCH Selection Using FL

**Input:**  $N$  nodes information and BS coordinates.

**Output:** PCH nodes in the network.

**Node-Information:**

- *Node.type* = "N" (Cluster Member)
  - *Node.energy* = current energy (All nodes start with initial energy)
  - *Node.location* = current node's coordinates
- 1) For each node in the same cluster
    - a) Sends node's information to BS
    - b) Calculates the chance value using FL
  - 2) Chooses PCH with the highest chance value
  - 3) Receives data from SCH
  - 4) Transmits data to BS
  - 5) End

**C. SCH SELECTION USING FL**

After creating  $N_c$  clusters and selecting PCH, SCH will be chosen. It contributes to lower energy usage by gathering sensed data from CMs, aggregating it, and delivering the aggregated data to PCH. The election of SCH is decided using FL.

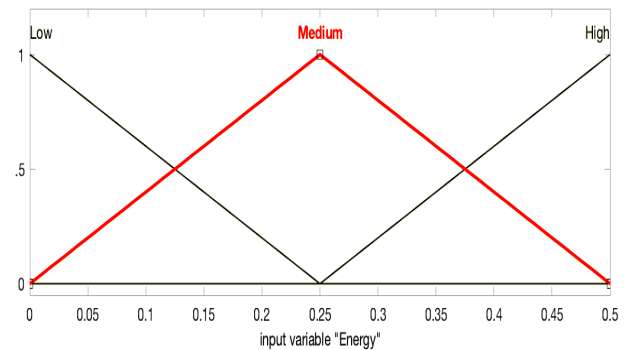


FIGURE 7. Residual energy.

In every round, each CM in our proposed technique runs FL to measure its probability of being SCH. Consider that selecting SCH necessitates the consideration of two-node attributes. As a result, two input variables were used for crisp input parameters evaluated for FL:

**Residual-energy:** available energy level in each node.

**Distance-to-PCH:** distance between CM and its PCH.

The Euclidean distance is used to estimate the distance between CM and its major PCH, as shown in (4). As a SCH, if a node is close to PCH, it might use less energy for data transmission. Each input function (fuzzy variable) has three  $M_f$  that show a different degree of function. Three levels were used for the lingual representation of the node's energy, as shown in Fig.7: low, medium, and high. Here,  $M_f$  ranges from 0 to 0.5, as calculated form (11) [2].

The node's distance-to-PCH as shown in (Fig.8) has three levels for the lingual representation: near, adequate, and distant. Here,  $M_f$  ranges from 0 to 140, as calculated form (14) [2].



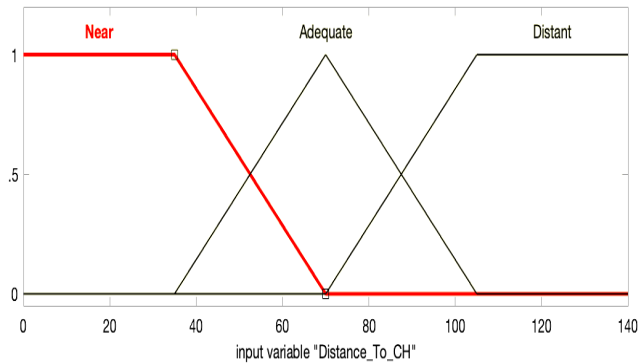


FIGURE 8. Distance to PCH.

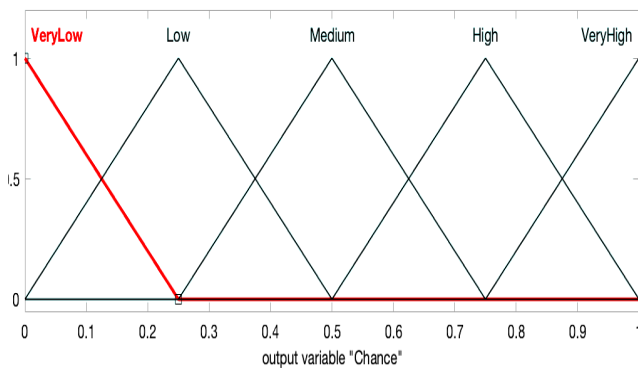


FIGURE 9. An expert-defined fuzzy output function: SCH Selection Chance.

Five membership functions were used because the difference in the relevance of the inputs might be represented more clearly in the experiments, yielding better outcomes [46], [47].

Triangular  $M_f$  was used to represent low, medium, high, and adequate fuzzy sets. Meanwhile, trapezoid  $M_f$  was used to represent near and distant fuzzy sets.

Equation (14) was used to determine the maximum values of our parameter distance to PCH.

$$Max\_distance\_to\_PCH = \sqrt{(X_m)^2 + (Y_m)^2} \quad (14)$$

Figs. 7 and 8 show the graphical representation and associated linguistic states of the established  $M_f$ : energy level and distance to PCH.

Fig.9 shows the graphical representation and associated linguistic state for an expert-defined fuzzy output function  $M_f$  (chance value) for SCH selection.

Expert-defined ( $2^3 = 8$ ) fuzzy rules are used to describe the interaction between variables in the fuzzy rule base [50] for SCH selection based on the output chance value, as presented in Table 3 and are then examined using the Mamdani model. These rules are true for high energy nodes located near PCH.

Furthermore, the final crisp number (a chance value) was obtained using the CoA defuzzication procedure. In every cluster, the chance values from all nodes were compared, and SCH was chosen with the most chance for the node. If two or more nodes are equal to the maximal chance value, SCH is the node with the highest energy. It gathers, combines, and

TABLE 3. If-then rules for a fuzzy inference scheme [50].

	Energy Level	Distance To PCH	SCH Selection Chance
1	low	distant	very low
2	medium	distant	low
3	high	distant	medium
4	low	adequate	low
5	medium	adequate	medium
6	high	adequate	medium
7	low	near	medium
8	medium	near	high
9	high	near	very high

transmits data from CMs to PCH. The processes required for selecting SCH are described in Algorithm 2.

**Algorithm 2** SCH Selection Using FL

**Input:**  $N$  nodes information and BS coordinates.

**Output:** SCH nodes in the network.

**Node-Information:**

- $Node.type = "N"$  (Cluster Member)
- $Node.energy = current\ energy$  (All nodes start with initial energy)
- $Node.location = current\ node's\ coordinates$

- 1) For each node in the same cluster
  - a) Sends node's information to BS
  - b) Calculates the chance value using FL
- 2) Chooses the SCH with the highest chance value
- 3) Receives data from CMs and aggregates it. The received data are aggregated according to the standard energy model [17], [18] using the defined aggregation ratio  $E_{DA}$  prior to relaying toward the PCH. The corresponding value of  $E_{DA}$  is  $5\ nj/bit/m^4$  as used in [2], [41].
- 4) Transmits aggregated data to PCH
- 5) End

**D. INTRACLUSTER DATA COMMUNICATION**

After cluster formation with selecting PCH and SCH nodes, BS sends the message information. It comprises PCH's id, SCH's id, and the CM corresponds to a cluster. The CM selects a time-division multiple access (TDMA) slot to transmit data, and then goes to sleep. When SCH receives data, it aggregates the sensed data and forwards it to PCH. After that, PCH sends the data to the BS. Fig.10 illustrates the overall workflow of the proposed protocol.

**E. TIME COMPLEXITY ANALYSIS**

The iterative algorithms of hybrid PSO and K-means clustering algorithm, and FLS require time to provide the final output. Thus, an analysis of time complexity is performed. It represents the function  $\mathcal{O}()$ . It is determined by system inputs, outputs, and the time-dependent processing variables used to perform the proposed protocol. Clusters are constructed at the start of the protocol using the hybrid PSO and K-means clustering algorithm. The time complexity of

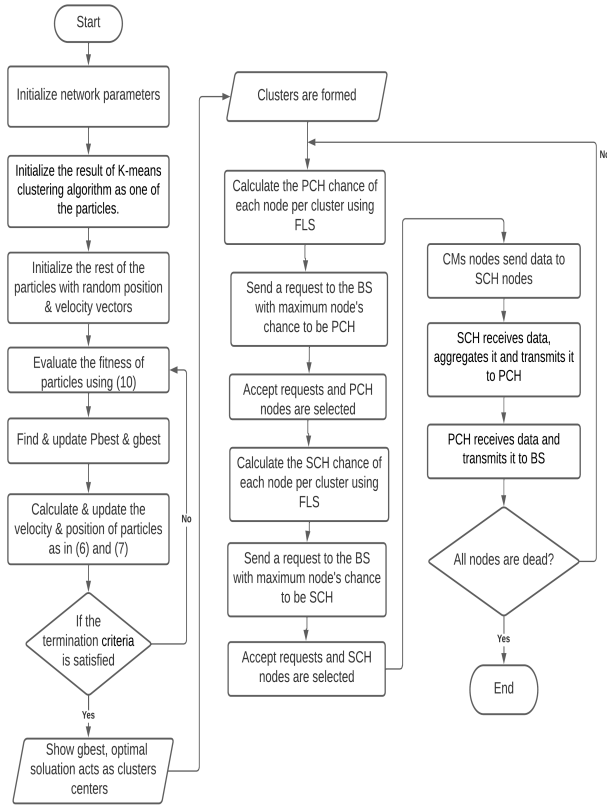


FIGURE 10. Proposed protocol workflow.

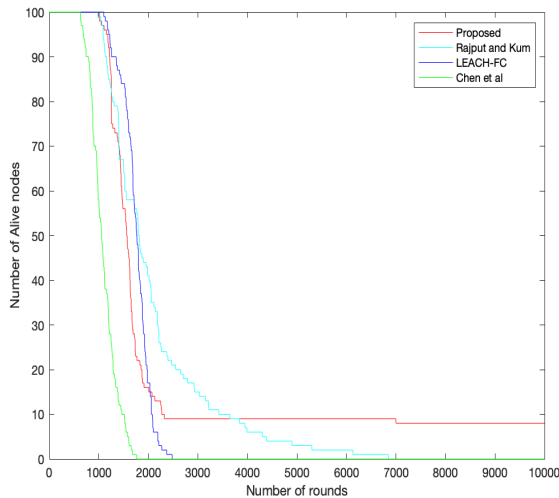


FIGURE 11. Number of alive nodes related to rounds of network for scenario 1.

this cluster formation process is estimated as  $\mathcal{O}(n^2)$  as the pairwise distances between sensor nodes must be determined. Here,  $N$  is the total number of sensor nodes in the network. All nodes execute FLS to estimate a PCH chance as PCH selection criteria. The FLS has three inputs, each defined by three membership functions. Thus, 27 rules are derived to estimate a PCH chance. All nodes run FLS to estimate a SCH chance as SCH selection criteria. The FLS has two inputs, each defined by two membership functions. Thus, eight rules

TABLE 4. Time complexity analysis of the proposed protocol.

S. no.	Protocol operations	Time complexity
1	Hybrid PSO and K-mean Clustering algorithm	$\mathcal{O}(n^2)$
2	PCH selection by FL	$\mathcal{O}(n \times FL_{rules})$
3	SCH selection by FL	$\mathcal{O}(n \times FL_{rules})$

TABLE 5. Simulation parameters [2], [20], [40].

Parameter Name	Parameter Value
Number of nodes	100, 1000
Size of network	$100 \times 100 \text{ m}^2$
BS's location	(50,150)
Initial energy	0.5J
Size of the data	4000 bits
Radio electronics energy	50nJ/bit
Radio amplifier energy (free space model)	10pJ/bit/m <sup>2</sup>
Radio amplifier energy (multi-path model)	0.0013pJ/bit/m <sup>4</sup>
Cross over distance	87.7
Computation energy for beam forming	5nJ/bit/signal
Data aggregation energy	5 nj/bit/ m <sup>4</sup>
$C_1, C_2$	1.49
W (INERTIA weight)	0.72

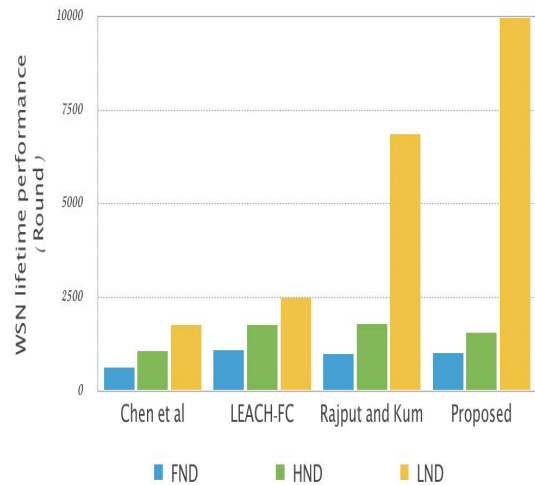


FIGURE 12. FND, HND, and LND of scenario1.

are derived to estimate a SCH chance. The time complexity of this process is computed using the formula  $\mathcal{O}(n \times FL_{rules})$ . Table 4 summarizes the time complexity analysis.

## V. SIMULATION RESULTS

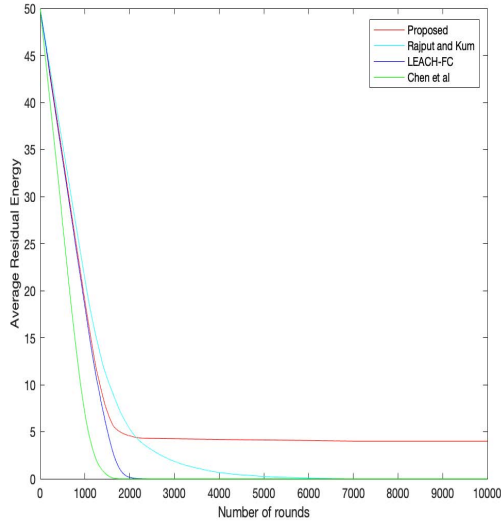
The proposed protocol is based on an optimization technique and FL, both of which are easily implemented using MATLAB. The proposed technique's results are compared with conventional algorithms, such as FCM clustering and FLS-based CH selection to enhance the sustainability of WSNs for environmental monitoring applications (Rajput and Kum) [19], LEACH-Fuzzy Clustering (LEACH-FC) protocol [2], and LEACH based on the energy consumption equilibrium (Chen et al.) [20].

Our comparisons are split into three groups: alive nodes related to rounds, bits transmitted to BS related to rounds, and the remaining network energy related to rounds.

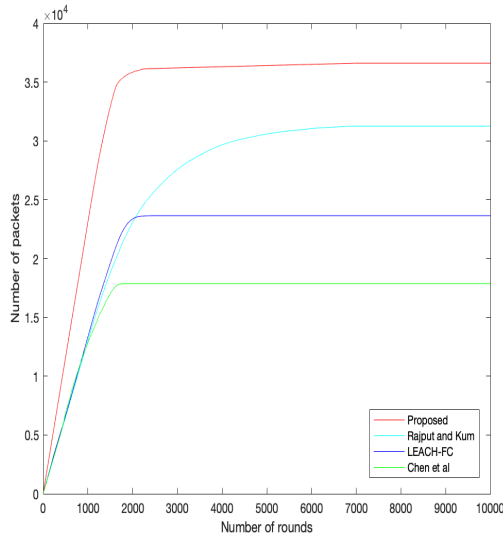
Table 5 presents the simulation parameters used. In scenario 1, a total of 100 sensor nodes and BS are distributed in a monitoring area of  $100 \text{ m} \times 100 \text{ m}$ . In scenario 2, a total

**TABLE 6.** FND, HND, and LND of scenario 1.

Protocol	FND	HND	LND
Proposed Protocol	1014	1563	— (92 dead nodes)
Rajput and Kum [19]	978	1798	6851
LEACH-FC [2]	1102	1763	2481
Chen et al [20]	628	1058	1764



**FIGURE 13.** Average remaining energy related to rounds of network for scenario 1.



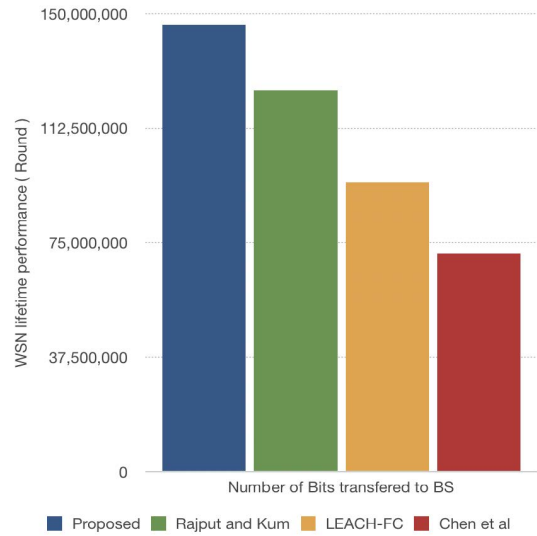
**FIGURE 14.** Throughput related to rounds of network for scenario 1.

of 1000 sensor nodes and BS are distributed in a monitoring area of 100 m × 100 m.

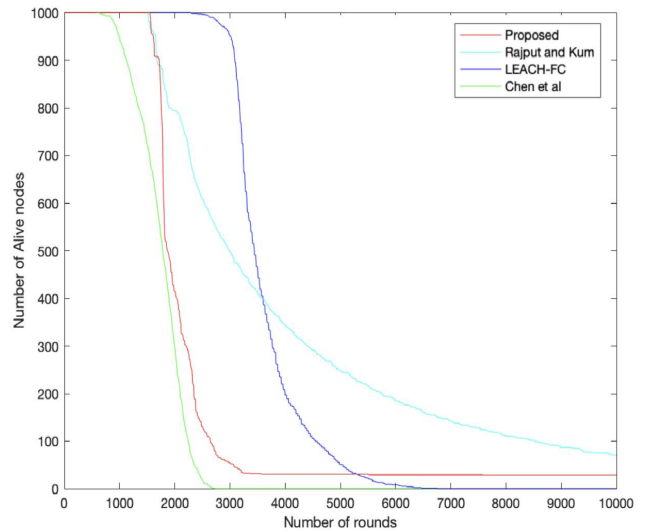
**A. SIMULATION RESULTS FOR SCENARIO 1**

Table 6 and Fig.11 compare the proposed protocol with Rajput and Kum, LEACH-FC, and Chen *et al.* The results proved that the proposed protocol outperforms others for the network lifetime.

Fig.12 shows that the last node died in the proposed protocol at more than 10,000 rounds (92 dead nodes), in Rajput and Kum at 6851 rounds, in LEACH-FC at 2481 rounds,



**FIGURE 15.** Bits transferred to BS related to rounds of network for scenario 1.



**FIGURE 16.** Number of alive nodes related to rounds of network for scenario 2.

and in Chen at al. at 1764 rounds. The results confirmed that the proposed protocol outperforms others by 46% and more.

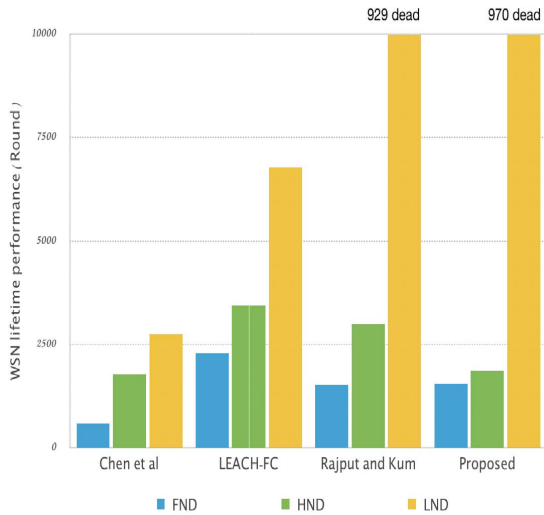
Fig.13 shows the stability of the network by comparing the average remaining energy in the network related to each round. Therefore, the proposed protocol consume less energy than other protocols, such as Rajput and Kum, LEACH-FC, and Chen *et al.*

Fig.14 and Fig.15 show that  $196 \times 10^6$  bits were transferred in the proposed protocol at 92% of the network lifespan. Meanwhile,  $124 \times 10^6$ ,  $94 \times 10^6$ , and  $71 \times 10^6$  bits were transferred to the BS in Rajput and Kum, LEACH-FC, and Chen *et al.*, respectively.

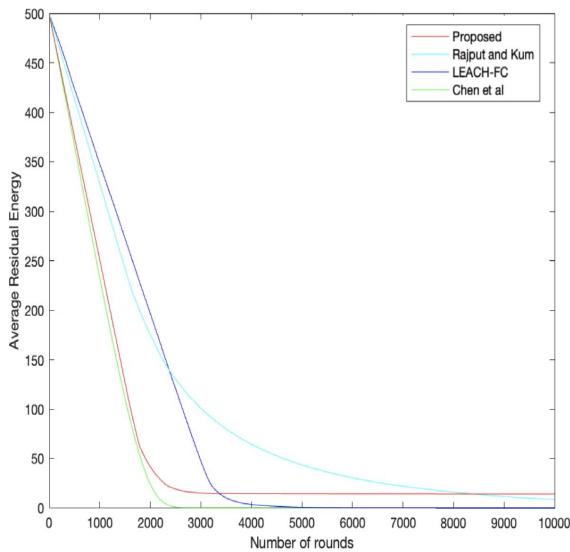
Note that the proposed protocol technique transmits more bits to BS than Rajput and kum, LEACH-FC, and Chen *et al.*

**TABLE 7.** FND, HND, and LND of scenario 2.

Protocol	FND	HND	LND
Proposed Protocol	1551	1866	— (970 dead nodes)
Rajput and Kum [19]	1519	2988	— (929 dead nodes)
LEACH-FC [2]	2290	3442	6766
Chen et al [20]	587	1784	2725



**FIGURE 17.** FND, HND, and LND of scenario2.

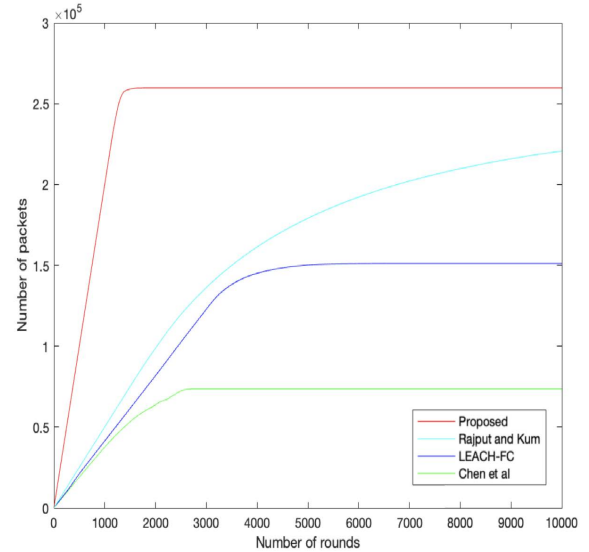


**FIGURE 18.** Average remaining energy related to rounds of network for scenario 2.

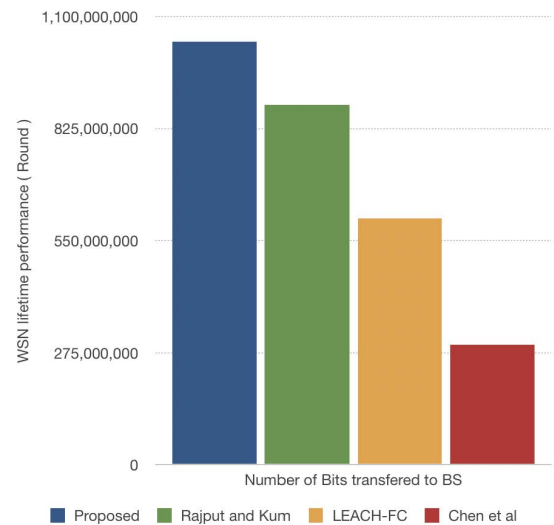
**B. SIMULATION RESULTS FOR SCENARIO 2**

As Shown in Table 7 and Fig.16, the proposed protocol is compared with Rajput and Kum, LEACH-FC, and Chen *et al.* The results proved that the proposed protocol outperforms others for the network lifetime.

Fig.17 shows that last node died in the proposed protocol at more than 10,000 rounds (970 dead nodes), in Rajput and Kum at more than 10,000 rounds (929 dead nodes), in LEACH-FC at 6766 rounds, and in Chen *et al.* at



**FIGURE 19.** Throughput related to rounds of network for scenario 2.



**FIGURE 20.** Bits transferred to BS related to rounds of network for scenario 2.

2725 rounds. The results confirmed that the proposed protocol still outperforms other protocols.

Fig.18 shows the stability of the network by comparing the average remaining energy in the network related to each round. Therefore, the proposed protocol consumes less energy than Rajput and Kum, LEACH-FC, and Chen *et al.*

Figs.19 and 20 show that  $1 \times 10^9$  bits were transferred in the proposed protocol at 97% of the network lifespan. Meanwhile, in Rajput and Kum,  $882 \times 10^6$  bits were transferred at 92% of the network lifespan to the BS. In LEACH-FC,  $604 \times 10^6$  bits were transferred to the BS, and  $294 \times 10^6$  bits were transferred in Chen *et al.*

Note that the proposed protocol technique transmits more bits to BS than Rajput and kum, LEACH-FC, and Chen *et al.*



## VI. CONCLUSION

This paper proposes a fuzzy Logic (FL) low energy adaptive hierarchy (LEACH) technique-based particle swarm optimization (PSO). Clusters were generated using a probabilistic algorithm in LEACH, but they were made using the hybrid PSO and K-means clustering algorithm in our proposed technique. We used three parameters, namely, energy level, distance to cluster center, and distance to BS, to select a PCH using FL. Two parameters were used to select a SCH using FL: energy level and distance to PCH.

Both improvements were made to extend the network's existence and boost its throughput. The simulated results showed that the network lifetime was improved by more than 46% and packet transmission by 17.6%. Thus, there is an improvement for the proposed protocol technique compared to other protocols, such as Rajput and Kum, LEACH-FC, and Chen *et al.*

In future studies, real-time implementation could be conducted as a follow-up to this paper. Delay may be used as a performance metric, and the approach must be modified to work with delay-sensitive applications.

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