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OPTIMIZED QOS-BASED MOBILE SINK PATH PLANNING STRATEGY USING FUZZY C-MEANS AND FUZZY INFERENCE SYSTEM IN WSN

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Abstract:

Traditional Wireless Sensor Networks (WSNs) suffer from non-uniform energy consumption, where nodes near high-traffic zones deplete their batteries faster than others, forming energy holes that significantly decrease the total network lifespan. Introducing a Mobile Sink (MS) can mitigate this issue by balancing the network load and redistributing data collection tasks. However, excessive or inefficient sink movement may increase communication overhead and cause frequent topology changes, leading to unstable performance. Thus, designing an adaptive and energy-aware trajectory for the mobile sink is crucial for efficient data gathering. This research deals with an adaptive fuzzy-based mobile sink path planning mechanism, termed RP-FCM-FIS, aimed at enhancing energy extending and usage network lifespan in WSNs. The suggested model partitions the sensing field into the optimal rendezvous points (RPs), and grid-based clusters are dynamically identified by utilizing the Fuzzy C-Means (FCM) algorithm. Thereafter, a Fuzzy Inference System (FIS) determines the sink's next motion according to four decision parameters, residual energy, traffic load, sensor density, and the source node's angle. Simulation results validate that the RP-FCM-FIS protocol obtains superior energy stability, substantially extends network lifespan, and minimizes the standard variation of energy consumption compared to benchmark algorithms such as MSC-BES-HNN, MSPO-ABC, and FA*-Static.

Keywords: WSN, Mobile sink, rendezvous points, Fussy system, FCM.

1-INTRODUCTION

A WSN is a self-organizing wireless system composed of a huge number of mobile or stationary sensors [1]. These networks are more applied in various domains such as healthcare monitoring, military surveillance, building automation, environmental observation, and smart homes [2]. Every sensor node typically has limited hardware resources such as memory, processor, networking facilities, and battery capacity [3]. In recent years, prolonging the lifespan of the network revolutionized the state of the art, primarily due to the constraints of wireless communication bandwidth and the limited energy reserves of sensor nodes that are

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often deployed in unreachable over hazardous environments [4]. Replacing or recharging the depleted batteries of such nodes is usually hard [5].

Regarding energy efficiency, the communication distance is a critical factor in assessing overall energy consumption. The amount of energy depleted for a sensor node to transmit data rises superlinearly with the distance between the sensor node's source and the destination [3][6]. SNs expend the majority of their energy during data transmission, forwarding, and reception. Among these operations, multi-hop forwarding consumes more power because it compares to reception and transmission of data packets [7]. Correspondingly, due to forward data excessively the sensor nodes that are one hop away from the sink use more energy, and the nodes which are farther away from the sink preserve 93% more energy [8], This can lead to the emergence of a "hot spot" or "bottleneck" problem may increase, which will generate energy holes, affect the network lifetime, and the isolation of sink from the network [9]

In (WSNs), there are types, homogeneous: all sensor nodes in the field are equipped with identical capabilities in such a way that all wireless sensor networks have the same memory storage capacity, computing power, battery capacity, etc. The basic principle of in homogeneous wireless sensor networks is to distribute the energy consumption uniformly among all sensor nodes where data sensing and transmission are performed in a turn-by-turn manner among sensor nodes[10] It is the primary focus of our study, But the other type, heterogeneous: has different characteristics in capabilities where a variety of sensors participate in a large wireless network usually organized into groups of simple nodes that form the members of the group, and the most capable and powerful nodes are the heads of the group [11][12].

To overcome these problems and extend the network lifetime, researchers have proposed the concept of a mobile sink (MS)[13], introduced a mobile data observer, which is a vehicle or mobile robot which limitless power capacity, to function as a mobile sink for data collection in WSNs, which triggered a boom of investigation in the fields of the mobile wireless sensor networks Designing the path of a mobile sink is a challenging issue due to its impact on network coverage, network lifespan, data delivery, and data delivery. For quick data delivery, it is desirable to reduce the path of the mobile sink. Anyway, shorter path lengths lead to larger multi-hop communication, increased multi-hop path lengths, and result in higher hop counts. This, in turn, causes higher energy consumption of the sensor nodes [14]. On the other hand, a longer MS tour shortens multi-hop path lengths and reduces hop counts, thereby lowering energy consumption per node, but may cause data collection and buffer overflow (latency) to be delayed [15]. A mobile sink's movement is generally limited by a different of factors, such as the maximum distance between them, the maximum number of practical locations it can visit, and the minimal sojourn time needed to stay at each position [16]. These elements guarantee the mobile sink's effective movement and conserve the energy of the sensor nodes to increase the network's lifetime. To maximize network longevity and performance, these factors must be balanced in an effective path design [17].

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In literature, MS has been widely explored as a means to reduce energy-hole issues in WSNs [18]. Nonetheless, when the MS directly collects each node via short-range communication, the resulting data collection latency becomes inevitable. To deal with this, researchers have proposed the rendezvous point (RP)-based data acquisition model [19]. A significant concern is how to schedule an efficient trip route for the MS to collect data from sensors, as sensing data typically possesses timeliness (e.g., delay-sensitive applications or event reporting [20][21]).

It makes intuitive sense to let the mobile sink to visit each sensor; however, this will result in the same problem as the NP-complete traveling salesman problem (TSP) [22]. However, because the MS is liable to violate the latency limitation of sensing data due to moving along a considerably longer path, such a solution could not be possible when the scale of the WSN is large. As an alternative, a subset of sensors can be chosen as rendezvous points (RPs) in order to shorten the journey [23]. Allowing the MS to minimize its route length and balance energy consumption across the network.

2-RELATED WORK

In mobile WSNs, route planning for sink nodes is a hot topic [24]. Numerous studies have been put out by researchers to use MS for effective and fruitful data collection in WSNs [25]. However, MS mobility management is a significant problem that falls into two general categories: controlled mobility and random mobility [13]. To solve these problems for effective data collecting, the form of the optimum route (FCOR) by the mobile sink (MS) technique and fuzzy-based clustering is proposed. The CH is chosen using the fuzzy logic method based on the node's remaining energy, node distance parameters, and node connectivity. Discovering the MS's ideal movable trajectory is crucial to achieving energy efficiency. Finding a better solution route can be accomplished more effectively with the improved ant colony optimization (IACO) method. According to simulation data, FCOR improves throughput, energy efficiency, and reduces network delay in WSNs [26]. This article proposed an end-to-end data collecting strategy based on ant colony optimization to carry out both the touring path design and the collection point selection simultaneously. The suggested algorithm builds a data-forwarding tree first, then at the same time prepares a touring path and heuristically chooses collection locations. According to the performance evaluation, the end-to-end strategy can extend the wireless sensor network's lifetime more than alternative approaches, particularly when there is an uneven distribution of sensors. It is also possible to integrate the end-to-end strategy with other methods [27]. In another study, an Artificial Bee Colony (MSPO-ABC) [9], based path optimization strategy for mobile sink trajectory design in WSNs was proposed. The authors formulated the overall network energy consumption as a minimization problem of total hops between sensor nodes and the mobile sink's rendezvous points. They improved the convergence speed of the standard ABC algorithm by introducing a cumulative factor during the employed bee phase, and they enhanced global search capability using a Cauchy mutation operator. Simulation results demonstrated that this approach achieved higher energy efficiency and better real-time data collection performance compared with traditional static-sink methods. However, since the ABC-based approach focuses mainly on global optimization, it does not

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dynamically adapt to real-time variations in node energy or traffic as efficiently as fuzzy-based adaptive movement systems. This study addresses this issue and proposes EDEDA, an energy and delay-efficient data gathering technique. The sensor field is separated into virtual grids, and a specific a certain number of grid cells—referred to as visiting points (VPs)—are identified so that a mobile sink can sojourn in them and gather data from 9 nearby grid cell heads in a single hop. Furthermore, the mobile sink mobility pattern is modeled as a Hamiltonian cycle that starts at the base station (BS) and ends there after visiting each VPs. After each cycle, the collected data is offloaded to the BS by the mobile sink. EDEDA beats current routing protocols in terms of throughput and energy consumption, according to simulations performed on NS-2 to assess its performance at varying numbers of sensor nodes. Additionally, compared to TCBDGA, PSOBS, RkM, and VGRSS, respectively, EDEDA improves data acquisition latency by 25.72%, 25.72%, 19.54%, and 14.57% for different numbers of sensor nodes in 2023. [28]. The authors suggested a cluster-based network that travels across a grid system with a cluster embedded in each grid and a centralized static sink, and a mobile sink. Each cluster head sends the data to the closest sink after calculating the distances to the regional MS and the centralized static sink. Salarian and associates. On the other hand, swarm optimization and evolutionary algorithms also have important rules for resolving issues in real time. Srivastava, A. K. et al. [29] forwarded the genetic algorithm (GA) to the sink mobility march. By determining the ideal number of RPs based on three decision variables that were: (1) the minimum MS traveling distance, (2) the minimum number of SNs tow-hops away from the RPs, and (3) the traffic load at the RP, GA created an MS trajectory. Preeth et al. [30] proposed an integrated hybrid model that uses an Adaptive Neuro-Fuzzy System (ANFS) for cluster head organization with an Emperor Penguin Optimizer (EPO) to design an efficient path for MS. The EPO goal of identifying the fewest number of RPs. They showed excellent result, nevertheless, utilizing a swarm intelligence algorithm along with the ANFS is computationally complex in large-scale areas. In 2021, Bilal R. Al-Kaseem et al. [18] proposed a four-step approach to reduce energy consumption and extend network lifetime. The sensing field was divided into equal regions according to the number of mobile sinks to eliminate energy holes. A heuristic clustering method, the Stable Election Algorithm (SEA), was introduced to minimize message exchange and cluster head rotation. The optimal sojourn locations were determined using the Minimum Weighted Vertex Cover Problem (MWVCP), and multi-objective evolutionary algorithms (MOEAs) were applied to optimize the sink trajectories, resulting in improved energy efficiency and prolonged network lifetime [31]. A number of approaches have leveraged mobile sinks and rendezvous points (RPs) to mitigate hotspot and energy-hole problems in wireless sensor networks (WSNs). Chaya Shivalinge Gowda et al. [32] proposed a hybrid framework in which sensor nodes are clustered via mean-shift clustering, and cluster heads (CHs) are selected using a Bald Eagle Search (BES) metaheuristic. Instead of visiting all CHs, a subset of RPs is elected based on a weighted metric combining packet load and hop distance. A hybrid neural network (HNN), optimized via a Group Teaching Algorithm, computes an energy-efficient path through the chosen RPs—this integrated model, referred to as MSC-BES-HNN, effectively reduces energy consumption and delay in data collection. However, the combined use of clustering, metaheuristic optimization,

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and neural learning may impose heavy computational and memory burdens, making deployment in resource-constrained WSNs challenging. [33] suggested ring routing for a data mechanism that creates a virtually node-wide, practically closed ring to advertise and store MS's present location. The MS modifies the ring node's placement when it pauses at a one location by selecting one of its nearby sensor nodes as an anchor node. The source node delivers sensory input to the anchor node after first obtaining the anchor node location from the ring. The data is sent to MS by the anchor node. There is little overhead involved in building the ring structure.The procedure of obtaining the anchor node's location data from the ring, however, could be time-consuming and energy-intensive for large networks. Data delivery and energy consumption may rise as a result of this circumstance.

3. System and Energy Consumption Model:

Energy consumption is a fundamental parameter in evaluating the lifespan of a WSN. The lifetime of WSNs is typically defined as the duration from the start of time point when network operation until the first sensor node exhausts its runs out of energy. Once a node’s energy is depleted, it can no longer transmit or relay data to the sink node,

This study proposes an efficient method to plan a tour for the Mobile Sink (MS) to collect data from all sensor nodes (SNs) in a homogeneous WSN. The sensor nodes are assumed to be randomly distributed over a regular area. Some reasonable assumptions are made for this model to network representation:

1-MS is characterized by an infinite amount of energy and a constant speed.

2- Every SN has a unique ID number, remains static in the area, and is aware of its location coordinates by using a positioning system.

3- The WSN is homogeneous, meaning all SNs share identical characteristics, including communication range, buffer size, and energy capacity.

4- Two sensor nodes can communicate directly if the distance between them is within the communication range, and each node can dynamically adjust its transmission power based on the receiver’s distance.

5- Data transmission follows a Time Division Multiple Access (TDMA) mechanism to efficiently allocate communication slots and minimize interference between nodes.

Consumption by allowing the transceiver of each node to remain in sleep mode for long durations when it is not scheduled to transmit or receive [31]. Although energy depletion also occurs during sensing and data processing, this study primarily focuses on energy consumption during communication, which includes both data transmission and reception operations.

As depicted in Figure 1, the radio energy dissipation model represents the power required for a node to send and receive data packets. When a node transmits an m-bit data packet over a distance d, energy is consumed by both the radio electronics and the power amplifier. Conversely, when receiving data, only the electronic circuitry is activated.

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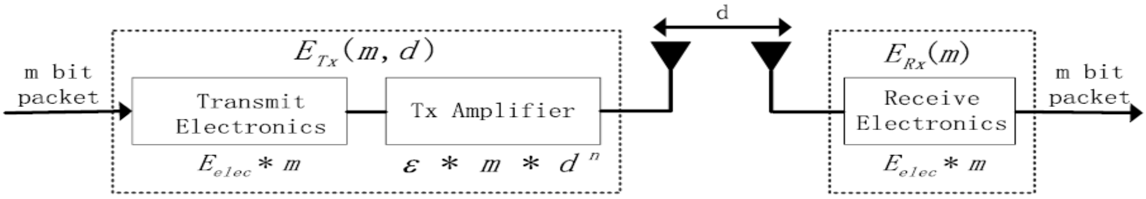

Figure1. Radio Energy

The energy is dissipated based on the communication distance (d), which classifies the channel model into two models a "free propagation model" and a "multi-path fading model." Therefore, when the communication distance between the transmitter and the receiver is lower than the attenuation threshold (d_0), which can be represented by equation (4), the transmission model is free propagation, thus the power of transmission is attenuated by d^2 (d^2 power loss). In contrast, if the distance is greater than d_0, the transmission model is a multi-path fading, and the power of transmission is attenuated by d^4 (d^4 power loss). Energy consumed (ET) to transmit an m-bit packet between two sensor nodes S_1 at the location (x_1, y_1) and sensor node S_2 at the location (x_2, y_2), is calculated as:

$$E_{Tx}(m, d) = E_{Tx-elec}(m) + E_{Tx-amp}(m, d)$$

$$= \begin{cases} E_{elec} * m + \varepsilon_{fs} * m * d^2, \ d \leq d_0 \\ E_{elec} * m + \varepsilon_{amp} * m * d^4, \ d > d_0 \end{cases} \qquad (1)$$

The energy consumed by node S_1 to receive the m-bit packet (E_R)is calculated as follows:

$$E_R = m_b \, E_{elec} \qquad (2)$$

$$d_0 = \sqrt{\frac{\varepsilon fs}{\varepsilon amp}} \qquad (3)$$

Here, E_{elec} represents the electronics energy. The terms ε_{fs} and ε_{amp} refer to the amplifier energy, which is influenced by the receiver's sensitivity and noise figure. The distance between the sensor nodes S_1 and S_2 is denoted as d.

$$d = \sqrt{(x_1 - x_2)^2 - (y_1 - y_2)^2} \qquad (4)$$

4- PROPOSED APPROACH

4.1 Grid-Based Network Partitioning

In the proposed methods, new algorithms are developed to identify rendezvous points (RPs) that serve as residency locations for the mobile sink (MS) while collecting data from other nodes within the network. One algorithm is based on fuzzy C-means to find (RPs), while the other algorithm uses a fuzzy system to determine the optimal path for the mobile sink to move through the network.

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Volume 38 No. 9s, 2025

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It is assumed that the mobile sink knows of the sensor nodes' locations beforehand. Therefore, the objective is to construct a network topology and select an appropriate number of RPs, which are regarded as the residence locations of MS, to acquire data from the network. As to how many sensor nodes there are overall, the base station divides A * A sensory field into multiple "Grid" cells of the same size.

Method to calculate the total number of grid cells in [34]. The authors of this heuristic use simulations to analyze the network's overall energy usage. A randomly deployed network with different percentages of sensor nodes and selected RPs is conducted for simulation. The findings Results that 5% of all sensor nodes chosen as RPs perform better in terms of energy consumption.

Equation (5) defines the total number of grid cells H (or rendezvous points, RPs) used to partition the sensing field according to the total number of deployed sensor nodes M, as shown in Figure 2. The value of H is always chosen as a perfect square to ensure uniform grid formation, where √H × √H represents the grid structure. As the number of nodes increases, the sensing field is divided into a greater number of grids to balance node density and energy distribution, thus improving data collection efficiency and reducing communication overhead.

$$H = \begin{cases} 4, & M \times 0.05 \leq 5 & M < 100 \\ 9, & 5 \leq M \times 0.05 \leq 10 & M = 101 \; to \; 200 \\ 16, & 10 \leq M \times 0.05 \leq 16 & M = 201 \; to \; 300 \\ . & . & . \\ . & . & . \end{cases} \qquad (5)$$

In the grid model, determining the distance value (x,y) of the grid side length (l) is essential for circling the energy holes area, therefore, Eq. (6) is utilized to calculate (l). For better encirclement of the energy holes area, the consideration is that (l) has a relationship with the radius of the TR of SNs, that is, if the TR radius has a low distance value, (l)should have a higher value than TR. In contrast, the higher TR radius of SNs, the more equal (l) to TR.

l = TR*2 (6)

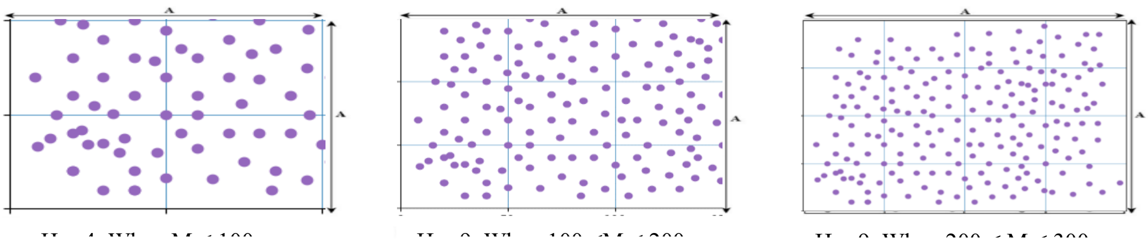

Fig. 2 Different virtual grid structure for 100, 200 and 300 sensor nodes respectively

Figure 2. The virtual grid structure is distinct for 100, 200, and 300 sensor nodes. respectively

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This grid formulation is a key step in the proposed methodology. By determining the number of grids H according to the total number of sensor nodes M, the network achieves a balanced spatial distribution. This balance allows for efficient selection of the optimal rendezvous points within each grid and enables the mobile sink to perform energy-aware movement decisions with minimal communication overhead.

4.2 Eliminating RP using FCM algorithm.

The proposed approach adopts a grid-based network model, where the sensing field is separated into equal square grids. Each grid contains a sum of sensor nodes, choose the optimal rendezvous point (RP) in each grid based on the Fuzzy C-Means (FCM) algorithm. Based on network conditions, the fuzzy inference system (FIS) leads the mobile sink (MS) to move efficiently among these grids.

In the suggested approach, the rendezvous point (RP) inside each grid is not chosen based on the geometric center or randomly. Instead, it is determined to utilize the Fuzzy C-Means algorithm to locate the most centralized and relevant position among the active sensor nodes, as shown in Figure 3. This approach reduces transmission distances, enhances data collection efficiency by minimizing the number of hops, often enabling single-hop transmission, and improves energy balance and Quality of Service (QoS) across the network

After dividing the sensor field of size A×A into equal-sized square grids based on the transmission range TR, each grid acts as a localized sub-network containing a subset of the total sensor nodes. Within each grid, the goal is to determine the most suitable location for the mobile sink to stop based on node density within the grid, and collect data. These positions are referred to as Rendezvous Points (RPs).

To determine the optimal (RPs) within each grid, the FCM algorithm is utilized. Unlike conventional hard clustering methods, (FCM) enables each node to belong to the cluster with a degree of membership, enabling a more flexible and accurate estimation of the central and high-density location.

Let us define X = {x1, x2, ..., xn}, represent the set of sensor nodes within a given grid, where each xi represents the coordinates of node i. c represnt the optimal point (RP). ui the degree of membership of node xi to the cluster centre c.

Since only one RP per grid is required, we configure FCM to generate a single RP per grid (K=1). The objective function minimized by FCM is:

$$J_m = \sum_{i=1}^{N} . \sum_{k=1}^{C} (u_{ik})^m \, \|x_i - c_k\|^2 \qquad (7)$$

Where m > 1 denotes the fuzzification coefficient (commonly set to m = 2), ||xi - c|| is the Euclidean distance between node xi and the center c, ui ∈ [0,1] indicates the fuzzy membership of node i.
Membership values and the corresponding optimal locations of rendezvous points (RPs) are updated iteratively using.

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$$u_{ik} = \frac{1}{\sum_{j=1}^{c}\left(\frac{\|x_i - c_k\|}{\|x_i - c_j\|}\right)^{\frac{2}{m-1}}} \quad (8)$$

$$c_k = \frac{\sum_{i=1}^{N}(u_{ik})^m x_i}{\sum_{i=1}^{N}(u_{ik})^m} \quad (9)$$

The algorithm repeats these updates until the position estimate (c) converges, i.e., the change between successive iterations becomes smaller than a predefined threshold (ε).

This process is applied independently to each grid as follows.

1. For each grid, identify all sensor nodes located within its boundaries. Apply the FCM algorithm to determine (RP) as the location that is both most representative and most densely connected. Store this RP as the designated stop position for the mobile sink in that grid.

2. After obtaining all RPs from every grid as Figure 3, a set of optimal rendezvous points is formed, $RP_{set} = \{RP_1, RP_2, ..., RP_k\}$, where k denotes the total number of (RPs). These points are subsequently utilized by the fuzzy decision system in the next phase to determine the adaptive movement sequence of the mobile sink.

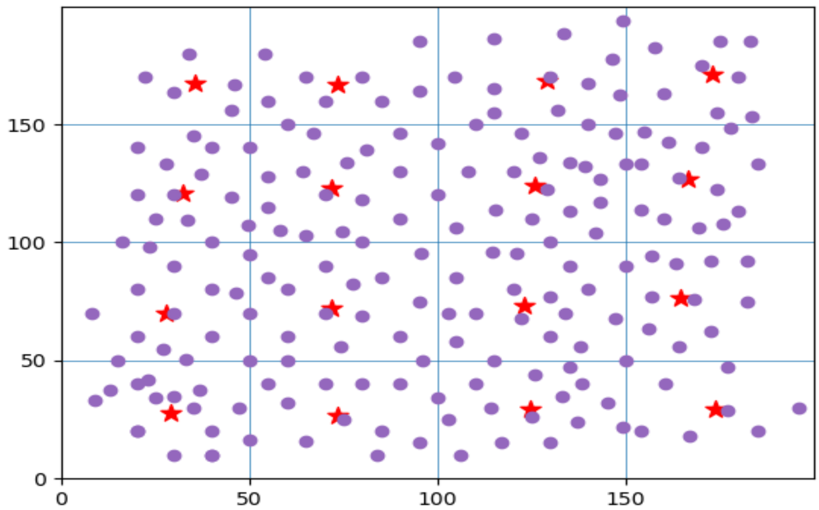

Figure 3: ★ Rendezvous Points (RPs), ● Sensor Nodes

4.3 Fuzzy Inference System for Mobile Sink Movement Decision

In the proposed approach, after determining the optimal (RPs) for each grid using (FCM), the mobile sink (MS) decides its movement pattern through a fuzzy decision system. This system dynamically evaluates neighboring grids based on critical energy and traffic parameters to avoid rapid energy depletion, especially in high-traffic zones, and to maintain uniform energy consumption throughout the network.

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Grid Evaluation Criteria at each transmission round r, the MS evaluates its current grid and up to eight neighboring grids to determine the most suitable next destination. The evaluation process is based on four fuzzy input variables, as shown in Figure 4. Unlike studies that rely on the geometric center of each grid, our method uses FCM to identify a more optimal, data-centric rendezvous point within each grid. This ensures the MS avoids low-density or inactive zones, reduces intra-grid hops and latency, and prolongs the overall network lifetime.

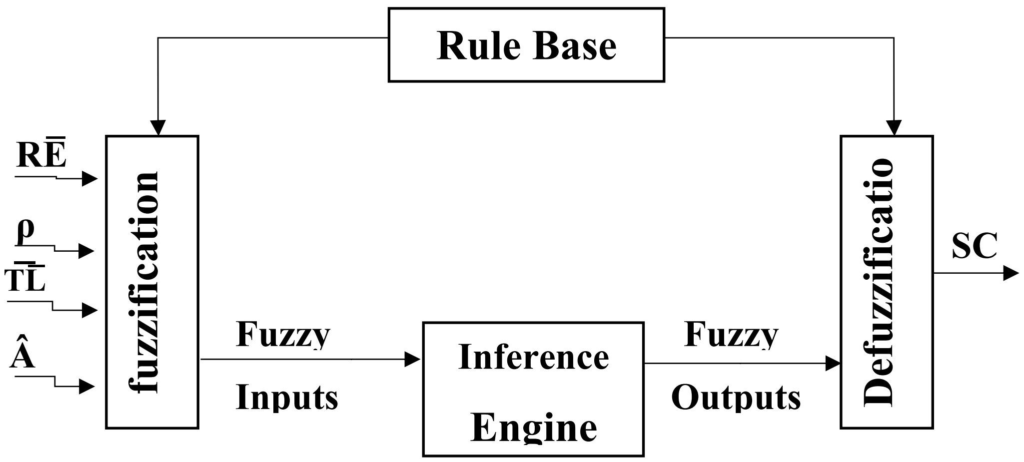

Figure 4. Fuzzy Inference System Structure of RP-FCM-FIS Protocol.

Fuzzy Inference System

The fuzzy system is built using Mamdani inference. Each fuzzy input is divided into linguistic levels such as Low, Medium, and High. A total of 375 fuzzy rules are used to cover all input combinations.

Fuzzy Input and Output Variables

4.3.1 Average Residual Energy($\overline{RE}$)

This is the most important factor in lifetime extension strategies. A grid with a higher average residual energy has a higher chance of being selected. This variable contributes approximately 40% to the fuzzy rule base evaluation.

4.3.2 Sensor Density(ρ)

Grids with higher sensor density are more likely to be chosen. However, in practice, energy distribution might not always be uniform due to varying sensing loads. This variable contributes about 20% to the rule base.

4.3.3 Average Traffic Load($\overline{TL}$)

Grids with lower average traffic are favored due to lower data latency and reduced computation. This variable holds about 20% weight in the fuzzy system.

4.3.4 Source Nodes Angle ($\hat{A}$)

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This parameter reflects how close a candidate grid is to the region where source nodes are located. A closer grid reduces the number of hops required for transmission, contributing about 20% to the rule evaluation.

Each grid is evaluated and assigned a Selection Chance (SC), which is the fuzzy system's output. The grid with the highest SC is chosen, and the MS moves to the FCM-determined RP within that grid. The MS then broadcasts its new position to the entire network.

Membership graphs of fuzzy inputs and outputs using triangular membership functions, illustrated in Figure 5

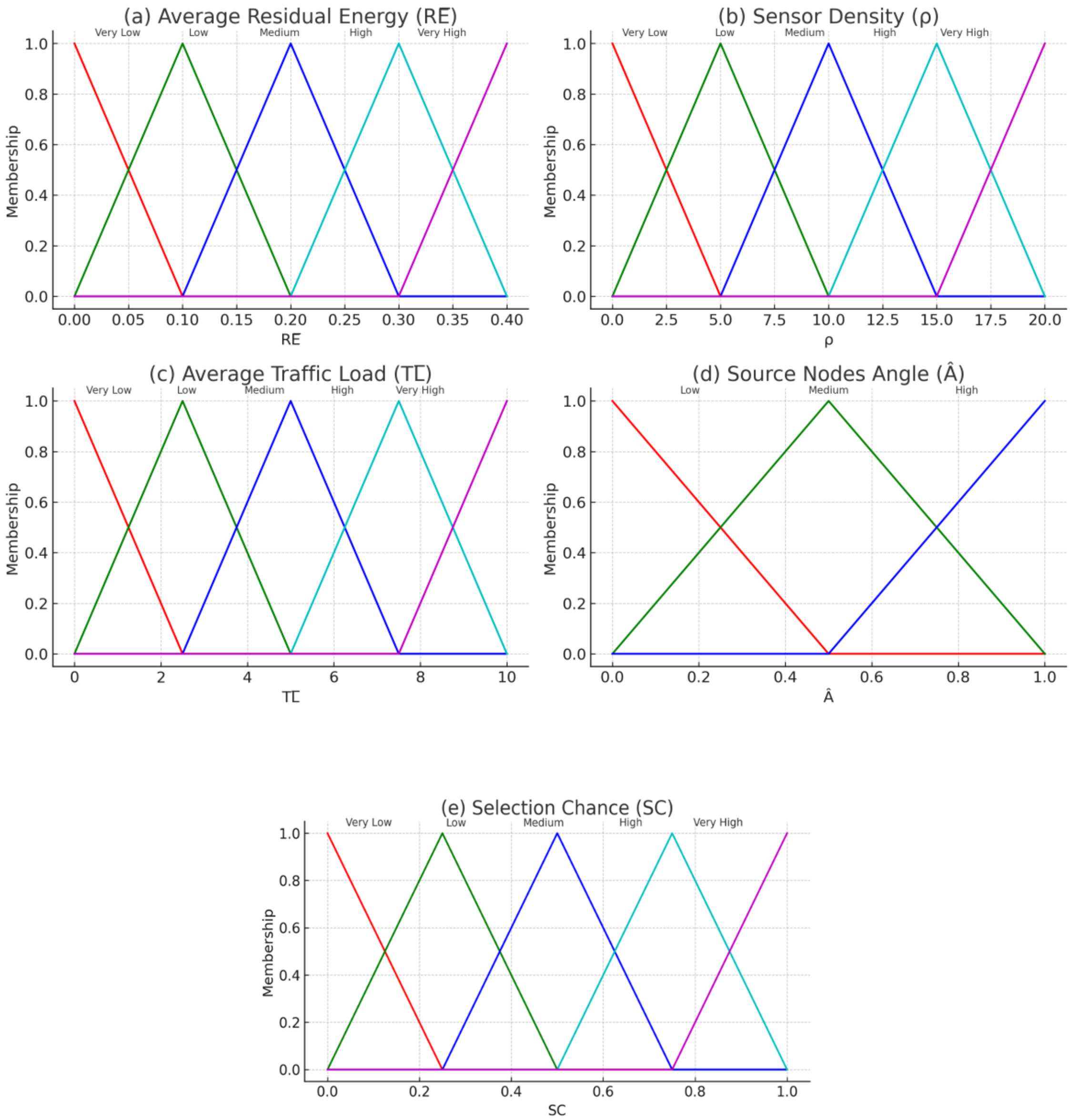

Figure 5. Membership function of the input and output FIS.

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The fuzzy inference system in the proposed method considers four input variables ($R\bar{E}$, ρ, $T\bar{L}$, and $\hat{A}$). The first three inputs are divided into five linguistic levels (‘Very Low’, ‘Low’, ‘Medium’, ‘High’, ‘Very High’), while $\hat{A}$ is represented by three levels (‘Low’, ‘Medium’, ‘High’). By using the If–Then rules, the fuzzy output is mapped with the inputs, resulting in a rule base that contains a total of 375 rules to cover all possible implications. The output selection chance (SC) is then defuzzified using the center of gravity method, and the mobile sink moves to the RP of the grid with the highest SC. Finally, the new sink position is broadcast to all sensor nodes in the network.

5-Performance Evaluation

proposed sink mobility method in homogeneous WSNs, the performance of the proposed RP-FCM-FIS strategy was evaluated by comparing it with three recent state-of-the-art approaches, namely MSPO-ABC, MSC-BES-HNN, and FA*-Static, under identical simulation conditions. The evaluation aimed to verify the effectiveness of the proposed method in achieving balanced energy consumption, mitigating energy-hole formation, and extending the overall network lifetime.

5.1 Simulation Setup

All algorithms including the proposed RP-FCM-FIS were implemented in Python 3.8 using Spyder IDE within the Anaconda environment. The simulation scenario consisted of 200 homogeneous sensor nodes randomly distributed within a 200 × 200m² sensing field. Each sensor node was initialized with equal energy capacity and a transmission range of 25m. To optimize sink mobility and ensure uniform coverage, the sensing field was partitioned into square grids of 50m side length, enabling the mobile sink (MS) to move between adjacent grids either horizontally or vertically by 50 m, or diagonally by 70.7m. The simulation was executed for 10,000 transmission rounds, during which all protocols generated an equal number of packets per round. The same radio energy dissipation model defined in was applied to all compared methods. This setup enabled an accurate comparison of the proposed RP-FCM-FIS model against MSPO-ABC, MSC-BES-HNN, and FA*-Static in terms of reducing energy imbalance, delaying the first node death, and extending the overall network lifetime, illustrated in Table 1.

Table 1. Parameters of Simulation

Parameter	Value
Region size	200m x 200m
Node deployment	Randomly
No. of sensors	200
No. of grids	16 (Grid side = 50m, diagonal = 70.7m)
Transmission range	25m
Initial sensor’s energy	0.4J

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Control packet length	2kb
No. of transmissions	10000R
Maximum traffic in the sensor's queue	10
E_{elec}	50 NJ/bit
E_{amp}	100 pJ/bit/m^2

5.2 Simulation results

The performance of the proposed RP-FCM-FIS strategy was evaluated by comparing it with three recent approaches. To accomplish this, several key performance indicators were measured, including traveling distance of the mobile sink, Standard deviation, Ratio of Remaining Energy, and Ratio of Sensors Still Alive.

Figure 6 shows the cumulative travelling distance of the mobile sink. The proposed RP-FCM-FIS protocol achieves the lowest movement cost during the early and middle rounds, demonstrating efficient sink mobility control. Although its distance increases in later rounds (≈ 990 m at round 10,000), this is expected as fewer active nodes require broader coverage. Compared to MSPO-ABC and MSC-BES-HNN, RP-FCM-FIS provides a better balance between movement overhead and network lifetime.

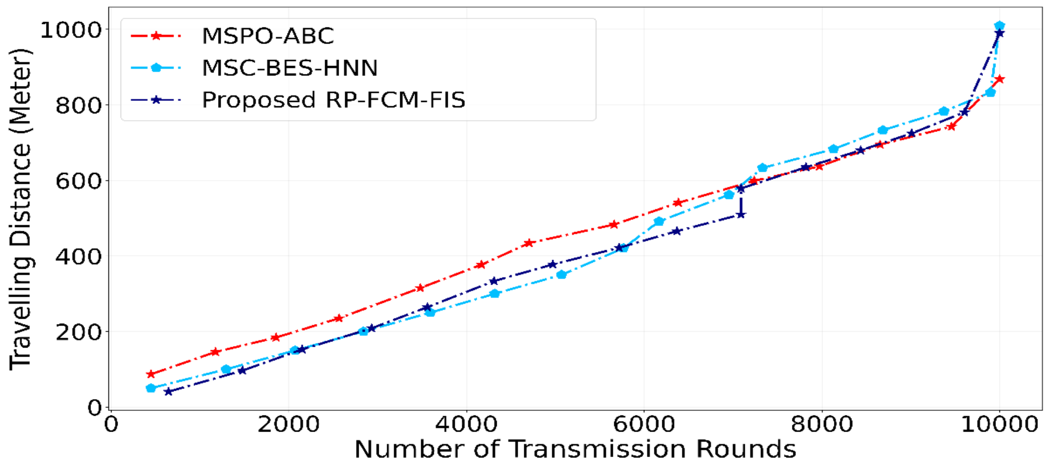

Figure 6: Traveling Distance of the mobile sink Analysis.

Figure 7. Standard deviation of energy consumption. The proposed The proposed maintains the highest remaining energy with a smooth and gradual decline, indicating efficient and balanced energy usage, while MSC-BES-HNN and MSPO-ABC show moderate depletion and FS*-Static experiences the fastest energy loss. Achieves the lowest SD, ensuring balanced energy distribution, while MSC-BES-HNN and MSPO-ABC show moderate performance, and FA*-Static suffers from the highest imbalance. In addition, the proposal maintains the highest remaining energy with a smooth and gradual decline, indicating efficient and balanced energy

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Volume 38 No. 9s, 2025
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usage, while MSC-BES-HNN and MSPO-ABC show moderate depletion and FA*-Static experiences the fastest energy loss. Protocol shows stable and balanced SD values without large fluctuations, reflecting intelligent sink mobility and efficient energy utilization.

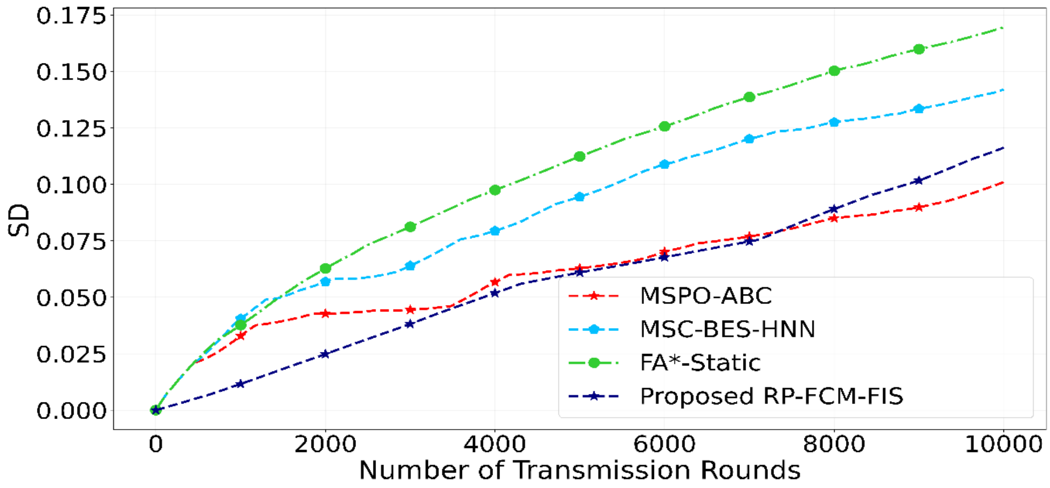

Figure 7. Standard deviation of energy consumption among sensor nodes

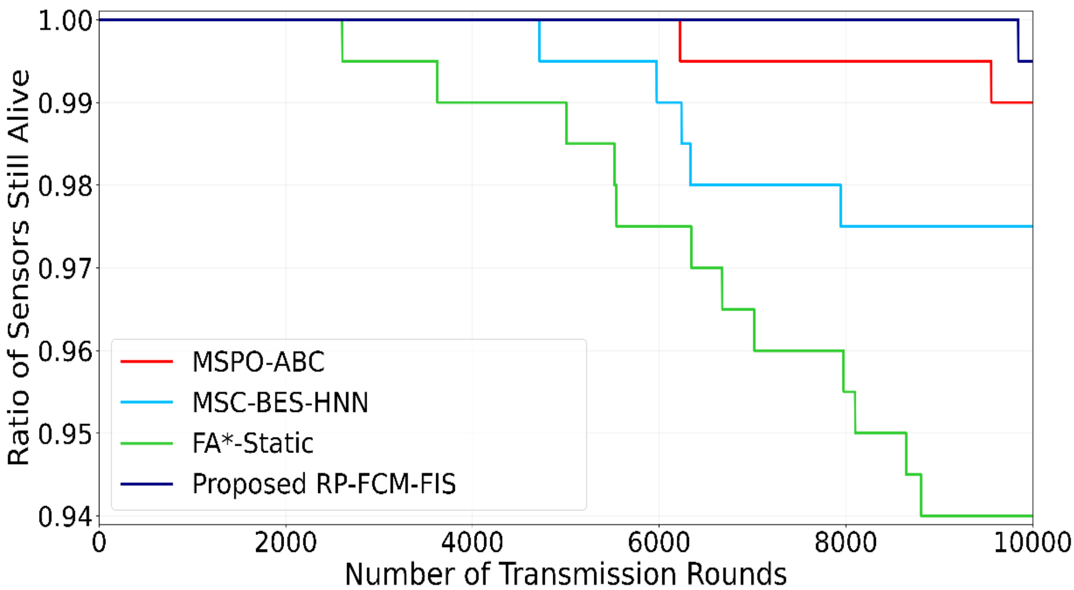

Figure 8. Ratio of alive sensor nodes over simulation rounds

Among all compared protocols, RP-FCM-FIS preserves nearly all sensor nodes alive up to around 9500 rounds, indicating extended network lifetime and efficient energy balance, while MSPO-ABC and MSC-BES-HNN experience earlier node deaths, and FA*-Static shows the weakest performance.

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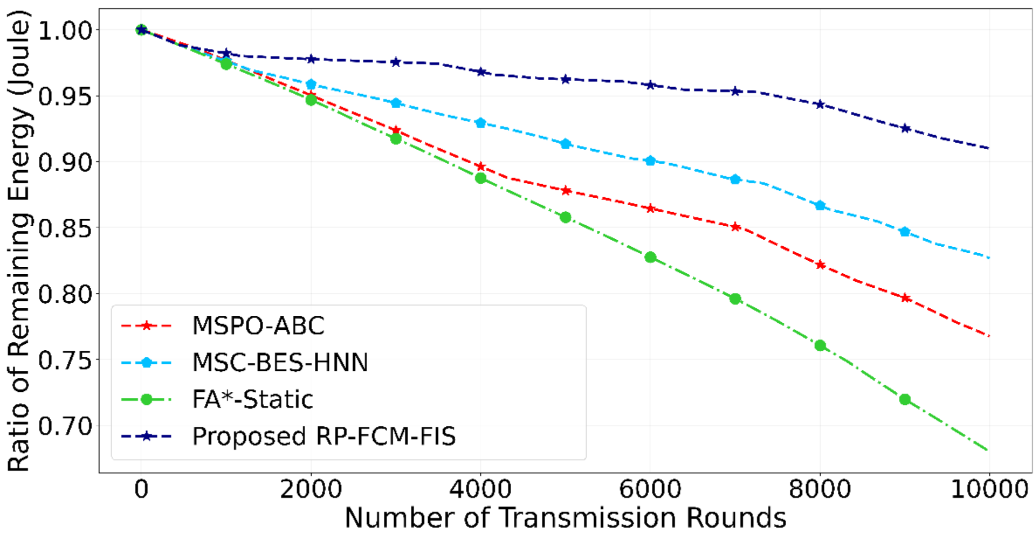

Figure 9. Ratio of alive sensor nodes over simulation rounds

The proposed maintains the highest remaining energy with a smooth and gradual decline, indicating efficient and balanced energy usage, while MSC-BES-HNN and MSPO-ABC show moderate depletion and FA*-Static experiences the fastest energy loss.

6- CONCLUSION.

This paper presented an adaptive path construction strategy for mobile sink movement in wireless sensor networks using a fuzzy inference system integrated with the C-Means algorithm. The network was divided into grids, and the best rendezvous points were dynamically updated in each round according to the residual energy, distance, and node density. The fuzzy inference system was then applied to determine the next sink position using four critical factors: residual energy, number of nodes, traffic level, and angle between the sink and the optimal position.

The simulation results demonstrated that the proposed method maintains the highest remaining energy with a smooth and gradual decline, indicating efficient and balanced energy usage, while MSC-BES-HNN and MSPO-ABC show moderate depletion, and FA*-Static experiences the fastest energy loss. Protocol outperforms existing approaches such as MSPO-ABC, MSC-BES-HNN, and FA*-Static in terms of energy balance, network lifetime, and sink mobility efficiency. RP-FCM-FIS achieved the lowest standard deviation of energy consumption, maintained the highest ratio of alive nodes up to nearly 9500 rounds, and exhibited smooth and stable energy depletion, confirming its ability to distribute the energy load evenly among sensor nodes..

The proposed algorithms are limited in their assumptions regarding the energy consumption of the SNs. Specifically, the assumption has been made that the SNs utilize energy exclusively for radio transceiver operations during data transmission and reception. However, it should be noted that the SNs also experience energy expenditure during data processing operations, such

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as noise elimination and data aggregation. In addition, the approach can be enhanced by incorporating reinforcement learning or other intelligent optimization techniques to improve sink movement prediction. These issues will be addressed in future research.

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