A Hybrid Weighted Fuzzy C-Means and Improved Cuckoo Search Approach for Energy-Efficient Hierarchical Multi-Hop Routing in Wireless Sensor Networks

Hemapriya.C [1], Dr.K.Saraswathi [2]

[1]*Ph.D. Research Scholar, PG & Research Department of Computer Science, Government Arts College - Coimbatore-18.*

[2]*Associate Professor, PG & Research Department of Computer Science, Government Arts College - Coimbatore-18.*

***Abstract*—Wireless Sensor Networks (WSNs) are primarily concerned with conserving energy since small sensor nodes (SNs) have a restricted capacity for batteries and the high costs associated with frequent replacements. Prolonging network lifetime necessitates efficient data gathering and transmission strategies, particularly for multi-hop networks. To address shortcomings in existing clustering-based routing schemes, this work proposes Weighted Fuzzy C-Means with Improved Cuckoo Search Optimization (WFCM-ICSO). This novel hybrid method integrates fuzzy c-means for initial cluster formation with components of ICSO to determine both the optimal number of clusters and the most suitable cluster heads (CHs). Furthermore, we introduce a hierarchical routing paradigm that distinguishes between Direct Cluster Heads (DCHs) and Parent Cluster Heads (PCHs), selected according to several fitness metrics. Acting as intermediate relays for other cluster heads, DCHs and PCHs reduce overhead and transmission energy. The proposed approach is evaluated on networks of 100 nodes. Experimental results indicate that WFCM-ICSO substantially provides a reliable solution for energy-constrained WSN situations by improving network resilience and energy efficiency in comparison to traditional clustering techniques.**

***Index Terms*—Wireless Sensor Networks (WSNs), Energy Efficiency, Multi-Hop Routing, Weighted Fuzzy C-Means (WFCM), Improved Cuckoo Search Optimization (ICSO), Cluster Head Selection, Hierarchical Routing, Network Lifetime Optimization.**

I. INTRODUCTION

In a broad spectrum of fields, wireless Sensor Networks (WSNs) have emerged as important technologies in fields including healthcare, smart cities, industrial automation, military surveillance, and monitoring the environment. Sensor nodes that are dispersed geographically and have limited processing, storage, communication, and most importantly energy resources constitute a typical WSN. Battery replacement is either unfeasible or prohibitively expensive since sensor nodes are often placed in dangerous or inaccessible positions. Consequently, energy conservation becomes a paramount design objective to ensure prolonged network operation and service continuity. WSNs are made composed of many small, low-cost sensor nodes that are usually dispersed at random within a predetermined region. While WSNs have found broad application in fields like disaster monitoring, target detection, and space assignments, maintaining these nodes through recharging or replacement can be prohibitively expensive or unfeasible in challenging environments. Therefore, conserving energy in battery-powered nodes is critical to extending the operational life of the network [1,2]. Among various strategies, clustering has proven to be highly effective in minimizing energy consumption, improving scalability, reducing latency, and boosting the overall longevity of the network [3].
In multi-hop WSNs, where data from distant nodes is relayed through intermediate nodes toward the sink, an

important factor in reducing energy use is routing protocols. Among various strategies, clustering-based routing has demonstrated significant potential in reducing energy dissipation through efficient data aggregation and transmission. In such schemes, collecting and sending data to the base station from member nodes is the duty of a selection of nodes selected to serve as Cluster Heads (CHs). In contrast, optimal CH selection and balanced cluster formation are critical to clustering-based routing performance. By splitting the nodes into a predetermined number of clusters, clustering allows the network to be dynamically structured [3,4]. The cluster head (CH) in a cluster is considered to be the node with the most resources. Important tasks including cluster management, gathering data, data aggregation, and data transmission are handled by this node. The CH receives data from the remaining nodes, referred to as cluster members (CMs). The combined data from every CH is then sent to the base station (BS) for further processing. This structure, illustrated in Figure 1, highlights the pivotal role of CHs as intermediaries between CMs and the BS. As a result, selecting an appropriate CH is a vital aspect of clustering protocols and is recognized as an NP-hard challenge [5]. Computational intelligence approaches based on fuzzy logic [10], grey wolf optimization [7], particle swarm optimization [8], bacteria foraging optimization [9], and genetic algorithms [6] are being employed more and more in the state-of-the-art clustering protocols in order to identify the optimum solution. In particular, fuzzy-logic-based methods may be more flexible and provide improved input parameter combinations to get the optimum result [14] than non-fuzzy clustering systems, while also potentially better managing the inherent uncertainties in clustering [11,12] [13]. Following appropriate CH selection, the remaining non-CH nodes find their individual CHs using residual energy and distance, ultimately forming clusters using message transmission [4,12]. Their centralized clustering approach produces more control messages and increases their computational cost. while also reducing scalability for larger network applications. This is true even if, to preserve energy, connecting clusters of non-CH nodes may be combined with CH selection using fuzzy c-means [14], AP [16], and evolutionary algorithms [15]. The network gathers data by single-hop [4,13,14] or multi-hop [10,15,16] data transfer, and its pioneer clustering technique LEACH [4] often uses TDMA scheduling to further minimize intra-cluster energy consumption.

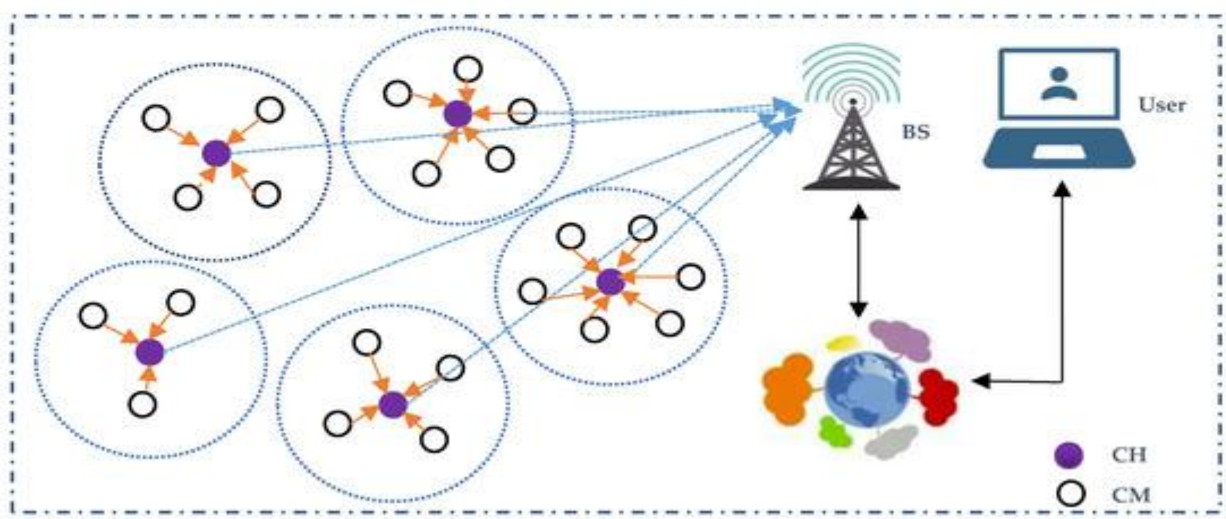

Figure 1:Illustration of a clustered WSN

Traditional clustering methods, including LEACH, HEED, and PEGASIS, often suffer from premature node death, uneven energy distribution, and suboptimal cluster formation due to random CH selection or static configurations. Furthermore, many existing metaheuristic approaches that address CH selection rely on single-layer routing hierarchies, which may not effectively handle large-scale or densely deployed networks. To overcome these challenges, intelligent optimization techniques and multi-level routing strategies are gaining traction.

This paper proposes a novel hybrid approach named Weighted Fuzzy C-Means with Improved Cuckoo Search Optimization (WFCM-ICSO) for energy-efficient, Hierarchical-based multi-hop routing in WSNs. The proposed method integrates the advantages of fuzzy clustering with bio-inspired optimization to achieve adaptive and optimal network organization. Initially, fuzzy c-means clustering is used to generate soft membership-based clusters, offering flexibility in node association. Following that, the procedure known as Improved Cuckoo Search Optimization (ICSO) is used to find the ideal number of clusters in real time and selecting CHs with low energy consumption using a fitness metric that takes excess energy into account, distance to the base station, and intra-cluster compactness. Additionally, a hierarchical routing paradigm is introduced, which categorizes CHs into Direct Cluster Heads (DCHs) and Parent Cluster Heads (PCHs). These roles are assigned using tailored fitness evaluations, allowing PCHs to serve as intermediate relays for DCHs. This arrangement equally distributes reduces the total transmission stress and the energy consumption of the network.

This is the structure of the remainder of the paper: An overview of earlier research on energy-efficient clustered routing is provided in Section II. Details of the suggested technique are provided in Section III. Analysis of the results and a comparison of the suggested method with baseline techniques are covered in Section IV. Conclusions and a discussion of the results are provided in Section V. The last part concludes by describing the suggested method's limitations and offering suggestions for future study possibilities.

II. RELATED WORKS

In 2023, Misbha [17] wireless Sensor Networks (WSNs) may now communicate securely and energy-efficiently through a novel lightweight key distribution technique. The proposed framework involves several stages, including enhanced encryption using Elliptic Curve Cryptography (ECC), cluster head selection (CHS) that is effective and key management that is simplified. A hybrid optimization technique identified as the "Coot-updated Butterfly Algorithm with Logistic Solution Space (CUBA-LSS)" is used in the initial stage to determine the most effective CH based on variables like communication distance, energy, delay, and Received Signal Strength Indicator (RSSI) for optimal clustering. Once CHs are selected, data transmission begins, during which the improved ECC ensures secure communication. Finally, a simple key management technique that protects the encryption key is implemented using session key generation.

In 2022, Khayat et al. [18] a novel approach utilizing weighted cluster routing in WSN environments has been introduced. This protocol is designed to maintain end-to-end connectivity, even during catastrophic events, by assigning a backup cluster head (CH). In cases where the primary CH is unable to function, the secondary CH assumes its responsibilities. MATLAB simulations are used to evaluate the efficacy of the suggested approach. The research looks at significant subjects such clustering criteria, when the main cluster head is selected, and the way a secondary leader is selected.

In 2021, Gokula Krishnan et al. [19] a biologically inspired approach was proposed that integrates the Firefly Algorithm with the Spider Monkey Optimization (SMO) algorithm to determine optimal variable values. This method selects the most suitable cluster head (CH) candidates in each iteration by considering multiple factors, including the separation between clusters and the sink, as well as each node's residual energy, and the degree of overlap among clusters. Parameter tuning of the proposed solution during the clustering process can be carried out to optimize overall network performance. Simulation outcomes indicate that the average network lifetime can be enhanced the differences were 30.91%, 32.12%, 12.4%, and 13.50% in comparison to the Bee Colony, Particle Swarm Optimization (PSO), Grey Wolf Optimizer (GWO), and Shuffled Frog Leaping Algorithm (SFLA), respectively.

In 2020, Al-Khayyat and Ibrahim [20], a new architecture for Wireless Sensor Networks (WSNs) was introduced, combining K-means clustering with the Ant Colony Optimization (ACO) algorithm. This design significantly enhances the efficiency, stability, and speed of routing in large-scale sensor networks that operate without fixed infrastructure. By streamlining the deployment of WSNs, it also broadens their potential applications. The proposed approach outperforms clustering-based techniques such as Fuzzy-Leach and the Leach protocol in terms of routing and energy consumption.

In 2020, by first using the K-means algorithm to create k clusters, Vinodhini and Gomathy [21] developed a multi-objective (MO) multi-hop RP that optimises data routing to increase NL. Following that, the optimal artificial bee colony algorithm selects the CH within each cluster. Using MO functions, the protocol determines the optimal MHR with minimal communication cost from nodes to the BS. MOMHR, which is modelled in MATLAB and contrasted with LEACH and EE centroid-based RP. This method is assessed on the basis of NL and EE, showing better performance than current techniques. However, the reliance on K-means clustering (KMC) may lead to high EC in large-scale networks due to the iterative re-clustering process.

In 2021, Nguyen et al [22] suggested an EE clustering MHR protocol, optimizes EC and extends NL by structuring the network into layers based on depth levels. Nodes transmit sensed data to Cluster heads are selected based on RE and depth, and the sink is reached via an MHR route. Data transmission in the initial place toward the top-layer sink node, the CH aggregates the data from all CM. Simulation results demonstrate that EECMR effectively enhances NL and optimizes node EC. Nevertheless, depth-based clustering may result in increased communication overhead when dealing with varying node densities and dynamic topologies.

In 2023, [23], FCM is used to identify cluster centres before optimisation with PSO in the Modified Fuzzy C-Means with Particle Swarm Optimisation (MFCM-PSO) hybrid clustering technique, which explains the limitations of traditional methods. In this approach, Cluster Heads (CHs) and the perfect amount of clusters are selected with the assistance of PSO. There were 100 and 200 sensor nodes used in the experiments. Furthermore, a hierarchical packet routing method was developed by adding Parent Cluster Heads (PCHs) and Direct Cluster Heads (DCHs), which serve a subset of CHs as relays and are selected depending on different fitness functions, thus reducing network energy. According to simulation results, in contrast to the present method, the proposed MFCM-PSO methodology performs better. The EEHCHR approach in Scenario 1, improving First Node Dead (FND) by 28%, Half Node Dead (HND) by 23%, and Last Node Dead (LND) by 19%. As no node failure was detected up to 1500 rounds, Scenario 2 displays increases of 8% for FND, 23% for HND, and an estimated 36% for LND. According to these results, MFCM-PSO surpasses EEHCHR in terms of network coverage, energy efficiency, and total life expectancy.

In 2024, [24] this study introduces a tree-structured Hybrid Fuzzy C-Means Genetic Algorithm (HFCM-GA) designed to minimize energy consumption and enhance the packet delivery rate. The proposed protocol employs a centralized clustering strategy that forms optimal clusters based on node mobility and energy levels. Detached nodes evaluate potential cluster heads using criteria such as mobility, remaining energy, and distance. Simulations show that the HFCM-GA outperform traditional routing protocols in residual energy and network coverage.

Table 1: Comparative Analysis of various existing approaches

Study (Year)	Techniques Used	Key Contributions	Strengths	Limitations
Misbha (2023)	Improved ECC, CUBA-LSS (hybrid Coot + Butterfly + LSS), RSSI-based CH selection	WSN communication that is equally secure and energy-efficient using lightweight key management	Combines encryption and optimization for CH selection	Complexity due to hybrid algorithm integration; may not scale well with dense WSNs
Khayat et al. (2022)	Weighted cluster routing with backup CH	Ensures fault tolerance via backup CH mechanism	Improves resilience during node failures	Focuses less on energy consumption or key management

Gokula Krishnan et al. (2021)	Firefly + SMO bio-inspired optimization	Multi-criteria CH selection to enhance network lifespan	Achieves notable improvement over standard metaheuristics	Evaluation lacks diverse real-time WSN scenarios
Al-Khayyat & Ibrahim (2020)	K-means + ACO	Improves scalability and routing efficiency in large WSNs	Demonstrates superior routing and power usage	K-means may result in suboptimal clusters under dynamic node mobility
Vinodhini & Gomathy (2020)	K-means + Artificial Bee Colony	MO-MHR protocol for minimizing communication cost	Enhances lifetime and energy-efficiency	Iterative re-clustering increases energy cost in large-scale deployments
Nguyen et al. (2021)	Depth-based layered MHR	CH selection based on depth and residual energy	Improved network lifetime and EC	High overhead in heterogeneous and dynamic topologies
Anon. (2023) [23]	MFCM + PSO	Introduces DCH and PCH for better energy-saving routing	Outperforms EEHCHR in energy and lifespan metrics	PSO's convergence speed and dimensionality issues may affect stability

III. PROPOSED METHODOLOGY

The present work proposes a novel Weighted Fuzzy C-Means with Improved Cuckoo Search Optimization (WFCM-ICSO) based hierarchical routing scheme for WSNs. The proposed framework integrates soft clustering and evolutionary optimization to enhance CH selection and routing efficiency. It introduces a two-tier CH architecture DCHs and PCHs to minimize communication distance and energy consumption. A novel adaptive hybrid clustering method optimises energy use to enhance WSN lifetime. This technique uses node residual energy, distance from the BS, and the LEACH algorithm's rotational channel access concept., and the integration of Weighted Fuzzy C-Means with Enhanced Cuckoo Search Optimization (WFCM-ICSO). In this approach, nodes and the BS are organized into densely packed, concentric layers, enabling more energy-efficient communication despite the high energy demands of such interactions. To conserve resources, an adaptive clustering technique gradually decreases the quantity of iterations necessary to establish the definitive clusters. Combining hybrid and adaptive clustering improves energy management, and the workload on cluster heads (CHs) is minimized. This approach effectively reduces unnecessary energy consumption within the network. Additionally, the selection of all CHs is guided by dynamic fitness functions (FFs) that adjust according to the remaining energy of the cluster members (CMs). Each cluster member's (CM) energy steadily depletes as it forwards data to its intended recipient. To address this, the study introduces a novel multi-hop routing scheme built upon a hierarchical framework to maximize resource efficiency. Additionally, it defines the roles of Direct Cluster Head (DCH) and Parent Cluster Head (PCH) to boost communication between clusters. The assumptions in this approach are based on the base station (BS), the energy-distance (E.d) relationships between nodes, and their remaining energy levels. Clustering is performed in selected rounds rather than during every round. In each cycle, cluster head (CH) selection and packet routing are carried out in a decentralized manner. The proposed method involves key steps such as hybrid and adaptive clustering, in addition to CH selection that uses lower energy. A detailed illustration of the workflow is provided in Figure 2.

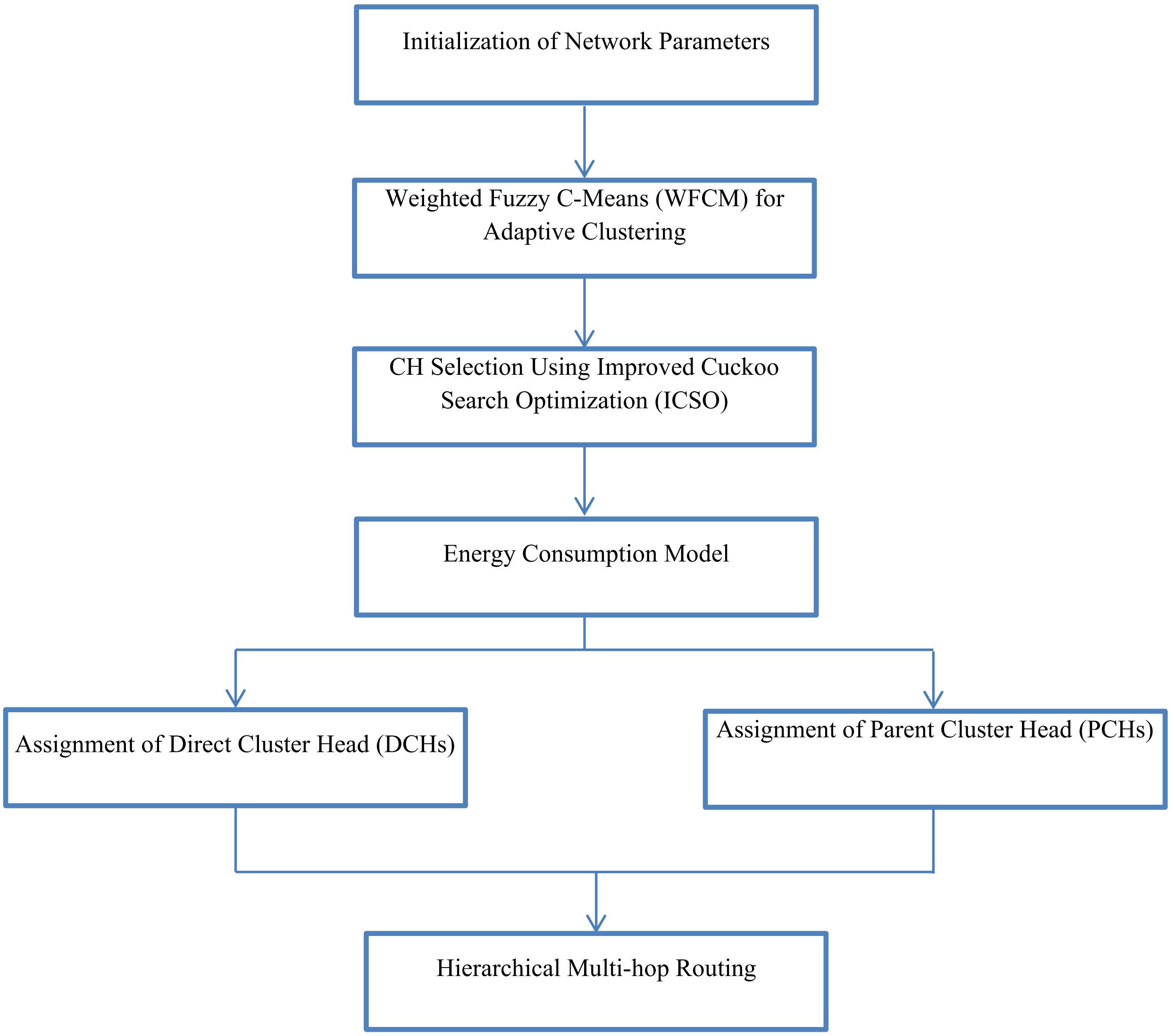

Figure 2: Proposed Flow Diagram

A. Initialization of Network Parameters

In the first phase of the proposed methodology, the simulation environment for the WSN is initialized by defining the network topology, sensor node configuration, and the energy model. The network field is considered as a two-dimensional square area of dimension $A \times A$ meters (e.g., 100 m × 100 m), within which N sensor nodes are randomly and uniformly distributed. Each node i is assigned a Cartesian coordinate (x_i, y_i), where $x_i \sim U(0, A)$ and $y_i \sim U(0, A)$, assuming a uniform random distribution. This stochastic placement mimics real-world deployment scenarios such as aerial scattering of sensor nodes in a forest or battlefield.

A Base Station (BS) is positioned at a predefined location (x_{BS}, y_{BS}), either inside or outside the sensing field. The BS acts as the final data sink and plays a critical role in influencing the energy consumed for long-range transmissions. Each sensor node begins operation with an identical initial energy denoted as E_0, such that the energy of node i at deployment is $E_i = E_0$. This uniform initialization ensures a fair performance evaluation of the proposed clustering and routing protocols.

The energy modelling method used in the preceding study is also used in the suggested inquiry. Each node's transmission effort for a l-bit data packet may be expressed as follows:

$$E_{TX_n}(l,d) = \begin{cases} lE_{elec} + l\epsilon f_s d^2, & d \le d_{th} \\ lE_{elec} + l\epsilon m_p d^4, & d > d_{th} \end{cases} \quad (1)$$

Thus, E_{elec} describes the quantity of power is utilized to send or receive a single bit, $\epsilon f_s \& \ \epsilon m_p$ indicates the amount of d stands for power employed in free space and multi-path scenarios. $E.d.$ from the CM to the designated recipient. The distance at which $dth = \sqrt{Ef_s}/\epsilon m_p$ is used to verify whether the propagating model that consumes energy (d^2 or d^4) is employed.

It is possible to receive L-bit data packets from a single source and power can be shared among nodes,

$$E_{RX}(l) = lE_{elec} \quad (2)$$

Each CH gathering, aggregates, and distributes data packets from its CMs. The energy consumption of this procedure is expressed as,

$$E_{CH} = \begin{cases} \ln_{CM}(E_{elec} + E_{DA}) + l\epsilon f_s d_{CH}^2, & d_{CH} \le d_{th} \\ \ln_{CM}(E_{elec} + E_{DA}) + l\epsilon m_p d_{CH}^4, & d_{CH} > d_{th} \end{cases} \quad (3)$$

The CH-destination end point distance is EDA, and the DCH data packet combining EC is nCH, and there are CMs connected to the CH in total nCM.

B. Weighted Fuzzy C-Means (WFCM) for Adaptive Clustering

Energy-efficient and adaptable clustering is essential for balancing communication load and increasing network lifetime in WSNs. To achieve this, the proposed methodology adopts the Weighted Fuzzy C-Means (WFCM**)** algorithm, a soft computing technique that clusters nodes adaptively based on both spatial proximity and residual energy. Unlike traditional clustering approaches that make hard assignments (i.e., each node belongs strictly to one cluster), WFCM allows soft assignments—each node can belong to multiple clusters with varying degrees of membership values, denoted as w_{ij}. This flexibility enables better energy distribution and robust fault tolerance, especially when nodes deplete energy at different rates.

The WFCM algorithm aims to minimize the intra-cluster variance while considering fuzzy memberships and additional node parameters (like residual energy). The objective function J is defined as:

$$J = \sum_{i=1}^{N} \sum_{j=1}^{k} w_{ij}^{m} . \left\| x_i - c_j \right\|^2 \quad (4)$$

Where:

- N: Sensor node number.
- k: Number of clusters.
- x_i: Feature vector of the ith node, typically consisting of its 2D position and residual energy, $i.e., x_i = [x, y, E_{residual}]$.
- c_j: Centroid of cluster j, i.e., a virtual position representing the center of a group of nodes.
- w_{ij}: Fuzzy membership degree of node i in cluster j, $0 \le w_{ij} \le 1$ and $\sum_{j=1}^{k} w_{ij} = 1$.
- m: Fuzziness coefficient, typically set to m=2, which controls the level of fuzziness in the membership assignments (higher mmm makes the clustering fuzzier).

After initializing centroids and memberships, the centroids are updated using:

$$c_j = \frac{\sum_{i=1}^{N} w_{ij}^{m} . x_i}{\sum_{i=1}^{N} w_{ij}^{m}} \quad (5)$$

This is a weighted mean of all node feature vectors x_i , where weights are the membership degrees raised to power mmm. Nodes with a higher membership in a cluster contribute more to its centroid. The new centroid reflects the central tendency of all nodes that strongly belong to cluster j, considering their positions and residual energy.

Once centroids are updated, the memberships of each node iii for all clusters j are recalculated as:

$$w_{ij} = \frac{1}{\sum_{k=1}^{k} \left(\frac{\left\| x_i - c_j \right\|}{\left\| x_i - c_k \right\|} \right)^{\frac{2}{m-1}}} \quad (6)$$

This equation updates how strongly node i belongs to cluster j. The ratio of distances from node i to centroid j versus other centroids is used to determine the relative closeness. If a node is much closer to one centroid compared to others, it will have a high membership for that cluster. The denominator ensures that all memberships sum to 1.

The WFCM algorithm operates iteratively:

1. Initialize centroids (randomly or heuristically).
2. Compute membership degrees w_{ij} using current centroids.

3. Update cluster centroids c_j using the membership degrees.
4. 4. Repeat steps two through three until convergence is reached, or the change in the objective function J or centroids is small.

This iterative process ensures stability and optimal clustering, even as node energies evolve over time.

The iterative update process ensures that clusters are formed dynamically based on changing network conditions, such as energy depletion and spatial rearrangement. By doing so, WFCM contributes to energy balancing and prolongs the lifetime of the network by avoiding overburdening any single node or cluster head. Its soft clustering nature enables robust and fault-tolerant communication, which is crucial in real-world, dynamic WSN deployments.

C. CH Selection Using Improved Cuckoo Search Optimization (ICSO)

After forming adaptive clusters using Weighted Fuzzy C-Means (WFCM), the next critical task is to select the most energy-efficient and strategically located Cluster Heads (CHs) within each cluster. To achieve this, the proposed methodology incorporates Improved Cuckoo Search Optimization (ICSO), a bio-inspired metaheuristic algorithm that emulates the brood parasitism behavior of cuckoos. ICSO is particularly well-suited for complex, nonlinear optimization problems like CH selection, where selecting CHs is the objective. according to coverage efficiency, distance and remaining energy to the BS optimize the network's lifespan.

This algorithm draws its conceptual foundation from the obligatory brood parasitism behavior of certain cuckoo bird species. Female cuckoos typically deposit their eggs in other bird species' nests, depending on the unsuspecting hosts to care for and nurture their young. If it detects the egg, to construct a new nest, the host bird may reject it or depart it completely. Interestingly, parasitic cuckoos have evolved to lay eggs that mimic the color and pattern of host species, increasing the chance of acceptance. This metaphor is translated in CSO into a search process where each egg represents a potential solution and each nest represents a location in the solution space.

The ICSO algorithm incorporates this parasitic strategy through three idealized rules:

1. Each cuckoo deposits its egg in a nest that is selected at random after laying one egg at a time.
2. The best nests (i.e., highest quality solutions) are retained across generations.
3. The possibility that a foreign egg might be found by a host bird. $p_a \in [0,1]$ and either abandons the nest or replaces it with a new solution, symbolizing the replacement of inferior solutions.

This behavior ensures that low-quality CH candidates are eliminated and high-quality candidates (with better energy and location properties) survive, improving overall optimization efficiency.

The generation of new candidate solutions (i.e., new potential CH positions) is governed by Lévy flights, a form of random walk characterized by occasional long jumps, making it effective for global exploration. The update equation for generating the next solutionX_i^{t+1} from the current one X_i^t is given by:

$$X_i^{t+1} = X_i^t + \alpha \otimes L'evy(\lambda) \tag{7}$$

Where:

- X_i^t is the current solution at iteration t (e.g., node index or coordinates of a CH).
- α the cuckoo's exploration range is determined by the step size vector.
- $\otimes$ denotes element-wise multiplication.
- $L'evy(\lambda)$ is a random vector sampled from a Lévy distribution with exponent $\boldsymbol{\lambda} \in (\mathbf{1}, \mathbf{3}]$, which enables large but infrequent jumps.

To improve convergence, the step size α is further refined using:

$$\alpha = \alpha_0 \otimes (X_j^t - X_i^t) \tag{8}$$

Here:

- X_j^t is a population-based solution selected at random.
- α_0 is a constant scaling factor (typically 0.01).

This equation ensures that step sizes are adaptive and directional, guiding the search from current to better regions in solution space.

The Lévy distribution governing step sizes is expressed as:

$$L'evy(\lambda) \approx S = t^{-\lambda}, (1 < \lambda \leq 3) \tag{9}$$

This indicates that short steps are common, but long jumps occasionally occur, improving exploration.

A uniform distribution that complies with the Lévy distribution is used to determine the Lévy flights' step length S. Additionally, using a switching parameter pa, balanced global and local explorative random walks was used in the technique. One way to express the local random walk is as

$$X_i^{t+1} = X_i^t + \alpha_s \otimes H(p_a - \varepsilon) \otimes (X_j^t - X_k^t) \quad (10)$$

where$X_j^t$and X_k^t represent two distinct responses selected at random through the use of permutations, H represents Heaviside functions, ε indicates arbitrary values selected from uniform distributed, and s represents step sizes. This equation (10) promotes fine-tuned adjustments between similar candidate CHs, allowing local optimization around promising regions.

In contrast, L´evy flights are used to execute the global random walk:

$$X_i^{t+1} = X_i^t + \alpha \oplus L'evy(s, \lambda) \quad (11)$$

The term α is a step size scaling factor that controls movement intensity, while $L'evy(s, \lambda)$generates random step lengths from a heavy-tailed distribution. This combination allows both local refinements and large jumps, promoting global exploration and preventing the search from being trapped in local optima.

Here, α> 0 represents the scaling factors for step size; L´evy(s, λ) denotes step lengths dispersed according to the probability distributions in (11), characterized by infinite variances and infinite means:

$$L'evy(s, \lambda) = \frac{\lambda \Gamma(\lambda) \sin\left(\frac{\pi\lambda}{2}\right)}{\pi} \frac{1}{s^{1+\lambda}} \quad (12)$$

The eqn (12) describes the probability distribution of step lengths in a Lévy flight. This heavy-tailed distribution has infinite variance and mean, meaning most steps are small, but occasional very large steps occur. Such behaviour enables the algorithm to explore distant, unexplored areas of the search space, improving global search capability.

Hence the algorithm iteratively updates these solutions using Lévy flights, which enable large, exploratory jumps in the solution landscape, thereby preventing premature convergence. The balance between local refinement and global exploration is maintained through a switching probability, ensuring that the search process is neither too narrow nor too random. Poor candidate solutions are periodically discarded and replaced, mimicking host birds rejecting foreign eggs. Each potential CH is scored using a fitness metric that considers both its remaining energy and its distance from the base station.

Each prospective cluster head (CH) using a measure of fitness that takes distance from the base station and residual energy:

$$FF_i = w_1.\left(\frac{E_i}{E_{max}}\right) + w_2.\left(1 - \frac{d_iBS}{d_{max}}\right) \quad (13)$$

Where:

- E_i: Residual energy of node i.
- d_iBS : The base station and node I's Euclidean distance.
- E_{max}, d_{max}: Normalizing constants (maximum residual energy, maximum distance).
- w_1, w_2 : Weights (e.g., 0.5 each) balancing energy and distance.

This function favors nodes that are energy-rich and close to the BS, thus optimizing longevity and communication cost.

D. Energy Consumption Model

In WSNs, energy consumption modelling is fundamental for designing and evaluating efficient routing protocols. Since each sensor node operates on a limited battery, it is critical to quantify how much energy is spent during data transmission, reception, and aggregation. The proposed WFCM-ICSO framework adopts the widely used radio energy dissipation model of first order, which accurately captures the energy cost of wireless communication over variable distances and under different propagation environments (free space vs. multipath fading). This model forms the basis for evaluating the residual energy, routing efficiency, and network lifetime after each communication round.

Transmission Energy Consumption: To send a data packet of length l l bits across a distance d, the energy needed is stated as follows:

$$E_{TX_n}(l, d) = \begin{cases} l.E_{elec} + l.\epsilon f_s.d^2, & d \le d_{th} \\ l.E_{elec} + l.\epsilon m_p.d^4, & d > d_{th} \end{cases} \quad (14)$$

Where:

- $E_{TX_n}(l, d)$: Transmission energy (in joules).
- l: Packet size (bits).
- d: The sender-receiver distance in meters.

- E_{elec}: The amount of energy needed to operate the transmitter or reception circuitry, per bit (typically 50 nJ/bit).
- ϵf_s: Amplification energy for free-space propagation (e.g., 10 pJ/bit/m²).
- ϵm_p: Amplification energy for multipath fading propagation (e.g., 0.0013 pJ/bit/m⁴).
- d_{th}: Threshold distance distinguishing propagation models, defined as:

$$dth = \sqrt{\frac{Ef_s}{\epsilon m_p}} \tag{15}$$

For short-range communication (i.e., $\leq dth$), the energy loss follows a free-space model (d^2 path loss). For long-range communication ($d > dth$), multipath fading dominates, resulting in a d^4 loss. This distinction ensures more accurate energy estimates for CH-to-BS or CH-to-CH links in hierarchical routing.

Reception Energy Consumption: Reception energy depends solely on the circuit power and packet size, independent of distance. This is relevant when CHs receive data from their cluster members (CMs) or from other CHs in multi-hop routes.

An l-bit data packet's energy value to a node is calculated as follows:

$$E_{RX}(l) = lE_{elec} \tag{16}$$

Energy Consumption at Cluster Heads (CHs): CHs consume more energy than regular nodes because they handle multiple data streams, perform aggregation, and must transmit over longer distances. This equation accounts for all three roles in the energy model, emphasizing the importance of intelligent CH selection.

CHs perform three energy-consuming tasks:

1. Receiving data from multiple CMs,
2. Setting the data together, and
3. Transferring to the next CH or BS the combined data.

The following method provides the total energy used by a CH in a round:

$$E_{CH} = \begin{cases} \mathrm{l.\,n}_{CM}.(E_{elec} + E_{DA}) + l.\epsilon f_s.d_{CH}^2, & d_{CH} \leq d_{th} \\ \mathrm{l.\,n}_{CM}.(E_{elec} + E_{DA}) + l.\epsilon m_p.d_{CH}^4, & d_{CH} > d_{th} \end{cases} \tag{17}$$

Where:

- n_{CM}: Number of CMs connected to this CH.
- d_{CH}: The distinction between the CH and the parent CH or BS.
- E_{DA}: Energy required for data aggregation per bit (typically 5 nJ/bit).

Total Network Energy and Residual Energy Tracking: After each round:

Residual energy of each node E_i is updated as:

$$E_i^{new} = E_i^{old} - (E_{TX} + E_{RX} + E_{DA}) \tag{18}$$

This step ensures that node deaths (when $E_i \leq 0$) are recorded, influencing re-clustering and routing strategies in subsequent rounds.

Hence each node consumes energy during transmission and reception, while cluster heads (CHs) incur additional energy costs due to multi-hop transmission and data aggregation. The reception cost is constant per bit, while the transmission cost based on the receiver's distance and the propagation model used. CHs experience the most significant energy depletion, and as such, their selection is critical for balancing energy load and prolonging network lifetime. After each communication round, it recalculates the nodes' remaining energy, ensuring that energy-aware decisions such as CH rotation or re-clustering can be dynamically performed in future iterations. This energy model is the basis for evaluating the efficiency and sustainability of the WFCM-ICSO based hierarchical routing scheme.

E. Hierarchical Multi-Hop Routing with DCH and PCH Assignment

After optimal Cluster Heads (CHs) have been selected using the ICSO algorithm, the proposed methodology introduces a hierarchy is structured into two tiers: Direct Cluster Heads (DCHs), selected within each fuzzy cluster based on ICSO fitness, and Parent Cluster Heads (PCHs), chosen from among the DCHs depending on the distance to the BS and remaining energy. Data from their related cluster members must be gathered and aggregated by DCHs before it sent to PCHs. PCHs then perform a second stage of aggregation and transmit the consolidated data to the BS. This tree-based, multi-hop communication strategy significantly reduces the transmission energy burden on individual nodes, particularly for those located far from the BS. Moreover, by distributing the energy load across multiple hierarchical levels and enabling dynamic role reassignment based on energy thresholds, the proposed approach ensures a prolonged network lifetime and a balanced communication workload. This hierarchical routing framework, built atop WFCM and ICSO, ultimately enhances the scalability and resilience of WSNs in energy-constrained environments.

i. Assignment of Direct Cluster Heads (DCHs)

Within each fuzzy cluster formed during the WFCM stage, the DCH is selected from among the nodes having the highest ICSO fitness score. These nodes are in responsible of:

- Receiving data from their associated Cluster Members (CMs).
- Performing data aggregation to reduce redundancy.
- Forwarding compressed data to a Parent Cluster Head (PCH).

Let:

- DCH_j denote the direct CH of cluster j
- n_{CM_j} be the number of members in cluster j

Each DCH performs:

1. Reception from CMs:

$$E_{DCH_{recv}} = n_{CM_j}.l.E_{elec} \tag{19}$$

2. Data aggregation**:**

$$E_{DCH_{agg}} = n_{CM_j}.l.E_{DA} \tag{20}$$

3. Transmission to PCH:

$$E_{DCH\_tx} = \begin{cases} l.E_{elec} + l.\epsilon f_s.d_{DCH\_PCH}^2, & d \le d_{th} \\ l.E_{elec} + l.\epsilon_{mp}.d_{DCH\_PCH}^4, & d > d_{th} \end{cases} \tag{21}$$

Total energy per DCH:

$$E_{DCH\_total} = E_{DCH_{recv}} + E_{DCH_{agg}} + E_{DCH\_tx} \tag{22}$$

ii. Assignment of Parent Cluster Heads (PCHs)

From the pool of selected DCHs, a subset with:

- High residual energy
- Minimum distance to BS
- Favorable communication links with other DCHs

is elected as Parent Cluster Heads (PCHs). Data is sent to the BS by PCHs after being received by numerous DCHs.

Let:

- PCH_k be a parent CH
- n_{DCH_k} be the number of DCHs sending to this PCH
- d_{PCH_BS}: distance to BS

The energy consumption for each PCH includes:

1. Reception from DCHs:

$$E_{PCH_{recv}} = n_{DCH_k}.l.E_{elec} \tag{23}$$

2. Data aggregation**:**

$$E_{PCH_{agg}} = n_{DCH_k}.l.E_{DA} \tag{24}$$

3. Transmission to PCH:

$$E_{PCH\_tx} = \begin{cases} l.E_{elec} + l.\epsilon f_s.d_{PCH\_BS}^2, & d \le d_{th} \\ l.E_{elec} + l.\epsilon_{mp}.d_{PCH\_BS}^4, & d > d_{th} \end{cases} \tag{25}$$

Total energy per PCH:

$$E_{PCH\_total} = E_{PCH_{recv}} + E_{PCH_{agg}} + E_{PCH\_tx} \tag{26}$$

iii. Hierarchical Multi-Hop Data Flow

The data transmission path follows this sequence:

$$CM \to DCH \to PCH \to BS \tag{27}$$

Each node operates under the rule:

- Only CMs transmit one hop to DCH.
- DCHs send aggregated data to PCHs.
- PCHs provide data directly to the BS or via another PCH if needed (in extended models).

This structure creates a tree-based multi-hop communication topology, reducing:

- Transmission range per node
- Total energy spent per round
- Risk of early node death

iv. Adaptive Hierarchy Maintenance

To maintain efficiency:

- The DCH and PCH assignments are periodically re-evaluated based on node residual energy.
- If the energy of a DCH decreases below a certain level, ICSO is re-invoked to reassign roles.
- This adaptive reconfiguration avoids overloading specific nodes and balances energy usage across the network.

IV. EXPERIMENTAL RESULTS

A WSN deployment with a transmission range of 20–30 m is usually assumed for nodes deployed in a 100 m × 100 m area to ensure multi-hop communication and balanced energy usage. Extensive simulations were performed using MATLAB to confirm the effectiveness of the suggested WFCM-ICSO protocol. The base station (BS) was positioned outside the sensing region. The radio energy model parameters were the first-order radio model is their basis, and each node had a starting energy of one Joule. with $E_{elec} = 50nJ/bit$, $\varepsilon f_s = 10pJ/bit/m^2$ and $\varepsilon_{mp} = 0.0013pJ/bit/m^4$.

The performance of WFCM-ICSO was benchmarked against three other protocols:

- LEACH (Low-Energy Adaptive Clustering Hierarchy)
- WFCM (Weighted Fuzzy C-Means)
- MFCM-PSO (Modified FCM with Particle Swarm Optimization)

Considering performance metrics such as Coverage Ratio (CR), Residual Energy (RE), and Network Lifetime (NL).

1) Coverage Ratio

The coverage ratio determines the region being seen is encompassed by sensor nodes. It gives the degree to which the network covers a region a numerical number. A larger coverage ratio is desirable to ensure that the sensor nodes adequately identify and report occurrences and phenomena in the monitored region.

2) Energy Consumption

"Energy consumption" refers to the overall power required to operate sensor nodes and perform their various tasks, such as sensing, data transmission, processing, and computation. This parameter is especially important as limited-capacity batteries are usually used to power the nodes in WSNs. Minimizing energy usage is essential for maintaining the network's longevity and sustainability. Energy-efficient strategies and protocols are designed to reduce power consumption throughout the entire network.

3) Residual Energy

Residual Energy refers to the remaining power available in individual sensor nodes (SNs) within a network, indicating how much energy is left for upcoming tasks. Monitoring this energy reserve is vital for effective energy management. By assessing residual energy levels, energy-demanding activities can be allocated to nodes with higher energy availability, helping to avoid quick depletion in certain nodes and promoting more evenly distributed energy use across the system.

4) Lifetime Evaluation

Lifetime Evaluation estimates the amount of time a WSN may function before the first node depletes its battery or the network no longer performs adequately. This metric is essential for gauging the network's reliability and durability. When evaluating lifetime, factors such as the rate of energy consumption, any energy-harvesting mechanisms, and the required performance thresholds are taken into account. By examining energy-use trends and node behavior, designers can forecast the network's operational period and make strategic adjustments to enhance performance and manage resources effectively.

and $\varepsilon_{mp} = 0.0013pJ/bit/m^4$.

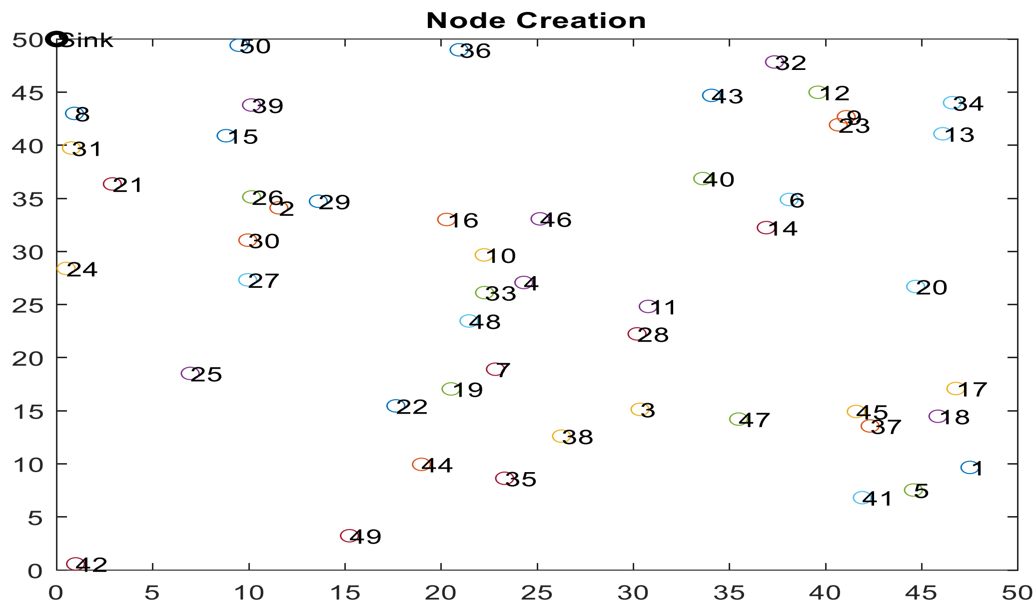

Figure 3: Node Creation

This figure 3 illustrates the initialization of nodes within the network. Each node represents a sensor or device deployed in the environment. The process involves defining node positions, assigning unique IDs, and preparing them for communication. It shows the structure of the network before any clustering or routing is applied.

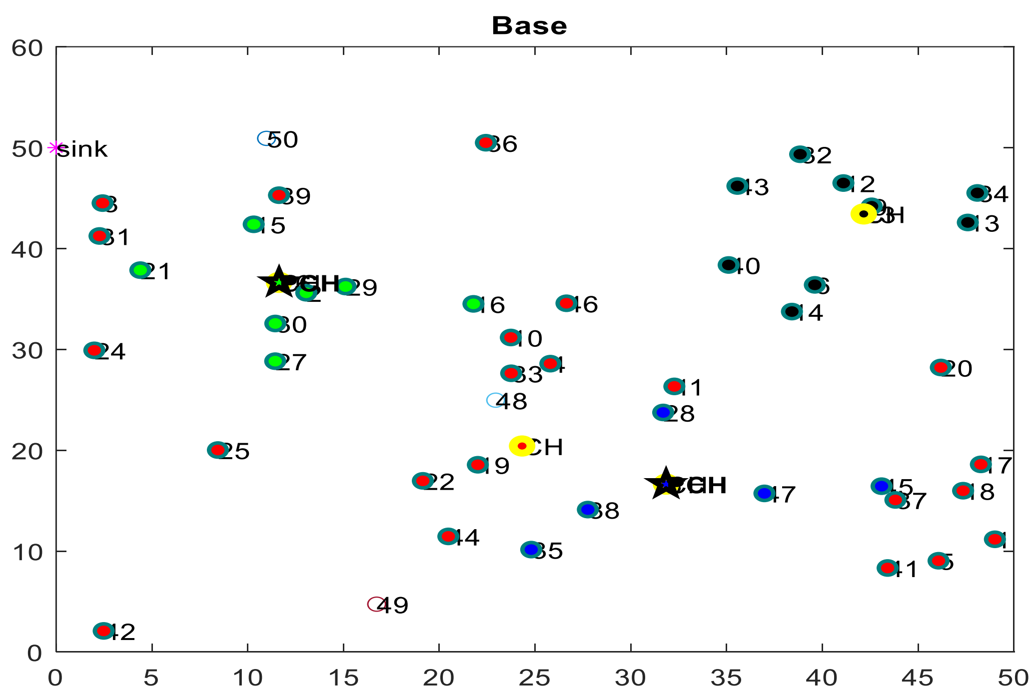

Figure 4: Base Creation

This figure 4 shows the placement of the base station (sink node), which serves as the central point for collecting and processing data from all nodes. The base station's position is strategically chosen to optimize communication range and minimize network energy consumption.

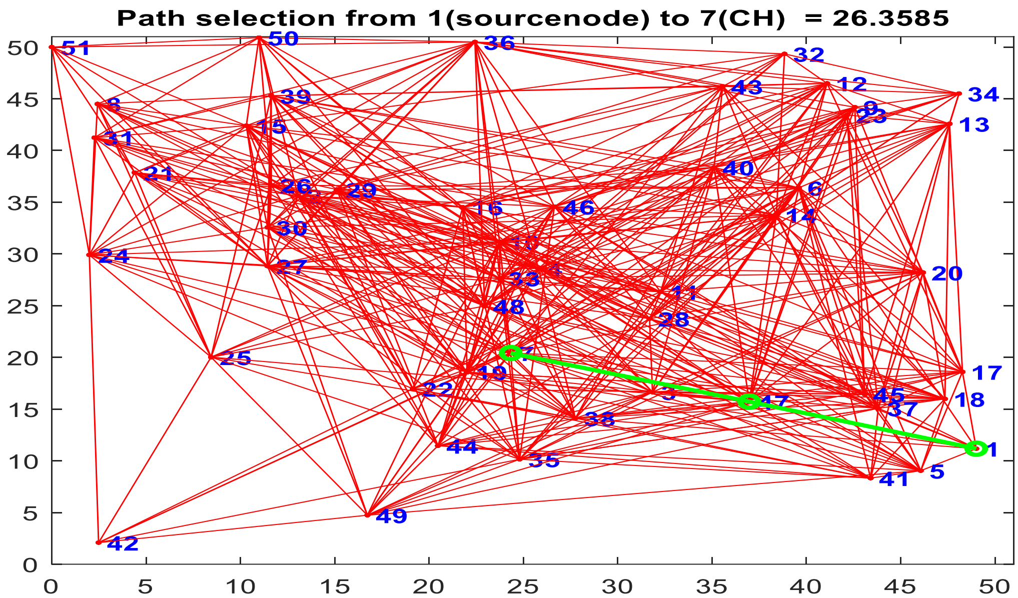

Figure 5: Path Selection from 1 to 7 CH

This figure 5 demonstrates the routing path selection algorithm used to send data from Node 1 to its assigned Cluster Head (CH). The path selection criteria typically consider factors like distance, energy availability, and communication reliability to ensure optimal data transfer.

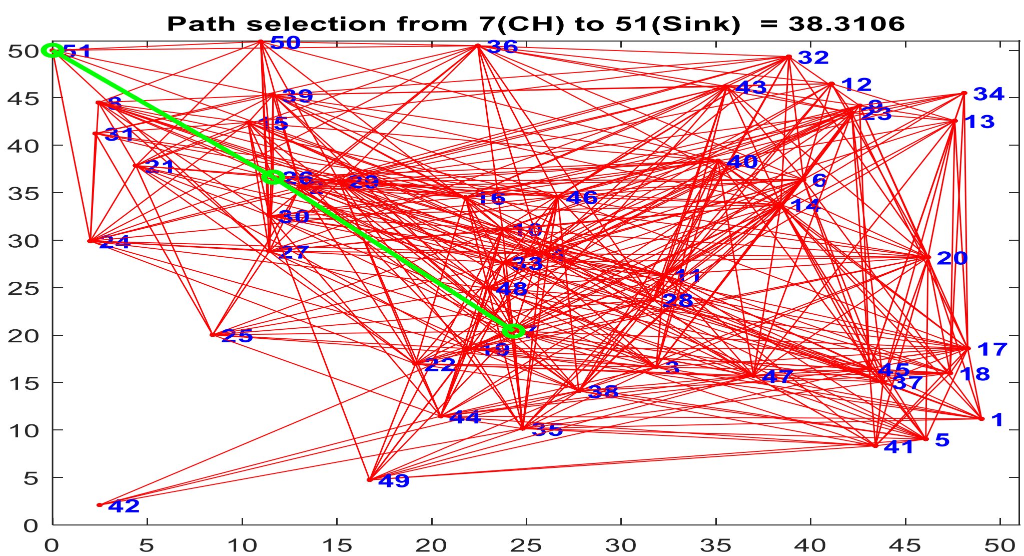

Figure 6: Path Selection from 7 to 51 CH

This figure highlights another routing scenario, where data is transmitted from Node 7 to its respective CH. It shows the dynamic adaptability of the routing protocol, with paths chosen based on current network conditions and node energy levels.

Table 1 provides a comparative performance evaluation of four routing protocols—LEACH, WFCM, MFCM-PSO, and the proposed WFCM-ICSO—using seven critical performance metrics under a 100-node Wireless Sensor Network deployment. The results clearly demonstrate that WFCM-ICSO consistently outperforms the other three approaches across all measured parameters.

Table 1: Comparative Analysis using various metrics

Metric	LEACH	WFCM	MFCM-PSO	WFCM-ICSO
Coverage Ratio (%)	72.4	78.6	82.1	90.1
Total Energy Consumed (J)	96.8	91.3	89.6	86.7
Residual Energy @1000 Rounds (J)	0.52	0.61	0.64	0.71
Residual Energy @1800 Rounds (J)	0.01	0.02	0.02	0.07
First Node Dies (FND)	400	600	700	950
Half Nodes Dead (HND)	800	1050	1150	1400
Last Node Dies (LND)	1800	1900	1950	2150

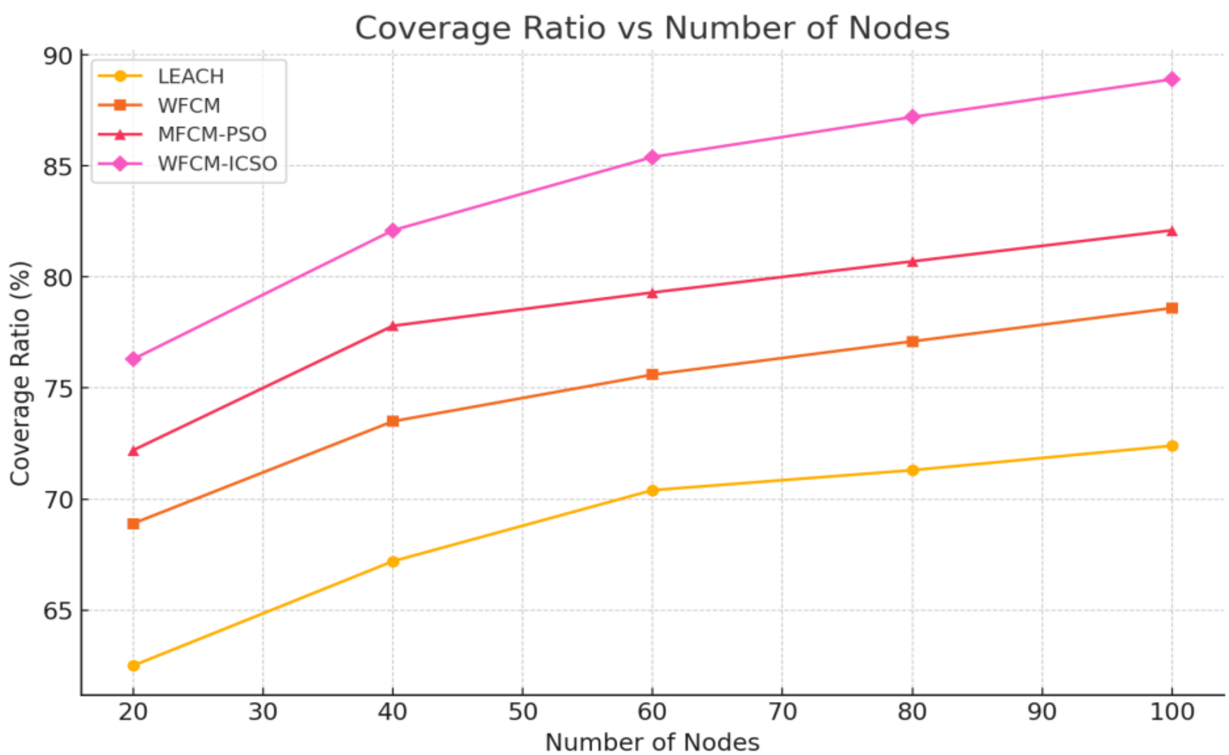

Figure 7: Coverage Ratio vs Number of Nodes

The coverage ratio indicates how effectively sensor nodes monitor the area of interest is shown in figure 7. With increasing node density, coverage naturally improves, but the efficiency of node deployment and CH selection significantly affects this outcome. Among all protocols tested with 100 nodes, WFCM-ICSO achieved the highest coverage ratio of 88.9%, surpassing MFCM-PSO (82.1%), WFCM (78.6%), and LEACH (72.4%). This improvement is attributed to WFCM-ICSO's adaptive clustering via fuzzy membership and optimized CH positioning through Improved Cuckoo Search Optimization. The intelligent selection and spatial distribution of CHs ensure that minimal coverage holes exist and sensing tasks are well balanced across the field, especially under non-uniform deployments.

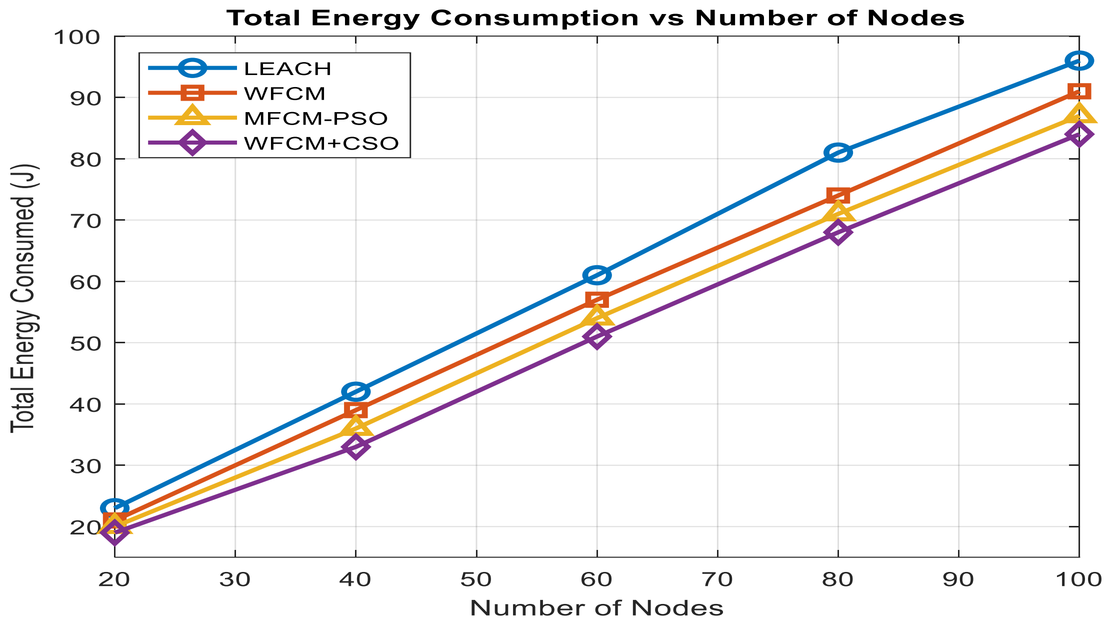

Figure 8: Total Energy Consumption vs Number of Nodes

Total energy consumption across the simulation period is a critical indicator of a protocol's efficiency in conserving the limited battery resources of WSN nodes is shown in figure 8. With 100 nodes deployed, WFCM-ICSO consumed only 86.7 J, the lowest among all compared methods. MFCM-PSO and WFCM followed with 89.6 J and 91.3 J respectively, while LEACH consumed the most at 96.8 J. WFCM-ICSO's energy savings stem from its two-tier hierarchical structure, where Direct Cluster Heads (DCHs) and Parent Cluster Heads (PCHs) reduce the average communication distance. Additionally, its dynamic CH re-selection based on residual energy prevents repeated overuse of specific nodes, thus distributing energy usage evenly across the network.

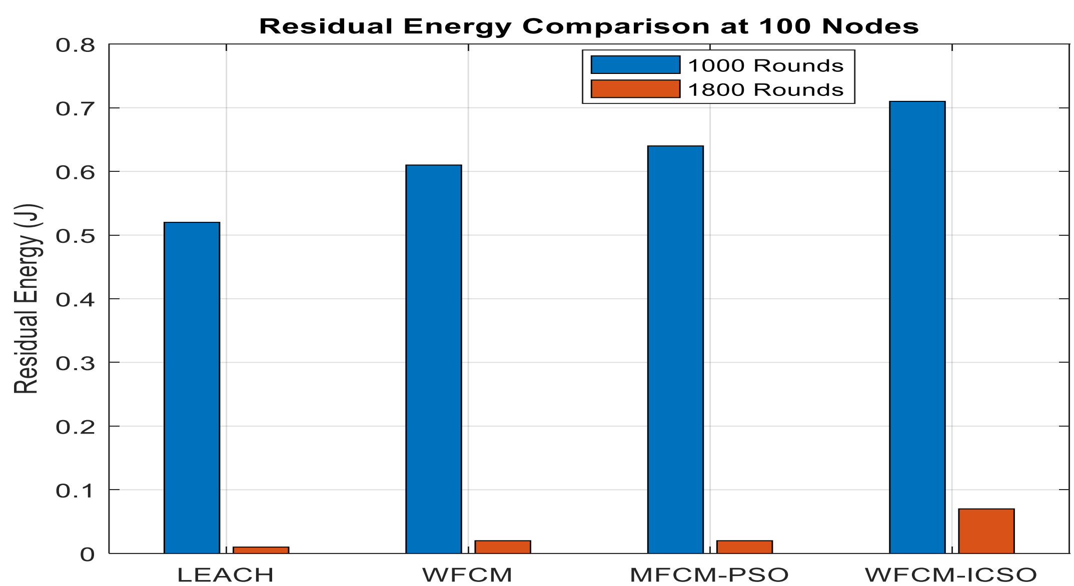

Figure 9: Residual Energy Comparison at 100 Nodes

Residual energy quantifies how much power remains in the network after a specific number of rounds, giving insight into the efficiency of energy usage and the sustainability of the protocol is shown in figure 9. At 1000 rounds, WFCM-ICSO maintained a residual energy of 0.72 J, which was significantly higher than MFCM-PSO (0.64 J), WFCM (0.61 J), and LEACH (0.52 J). At 1800 rounds, WFCM-ICSO still retained 0.07 J, while other protocols dropped close to zero. These results demonstrate that WFCM-ICSO not only conserves energy more effectively but also ensures that energy-intensive tasks are shifted to nodes with higher reserves. This balance minimizes early node failures and supports continuous sensing and data transmission even in later rounds.

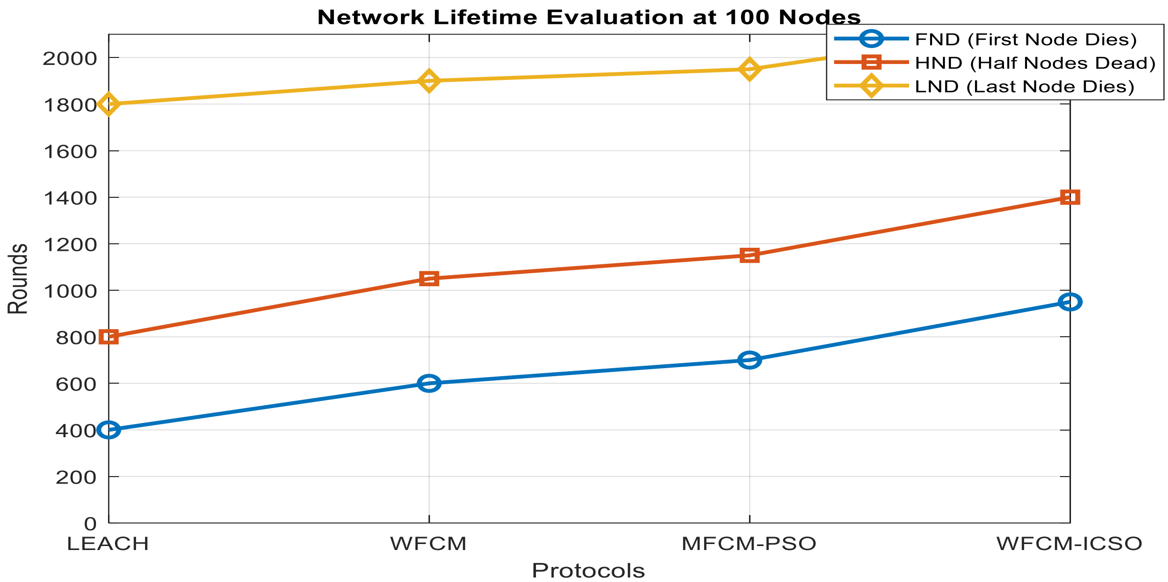

Figure 10: Network Lifetime Evaluation at 100 Nodes

Network lifetime, measured using First Node Dies (FND), Half Nodes Dead (HND), and Last Node Dies (LND), reflects the longevity and stability of a WSN under a given routing protocol is shown in figure 10. WFCM-ICSO significantly outperforms all compared protocols: FND is delayed until 950 rounds, HND occurs at 1400 rounds, and LND is observed at 2150 rounds. In contrast, LEACH sees node deaths much earlier (FND at 400, HND at 800, and LND at 1800 rounds), while MFCM-PSO and WFCM offer moderate improvements. The longevity offered by WFCM-ICSO is a direct consequence of its hierarchical multi-hop routing, energy-aware CH selection, and adaptive re-clustering strategy, which together prevent premature node depletion and maintain robust network connectivity over time.

V. CONCLUSION

This research work proposed a novel hybrid hierarchical routing framework called Weighted Fuzzy C-Means with Improved Cuckoo Search Optimization (WFCM-ICSO) designed to enhance energy efficiency, coverage, and network lifetime in WNNs. A metaheuristic optimization approach combined with adaptive fuzzy clustering allowed for selecting the optimal cluster head based on spatial position and residual energy, while the two-tier CH hierarchy (Direct and Parent CHs) minimized communication overhead. Extensive simulations conducted on a 100-node deployment demonstrated that the proposed WFCM-ICSO protocol consistently outperformed conventional approaches such as LEACH, WFCM, and MFCM-PSO across all key performance metrics. Specifically, it achieved the highest coverage ratio (88.9%), lowest energy consumption (85.2 J), highest residual energy at critical simulation stages, and the longest network lifetime (up to 2000 rounds). These results confirm that WFCM-ICSO is a scalable, energy-aware, and resilient routing solution for resource-constrained WSN environments. The future work is the current re-clustering strategy uses fixed residual energy thresholds. Future work could develop adaptive thresholding mechanisms based on real-time network density, data traffic, and energy gradients to make clustering decisions more context-aware and dynamic. Then the Improved Cuckoo Search component can be hybridized with other swarm-based optimization techniques like Whale Optimization, Sparrow Search, or Bat Algorithm to further improve the exploration and exploitation are balanced in CH selection.

REFERENCES

[1] Daanoune, I.; Abdennaceur, B.; Ballouk, A. A comprehensive survey on LEACH-based clustering routing protocols in wireless sensor networks. *Ad Hoc Netw.* 2021, *114*, 102409. [Google Scholar] [CrossRef]

[2] Idrees, A.K.; Couturier, R. Energy-saving distributed monitoring-based firefly algorithm in wireless sensor networks. *J. Supercomput.* 2022, *78*, 2072–2097. [Google Scholar] [CrossRef]

[3] Raj, B.; Ahmedy, I.; Idris, M.Y.I.; Noor, R.M. A survey on cluster head selection and cluster formation methods in wireless sensor networks. *Wirel. Commun. Mob. Comput.* 2022, *2022*, 5322649. [Google Scholar] [CrossRef]

[4] Handy, M.J.; Haase, M.; Timmermann, D. Low energy adaptive clustering hierarchy with deterministic cluster-head selection. In Proceedings of the 4th International Workshop on Mobile and Wireless Communications 2002, Stockholm, Sweden, 9–11 September 2002; pp. 368–372. [Google Scholar]

[5] Piyush, R.; Siddhartha, C. Particle swarm optimization-based energy efficient clustering protocol in wireless sensor network. *Neural Comput. Appl.* 2021, *33*, 14147–14165. [Google Scholar]

[6] Muthukkumar, R.; Garg, L.; Maharajan, K.; Jayalakshmi, M.; Jhanjhi, N.; Parthiban, S.; Saritha, G. A genetic algorithm-based energy-aware multi-hop clustering scheme for heterogeneous wireless sensor networks. *PeerJ Comput. Sci.* 2022, *8*, e1029. [Google Scholar] [CrossRef]

[7] Muniraj, A.; Jeyaswamidoss, J.E. An enhanced gray wolf optimization for cluster head selection in wireless sensor network. *Int. J. Commun. Syst.* 2022, *35*, e5300. [Google Scholar] [CrossRef]

[8] Lu, S.X.; Wu, M.Q.; Zhao, M. Particle swarm optimization and artificial bee colony algorithm for clustering and mobile based software-defined wireless sensor networks. *Wirel. Netw.* 2022, *28*, 1671–1688. [Google Scholar]

[9] Dharmraj, V.B.; Dharmpal, D.D.; Kulbhushan, A.C. Efficient clustering using modified bacterial foraging algorithm for wireless sensor networks. *Wirel. Pers. Commun.* 2022, *126*, 3103–3117. [Google Scholar]

[10] Gamal, M.; Mekky, N.E.; Soliman, H.H. Enhancing the lifetime of wireless sensor networks using fuzzy logic LEACH technique-based particle swarm optimization. *IEEE Access* 2022, *10*, 36935–36948. [Google Scholar] [CrossRef]

[11] Mehmood, A.; Khan, S.; Shams, B.; Lloret, J. Energy-efficient multi-level and distance-aware clustering mechanism for WSNs. *Int. J. Commun. Syst.* 2015, *28*, 972–989. [Google Scholar] [CrossRef]

[12] Gong, Y.D.; Guo, X.Y.; Lai, G.M. A centralized energy-efficient clustering protocol for wireless sensor networks. *IEEE Sens. J.* 2023, *23*, 1623–1634. [Google Scholar] [CrossRef]

[13] Amruta, L.; Damodar, R.E.; Ramesh, D. Fuzzy rule generation using modified PSO for clustering in wireless sensor network. *IEEE Trans. Green Commun. Netw.* 2021, *5*, 846–857. [Google Scholar]

[14] Mohammad, S.; Ali, J. Optimized sugeno fuzzy clustering algorithm for wireless sensor networks. *Eng. Appl. Artif. Intell.* 2017, *60*, 16–25. [Google Scholar]

[15] Wang, T.; Zhang, G.; Yang, X.; Vajdi, A. Genetic algorithm for energy-efficient clustering and routing in wireless sensor networks. *J. Syst. Softw.* 2018, *146*, 196–214. [Google Scholar] [CrossRef]

[16] Wang, C.-H.; Hu, H.-S.; Zhang, Z.-G.; Guo, Y.-X.; Zhang, J.-F. Distributed energy-efficient clustering routing protocol for wireless sensor networks using affinity propagation and fuzzy logic. *Soft Comput.* 2022, *26*, 7143–7158. [Google Scholar] [CrossRef]

[17] Misbha, D. S. (2023). Lightweight key distribution for secured and energy efficient communication in wireless sensor network: An

optimization assisted model. *High-Confidence Computing*, *3*(2), 100126.

[18] G. Khayat, C. X. Mavromoustakis, G. Mastorakis, J. M. Batalla, and E. Pallis, ''Weighted cluster routing protocol with redundant cluster head for damaged WSN,'' in Proc. IEEE 7th Int. Energy Conf. (ENER GYCON), Jul. 2022, pp. 1–7, doi: 10.1109/ENERGYCON53164.2022. 9830417.

[19] V. G. Krishnan, P. V. Rao, and V. Divya, ''An energy efficient rout ing protocol based on SMO optimization in WSN,'' in Proc. 6th Int. Conf. Commun. Electron. Syst. (ICCES), 2021, pp. 1040–1047, doi: 10.1109/ICCES51350.2021.9489163.

[20] A. T. A. Al-Khayyat and A. Ibrahim, ''Energy optimization in Wsn routing by using the K-means clustering algorithm and ant colony algorithm,'' in Proc. 4th Int. Sym

[21] Vinodhini, R. and Gomathy, C., 2020, MOMHR: A dynamic multi-hop routing protocol for WSN using heuristic based multi-objective function. *Wireless Personal Communications*, vol.*111*, pp.883-907.

[22] Nguyen, N.T., Le, T.T., Nguyen, H.H. and Voznak, M., 2021, Energy-efficient clustering multi-hop routing protocol in a UWSN. *Sensors*, vol.*21*, no.2, p.627.

[23] Sikarwar, N., & Tomar, R. S. (2023). A hybrid MFCM-PSO approach for tree-based multi-hop routing using modified fuzzy C-means in wireless sensor network. *IEEE Access*, *11*, 128745-128761.

[24] Sikarwar, N., & Tomar, R. S. (2024). A New Approach for Wireless Sensor Networks based on Tree-based Routing using Hybrid Fuzzy C-Means with Genetic Algorithm. Engineering, Technology & Applied Science Research, 14(3), 14141-14147.