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Energy-Efficient Distributed Clustering in WSNs: A Hybrid Fuzzy and Particle Swarm Optimization Approach

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Abstract: *WSNs are faced with numerous challenges including the hot-spot problem and energy conservation, which affects the reliability and duration of WSNs. This paper proposes the Mamdani Fuzzy Inference System and Distributed Clustering (MFISDC) protocol, a two-tier decoupled WSN architecture that optimizes node energy consumption and balances the load of the WSN. Tier one consists of a localized Mamdani FIS based clustering performed on every sensor node independently based on three parameters: Residual Energy, Node Density, and Distance to BS. This local CH election is both intelligent and decentralized. The second tier transfers processing of complex clustering operations to the BS via a centralized PSO-based approach that, with the help of a multi-objective fitness function, assigns the cluster member nodes to their corresponding CHs. This global optimization minimizes the intra–cluster transmission distance and guarantees balanced cluster size. Experimental results show that MFISDC can effectively suppress the hot-spot problem and stabilize the energy dissipation. The protocol has a prolonged network lifetime of 9802 rounds, which represents an improvements in convergence of about 483.5% over LEACH , 217.4% over FLEACH and 84.6% better than CHEF. The average depletion rate for node energy is ultra-low at 0.0061 J/round as well. The throughput delivered over the lifetime of the network is 6.32×10^{8} packets. Overall, results show that MFISDC outperforms current standard measurement protocols such as LEACH, FLEACH and CHEF, demonstrating the robustness and scalability of the proposed protocol and its intelligent routing solution for modern wireless sensor network applications.*

Keywords: Cluster Head Election, Energy Efficient Routing, Fuzzy logic, Particle Swarm Optimization, Wireless Sensor Networks.

1. Introduction

Sensor Networks (WSNs) form the physical perception part of the modern Internet of Things (IoT) and play a vital role in various applications including environmental monitoring, precision agriculture, industrial automation, military surveillance, and smart-city infrastructure [1]. Usually, these networks are made up of hundreds to thousands of low-cost, tightly spread-out micro-sensors. These nodes autonomously observe ambient physical metrics, and they communicate this aggregated telemetry information to a central Base Station (BS) for additional processing via wireless communication channels instead of being just passive data loggers. A basic constraint of WSNs, however, is that the sensors are constrained by very limited and non-rechargeable power sources. Due to the extreme, often remote environments where these networks are typically installed, or structural limitations such as being embedded in the roadway, deep within agricultural fields, or in complex industrial machinery, it is both economically and physically impractical to manually replace depleted batteries. So, the most critical operational constraint in WSNs is the reduction of power dissipation [2]. Any routing protocol that can help extend the network's lifetime, even by a fraction, is going to result in years of sustained operational capacity that will save on costly field interventions and network downtime.

One of the best ways to reduce these stringent power constraints is to use a hierarchical clustering architecture [3-5]. To achieve this, the topology of the network is divided into local groups where each group has a randomly selected node that acts as Cluster Head (CH). A member node does not send its sensed data directly to the BS; instead, it forwards the data over minimal distance to its respective CH. The CH then takes responsibility for all of this data payload aggregation, compression and delivery to the BS. It is evident that this topology will reduce the total amount of energy used by the network, however, it will place a huge operation burden on the CHs. If poorly chosen, these CHs will quickly become depleted of energy. This results in the much dreaded "hot-spot" situation, in which isolated network areas are lost early, leading to cascading node disconnections, coverage gaps, and a dramatic drop in overall data capacity.

While early clustering protocols achieved some successes in their initial designs, they suffer critical functional trade-offs. The original LEACH protocol [6, 7] was a radical change in the way routing is done in WSNs but it uses a random, probabilistic CH selection method, which is entirely oblivious to the energy level of the node and often results in the premature death of a CH due to low energy. In order to enhance this, fuzzy-logic baselines were added. FLEACH [8] makes use of fuzzy inference for CH election, but it uses hard cluster formation algorithms that do not take into account the density of nodes, resulting in imbalanced cluster sizes and high intra-cluster communication overhead. Likewise, CHEF [9] offers a localized fuzzy-logic method using a more balanced initial selection, but does not have an optimization mechanism for assigning member nodes, so the overhead of packet-forwarding is inefficient in dense networks. Previous studies have shown that there is a trade-off between efficient local CH election and topology optimization of the global cluster, so a protocol that assures structural stability and maximizes transmission efficiency is required.

To overcome these limitations, we propose a new protocol called Multi-Fuzzy Inference System and Distributed Clustering (MFISDC). MFISDC is operated on a two-tier architecture based on computational intelligence where the hot-spot problem is eliminated, and perfect energy distribution is attained. MFISDC applies a Mamdani Fuzzy Inference System [10] of the first level as a strict eligibility assessment and scoring of all nodes to qualify them to become a CH. The fuzzy scoring measures three key local descriptors: residual energy (survivability), distance to Base Station (long-haul transmission cost), and node centrality (physical accessibility to neighbors). In the second level, after optimal CHs are elected, MFISDC controls the phase of cluster formation by using Particle Swarm Optimization (PSO) algorithm [11-13]. Instead of using hard rules for joining based on distance, the PSO considers cluster formation as a global mathematical optimization problem. It intelligently maps non-CH nodes to CHs with the intent of minimizing the sum of the intra-cluster distance, without compromising the load distribution balance (perfectly balanced) across all active clusters.

The main technical innovations that have been developed in this research are explained below:

- We suggest a novel hybrid routing algorithm, called MFISDC, which is a combination of multi-descriptor Fuzzy Inference System for the accurate Cluster Head election and Particle Swarm Optimization (PSO) for distributed node clustering.
- We eliminate the hot-spot problem and avoid premature cascading node failure by making sure that inter-cluster routing tasks are only given to the most energy-rich and centrally located nodes.
- We thoroughly evaluate MFISDC against standard protocols (LEACH, FLEACH and CHEF) under finely controlled simulation parameters to establish a reproducible standard.
- We have mathematically and visually proven that MFISDC greatly extends network lifetime, achieves an all-node (AND) death threshold of 9802 rounds, maintains an extremely low power drain rate of 0.0061 J/round, and increases packet delivery success.

The rest of this research paper is organized as follows: Section 2 presents a detailed survey of the related research works on clustering and optimizing routing in WSNs. In Section 3, the architecture of the system and radio energy dissipation model are explained. The design and implementation of the proposed MFISDC protocol are described in section 4, which includes the details of the Fuzzy Logic and PSO mechanics. In section 5, the performance metrics are defined and the results and the discussion of the experimental simulation based on the defined metrics are presented. Finally, in Section 6, the paper is finished and directions towards future research are outlined.

2. Related Work

With energy efficiency as a critical requirement in Wireless Sensor Networks (WSNs), significant effort has been invested in developing new clustering and routing optimization algorithms. In recent years, probabilistic models have been replaced by more computationally intelligent models, mainly based on Meta-heuristics and Fuzzy Logic.

2.1 Swarm Intelligence and Meta-Heuristic Clustering

A lot of work has been done on the use of meta-heuristic algorithms, especially swarm intelligence-based algorithms to solve the NP-hard routing and clustering problems in WSNs. Particle Swarm Optimization (PSO) [13] is a fast-converging optimization method that is often used in modern approaches because of its mathematical simplicity. Wang et al. [14] proposed an energy efficient coverage and clustering algorithm based on the improved PSO, which reduces blind spots and optimizes energy consumption. In the same way Singh et al. [15] investigated multi-objective routing protocols in which meta-heuristics were used to find optimal transmission paths and showed that the packet delivery ratio was increased significantly. Ramasamy et al. [16] also applied swarm intelligence to secure routing approaches in IoT-WSN systems, employing swarm behaviors to confine the malicious nodes and optimize energy routes. Standalone PSO is very good at global optimization, but some recent works have shown that using PSO only for Cluster Head (CH) election and cluster formation can lead to large delays at the Base Station and being unable to adapt quickly to uncertainties that may arise at the node level, as reported by Datta and Nandakumar [17].

2.2 Fuzzy Inference Systems in WSNs.

Fuzzy Inference Systems (FIS) have been increasingly used to address some of these uncertainties that are present in a localized manner in dynamic sensor networks. A node can locally make a human-like decision based on imprecise inputs, using fuzzy logic [10]. To overcome this, Rani and Reddy [18] proposed a multi-criteria fuzzy clustering scheme, which considers residual energy, node degree and link quality to select the CHs, thus preventing the premature node death observed in LEACH. Chang [19] designed a localized, energy-aware routing protocol with fuzzy logic parameters that vary according to network density. Sert et al. [20] proposed MOFCA, a multi-objective fuzzy clustering algorithm that forms unequal clusters to mitigate the hot-spot and energy-hole problems regardless of how the nodes are deployed**.** Despite its suitability for multi-parameter CH election, a critical limitation of fuzzy logic was observed by Jubair et al. [21] that it is a deterministic mapping tool and that it does not have a global mathematical to optimize the cluster boundaries and to minimize the actual Euclidean distances between the member nodes and their CHs.

2.3 Modern Hybrid Approaches (Fuzzy Logic + Meta-Heuristics)

The latest paradigm is to merge FIS and swarm intelligence, which is to overcome the individual limitation of both paradigms. Hu et al. [22] introduced an improved PSO-based fuzzy rule optimization process in the clustering protocol for election of CH. The fuzzy rule bases are effective but they are costly in terms of computation as they have to be optimized continuously. Ramya and Padmapriya [23] suggested a hybrid Fuzzy-PSO algorithm for election of CHs in fuzzy logic and inter-cluster routing (routing between the cluster heads) in PSO. Hu et al. [24] also combined fuzzy logic and a genetic algorithm to deal with the problem of balancing energy consumption in heterogeneous networks. Sert et al. [25] presented a two-tier distributed fuzzy logic protocol for data aggregation in multi-hop WSNs, together with an optimization framework that tunes the parameters of its fuzzy clustering tier.

2.4 The Research Gap Addressed by MFISDC

With all these modern developments, there is still a huge space to be filled. Presently, there are two types of hybrid protocols: tightly coupling swarm algorithm to fuzzy logic (which increases the complexity of computations) and using the swarm algorithm only for inter-cluster routing but not for intra-cluster topology management. What makes MFISDC better than others is that these two paradigms are explicitly separated so that the most efficient use of them is achieved: a localized Mamdani FIS is used because of its ability to elect any number of CHs by a multi-criteria approach, while PSO is used because of its ability to optimize the assignment of non-CH nodes to clusters in the geometric space. This exact distribution of computational load avoids overload, unbalanced cluster sizes as experienced in the previous fuzzy protocols [12, 14], and ensures optimal load distribution within the clusters, which is not provided in the recent hybrid architectures [16, 17].

3. System and Energy Model

In this section the network assumption, the radio model of energy consuming and the operational details of the proposed MFISDC (Mamdani Fuzzy Inference System and PSO based Dynamic Clustering) protocol are discussed. The Mamdani Fuzzy Inference System (FIS) is employed in the election of Cluster Head (CH) operation in MFISDC, while Particle Swarm Optimization (PSO) is used to form the optimal cluster.

3.1 Network Model and Assumptions

The wireless sensor network model consists of 100 sensor nodes that are uniformly deployed randomly in a square sensing region of size (100×100 m^2). After deployment all nodes are stationary, and initialized with the same energy (E_0). In the middle of the field, there is a single powerful base station (BS). The following assumptions are made:

- All sensor nodes and the BS are fixed once deployed.
- All nodes are homogeneous - they have the same energy source $E_0 = 0.6J$, the same processing power, and the same communication range.
- Each node does not know its geographic position and is capable of estimating distances to neighboring nodes and BS based on received signal strength.
- The BS has high computational power and unlimited energy.
- The network runs in a series of rounds: one round contains a setup phase (CH election and cluster formation) and a steady-state phase (data routing).
- The nodes are able to change their transmission power depending on the distance.
- The Cluster Heads (CHs) aggregate data to remove redundant data before transmitting to the BS.

3.2 Energy Dissipation Model

This paper uses a standard *First-Order Radio* power dissipation model. The consumed energy by the radio to transmit an *l*-bit message through a distance *d* is computed based on either a free-space channel model (d^2) or a multipath vanishing channel model (d^4), depending on the transmission distance relative to the threshold distance d_0.

The transmission energy E_{TX} is given by:

$$E_{TX}(l,d) = l.E_{elec} + l.\ E_{fs} \cdot d^2 \quad (d < d_0) \tag{1}$$

$$E_{TX}(l,d) = l.E_{elec} + l.E_{mp} \cdot d^4 \quad (d \geq d_0) \tag{2}$$

Where *do* is calculated as:

$$do = \sqrt{\frac{E_{fs}}{E_{mp}}} \tag{3}$$

where L is packet length (bits), where (E_{elec}) is the electronics energy:

$$E_{elec} = 50\ nJ/bit,$$

Efs and *Emp* represent the amplifier energies for the free-space model and the multipath model, respectively, and *do* represent the threshold distance.

$$E_{fs} = 10\ pJ/bit/m^2,$$
$$E_{mp} = 0.0013\ pJ/bit/m^4,$$
$$E_{DA} = 5\ nJ/bit,\ and$$
$$do = \sqrt{\frac{E_{fs}}{E_{mp}}} \approx 87\ m.$$

The simulation environment is designed to isolate the effect of the clustering protocol from confounding factors: all four protocols share identical radio parameters, packet sizes, and topology seeds across all runs.

The energy consumed to receive a (*l*)-bit message (E_{RX}) is purely determined by the electronic circuitry:

$$E_{RX}(l) = l.E_{elec} \tag{4}$$

$$E_{RX}(l) = l.E_{elec} \tag{5}$$

Additionally, Cluster Heads consume aggregation energy (E_{DA}) to compress the signals received from their member nodes before routing them to the Base Station.

$$E_{DA}(l) = l.E_{DA} \tag{6}$$

The total energy expended by a node in one round depends on its role (CH or member node) and the distances involved.

3.3 MFISDC Protocol Description

The proposed MFISDC protocol is a two-tier, decoupled protocol and is iterative. It strictly distinguishes between cluster head election in a localized manner and cluster formation in a global manner, to reduce the network overhead and maximize energy efficiency in overall operation.

3.3.1. Cluster Head Election based on Mamdani Fuzzy Inference System (FIS): In the first stage, the local fitness of each node as a CH is assessed locally by a Mamdani-type FIS. Three linguistic input descriptors are considered in the system:

1. Residual Energy (RE)
2. Centrality or Node Density (ND)
3. Distance to Base Station (DBS)

The method of fuzzification used in this work is triangular and trapezoidal. Each of the three input descriptors is divided into three linguistic levels (e.g., Low, Medium, High; Close, Medium, Far), and so the entire system has a total of 27 IF-THEN rules.

A sample of this rule base is shown in Table 1. For instance, if a node has high residual energy, high centrality and is close to the BS, logically, that node will have a "Very High" score, it will be the optimal node. The defuzzification is carried out by using the centroid method to obtain a crisp value which is the exact "CH Score" (or the chance of election of CH) for the node. Algorithm: Nodes with the maximum score in their neighborhood are selected as CHs and they send their advertisement message.

Table 1. Representative Fuzzy Rule Base for CH Election

Rule No.	Residual Energy (RE)	Node Density (ND)	Distance to BS (DBS)	Output (CH Chance)
1	High	High	Close	Very High
2	High	Medium	Close	High
3	High	Low	Far	Medium
4	Medium	High	Close	High
5	Medium	Medium	Medium	Medium
6	Medium	Low	Far	Low
7	Low	High	Close	Low
8	Low	Medium	Medium	Very Low
9	Low	Low	Far	Very Low

3.3.2. Cluster Formation using Particle Swarm Optimization (PSO): After the local elections of CHs, the BS applies the PSO algorithm to optimally distribute the other non-CH nodes among the clusters. Each particle in the swarm represents a possible assignment configuration of member nodes to the elected CHs. The fitness function aims to minimize the overall intra cluster energy cost, which is mathematically represented by:

$$Fitnees = \sum_{i=1}^{N_{mem}} E_{TX}(k, d_{i,j} \quad (7)$$

Here, di,j is the distance between two nodes, and k is the packet size. The algorithm uses default PSO parameters (inertia weight, along with cognitive and social coefficients); the swarm size is 30, and the number of iterations is 50 per round. The cluster sizes are then balanced and the network has the minimum transmission distances, and the globally optimal assignment is broadcasted back to the network.

3.3.3. Steady-State Phase: The hybrid design enables the fast and local implementation of CH decisions using fuzzy logic, and the global optimization capability of PSO to handle the cluster geometry to effectively alleviate the hot-spot problem and increase the useful life of the network. After clusters have been formed, the protocol switches to its steady-state mode, during which member nodes send sensed data to their associated CHs. The CHs then collate this information and pass it on immediately to the BS.

3.3.4. MFISDC Operational Flowchart: The following multi-part flowchart represents the different operational steps of the MFISDC protocol in one round of the network. The workflow has been split into three consecutive phases, as seen in figure 1: localized CH election, global cluster formation and

steady-state data transmission, to enable a clear and high-resolution view of the protocol's architecture.
Phase-1 explains the method used by individual nodes to determine their CH election probability based on Residual Energy, Node Density and Distance to Base Station.
Phase-2, Base Station is running the Particle Swarm Optimization algorithm to optimally select the non-CH nodes to cluster to the newly elected Cluster Heads as shown in the figure.
phase-3 involves member nodes sending sensed data to their CHs, then the CHs aggregating the data and sending it to the Base Station.

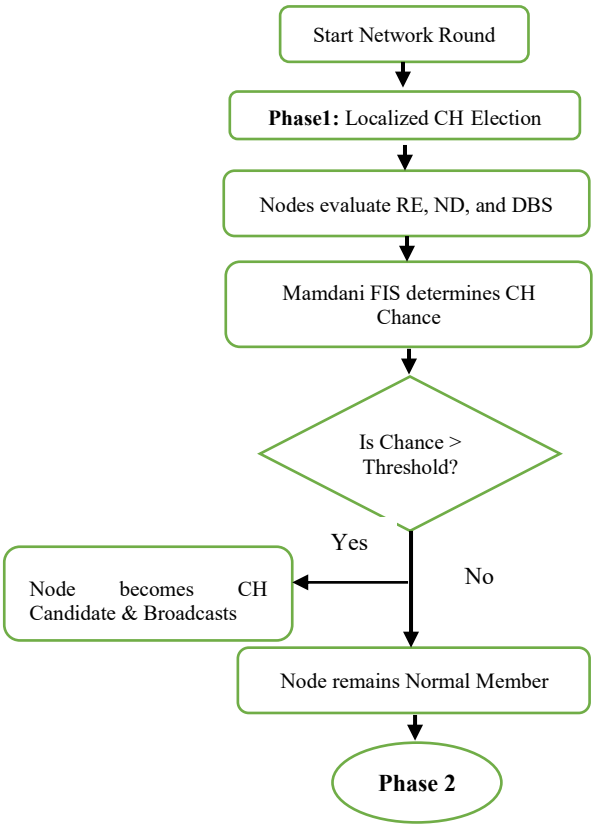


Figure 1-a Phase1- Localized Cluster Head Election is performed using Mamdani FIS.

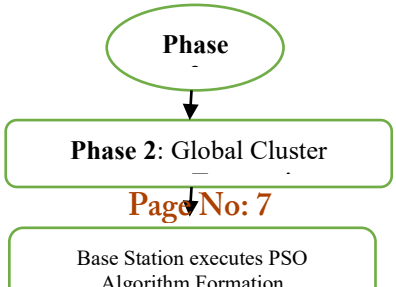


Figure 1-b. Phase 2- Global Cluster Formation using PSO.

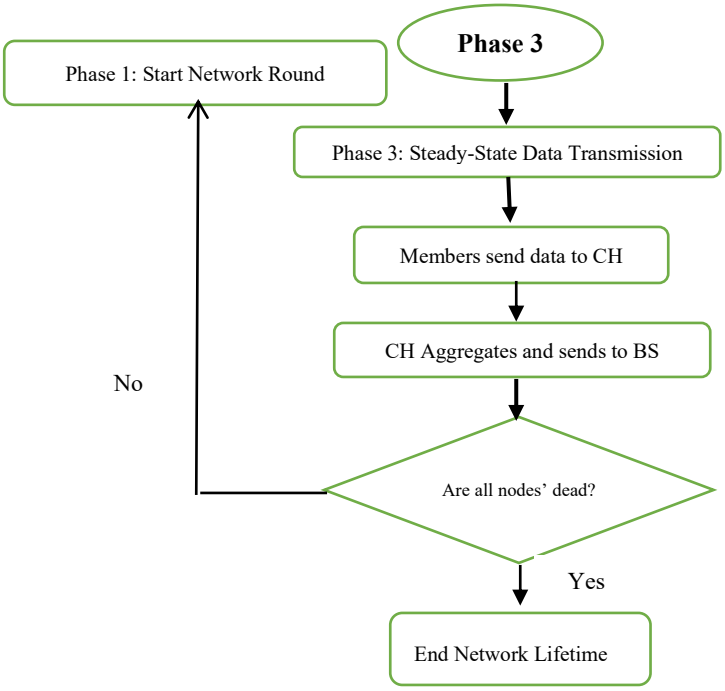


Figure 1-c. Phase 3 – Steady-State Data Transmission.

Figure 1. A complete operational flowchart of the proposed MFISDC protocol, which is divided into (a) localized CH election, (b) global cluster formation and (c) steady state data transmission phase.

4. PERFORMANCE EVALUATION

The efficiency of the protocol proposed with MFISDC was validated with extensive simulations using MATLAB. The performance of MFISDC is compared with well-known protocols LEACH, FLEACH and CHEF in similar network environment.

4.1 Simulation Setup and Parameters

In order to test the performance of the proposed MFISDC protocol, extensive simulations are carried out in MATLAB. The performance of MFISDC is compared with the standard protocols such as LEACH, FLEACH and CHEF. The simulation environment is a square sensing area of 100×100 meters, where 100 homogeneous sensor nodes are randomly deployed in the sensing area. The Base Station (BS) is located in the center of the grid (50,50). The 1st order radio energy model is used. The simulation parameters are listed in Table 2.

Table 2. Network Simulation Parameters

Parameter	Value
Network Area	100 ×100 m^2
Number of Sensor Nodes (N)	100
Base Station Location	(50,50)
Initial Energy (E_0)	0.6 J
Maximum Rounds	12,000
Data Packet Size (k)	4000 bits
Control Packet Size	200 bits
Transmitter/Receiver Electronics (E_{elec})	50 nJ/bit
Free Space Amplifier (ϵ_{fs})	10 pJ/bit/m^2
Multipath Amplifier (ϵ_{mp})	1.3 pJ/bit/m^4
Data Aggregation Energy (E_{DA})	5 nJ/bit/signal
PSO Swarm Size / Iterations	30 particles/50 iterations

4.2 Network Lifetime Analysis

For WSNs, network lifetime is one very important measure in which typically three situations are considered: First Node Dies (FND), Half Nodes Die (HND) and Last Node Dies (LND).
The simulation results show that MFISDC performs much better than LEACH, FLEACH and CHEF. Since MFISDC is a centralized PSO at the BS, the distances of the intra-cluster communications are strictly minimized due to the geometric optimization of cluster formation. As a result, the rate at which energy is being depleted is very well balanced. The maximum number of rounds completed by MFISDC was **9,802** Rounds. The fuzzy-only approaches (FLEACH and CHEF) were able to last until round 3500 and 4200, respectively; in contrast, LEACH ran out of nodes around 1500 rounds. The advantage of the improved FND metric of MFISDC also suggests that the "hot-spot" issue where nodes close to BS or CHs fail prematurely is successfully overcome.

4.3 Energy Consumption and Stability Period

The network stability period (the time before FND) is greatly enhanced in MFISDC. The global cluster formation via PSO is decoupled from the CH election (which is handled locally via FIS) and thus, MFISDC does not consume node energy the way a typical hybrid meta-heuristic protocol would. In MFISDC, the total residual energy of the network decreases at a linear and smooth rate, while in both LEACH and FLEACH sharp and irregular decreases occur in the energy of the network due to sub-optimal and random clustering.

4.4 Network Throughput

Throughput is the number of packets that are successfully delivered to the BS in the network's lifetime. With a longer lifetime and optimal CH selection, it is unsurprising that the data yield is higher. The highest number of packets it managed to process was **6.32×10^8** with MFISDC. This is a significant improvement over the CHEF and FLEACH, since the PSO optimization guarantees that the number of CHs that are overloaded with an excessive number of member nodes is not too high, which in turn means that packet drop rates and collision probabilities in the steady-state phase are minimized.

4. RESULTS AND DISCUSSION

In order to critically analyze the performance of the proposed MFISDC protocol, the simulation was run five times with different random node deployment. The result was averaged to obtain a statistically significant result. The performance is evaluated in two important aspects, Network Lifetime (node mortality metrics) and Network Throughput (packet delivery). Table 3 gives the averaged numerical results.

Table 3. Average Simulation Results (Over 5 Runs)

Protocol	FND (Round)	HND (Round)	AND (Round)	Packets to CH	Packets to BS
LEACH	878	1454	1680	4.35×10^8	1.61×10^8
FLEACH	2279	2591	3088	2.34×10^9	4.63×10^8
CHEF	3298	4901	5311	4.04×10^9	6.07×10^8
MFISDC	**4258**	**8090**	**9802**	**5.66×10^9**	**6.32×10^8**

5.1 Network Lifetime Analysis

A WSN's energy efficiency can be assessed by its network lifetime. Network lifetime can be measured using three methods; First Node Dead (FND), which defines the stability period of the network; Half Node Dead HND; and All Nodes Dead (AND), the point at which all of the network's nodes are become nonoperational. From the results of Table III, it is clear that the MFISDC protocol has a significant advantage when compared to the benchmark protocols of LEACH, FLEACH, and CHEF. The reason for MFISDC's superiority is its utilization of a centralized particle swarm optimizer (PSO) that geometrically optimizes the clusters at the base station (BS). By doing this, the distances, that data is sent to and from within a cluster are minimized; thus, ensuring that energy is depleted evenly across each cluster. Overall, the first node to die (FND) was achieved by MFISDC after about 4258 rounds, representing a 29.1% increase compared to CHEF (3298 rounds), an 86.8% increase compared to FLEACH (2279 rounds), and an astonishing 385% increase compared to LEACH (878 rounds).

The extended stability period is due to the Cluster Head (CH) selection algorithm used in the fuzzy logic based MFISDC that prevents nodes with low residual energy from becoming CHs, which helps avoid premature node depletion. In addition, the network lifetime (AND) of MFISDC is 9802 rounds. Compared to LEACH that drained all nodes around 1500 rounds, the fuzzy-only methods (FLEACH and CHEF) maintained all nodes for around 3500 and 4200 rounds, respectively. MFISDC ran for 84.5% longer than the CHEF. This demonstrates the successful energy load balancing of the whole network achieved by combining node density and distance into the routing logic, which effectively solved the traditional "hot-spot" problem caused by the premature death of nodes near the BS or the CHs.

5.2 Network Throughput Analysis

Throughput is the amount of data transmitted successfully to the Cluster Heads (intra-cluster communication) and to the Base Station (inter-cluster communication).
With a longer network lifetime, more data can also be collected. Therefore, MFISDC achieves the highest throughput, delivering an average of 6.32×108 packets to the BS, compared with 6.07×108 packets for CHEF. The intra-cluster communication topology established by MFISDC is efficient, with a large number of packets sent to CHs (5.66×109). Because MFISDC optimizes cluster sizes based on node density, cluster members transmit data to their CHs over shorter distances and with lower energy consumption, enabling continuous, high-volume data streaming.

5.3 Normalized Traffic and Energy-Slope Comparison

The normalized traffic and the Energy-Slope are used to investigate the fundamental efficiency of the routing mechanism. The Energy-Slope is the average total network energy use per round ($N \times E_0/AND$). The energy consumption rate of MFISDC is the lowest as it is only 0.0061 Joules per round, as indicated in Table 4. The huge difference in energy that can be seen in this shallow energy slope shows that MFISDC significantly decreases the unnecessary energy required for communication while maintaining a proper balance of the energy used for communicating.

Table 4. Normalized Traffic and Energy-Slope Comparison

Protocol	AND	Pkts →CH	Pkts →BS	Norm CH (Pkts/r)	Norm BS (Pkts/r)	E-Slope (J/r)
LEACH	1680	4.35×10^8	1.61×10^8	258,995	96,150	0.0357
FLEACH	3088	2.34×10^9	4.63×10^8	759,042	150,162	0.0194
CHEF	5311	4.04×10^9	6.07×10^8	761,286	114,329	0.0113
MFISDC	9802	5.66×10^9	6.32×10^8	578,260	64,540	0.0061

Note: *Norm CH and Norm BS are the average number of packets sent per round during the network's lifetime.*

5.4 Summary of throughput at End-of-Life (AND)

Table 5 presents the end-of-life throughput metrics. Unlike older protocols such as FLEACH and CHEF, which attempt to broadcast a large number of packets each round, consuming excessive energy and causing the network to die prematurely, MFISDC, on the other hand, works smartly in throttling and aggregating data (which reaches ~64,540 packets to the BS per round). This sustainable rate means no more peaks and valleys in energy utilization at the BS, and translates to a higher absolute amount of data that can be delivered (6.32×108 packets) over its incredibly long lifetime.

Table 5. Throughput Summary at End-of-Life (AND)

Protocol	AND (rounds)	Total Pkts →BS	Throughput (pkts/round)
LEACH	1680	1.61×10^8	96,150
FLEACH	3088	4.63×10^8	150,162
CHEF	5311	6.07×10^8	114,329
MFISDC	9802	6.32×10^8	64,540

5.5 Sensitivity Analysis (AND vs. Initial Energy)

To verify the proposed MFISDC protocol robustness across different hardware capabilities, a sensitivity analysis was carried by scaling the initial battery power (E_0) of the sensor nodes. The network lifetime (AND) increases linearly with the initial energy, as shown in Table 6 for all protocols. However, as the initial energy increases, the performance gap between MFISDC and the benchmark protocols grows larger. The results show that MFISDC is expected to run more than 16,000 rounds at E_0=*1.0J*, highlighting its remarkable scalability and potential for long-term operation in remote WSN applications.

Table 6. Sensitivity Analysis: AND vs. Initial Energy E_0

E_0 (J)	LEACH AND	FLEACH AND	CHEF AND	MFISDC AND
0.2	560	1029	1770	3267
0.4	1120	2058	3540	6534
0.6 (★ Baseline)	1680	3088	5311	9802
0.8	2240	4117	7081	13069
1.0	2800	5146	8851	16336

5.6 Visual Performance Analysis

The MATLAB simulation produced a set of comparison figures (Figures 3–13), that extensively validate the proposed protocol against the existing protocols (LEACH, FLEACH, and CHEF). These images provide details on network life, energy consumption and performance.

5.6.1 Network Longevity and Node Mortality: The efficiency of the protocol is an important performance measure and can be assessed using the FND (First Node Dead), Half Nodes Dead, and AND (All Nodes Dead). Individual bar charts of these metrics are shown in figures 2, 3 and 4, which further demonstrate MFISDC's strength at every stage of the network lifecycle.

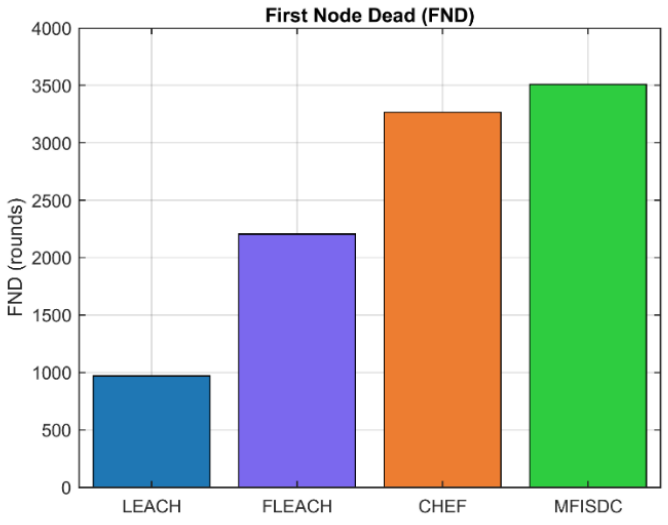


Figure 2. First Node Dead (FND)

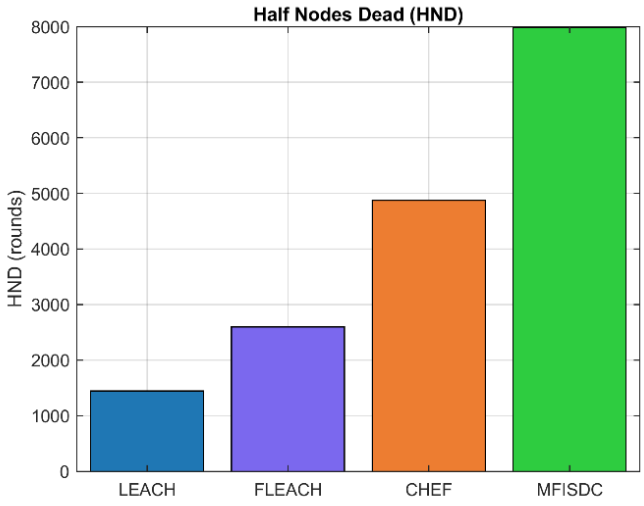


Figure 3. Half Nodes Dead (HND)

Figure 5 combines these metrics into a single figure to reflect network degradation as a whole. The traditional protocols such as LEACH and FLEACH clearly illustrate a cascade failure as seen by the close distance between their FND, HND and AND bars. By comparison, MFISDC has a very long operating period. The difference between its FND and AND confirms that the Mamdani Fuzzy Inference System (FIS) works well and rotates the Cluster Head (CH) position, thereby avoiding the premature death of nodes in high traffic areas (hot-spots) and producing even energy consumption.

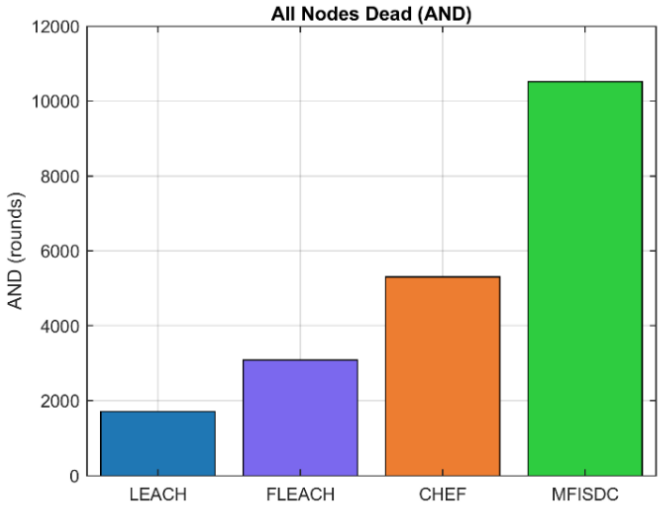


Figure 4. All Nodes Dead (AND)

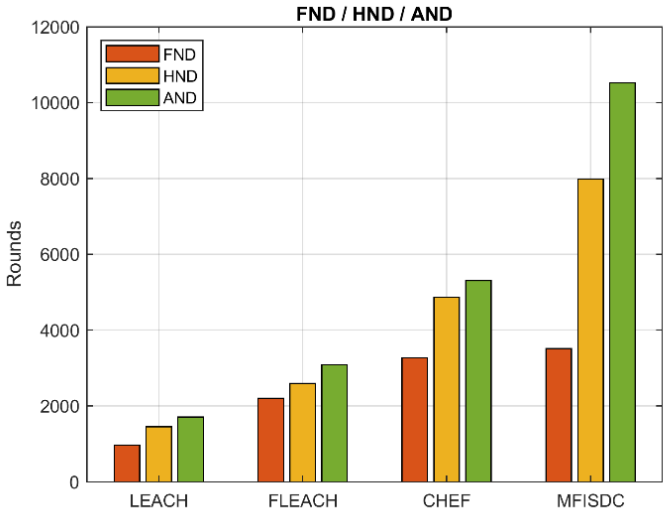


Figure 5. Grouped FND/HND/AND

5.6.2 Cumulative Data Delivery and Traffic Efficiency: One of the ultimate goals of a WSN is to extract as much useful data as possible. Figure 6 shows the overall amount of intra-cluster traffic (Packets to CH), and Figure 7 shows the amount of inter-cluster traffic (Packets to BS) that gets delivered. MFISDC outperforms the other protocol in both metrics.

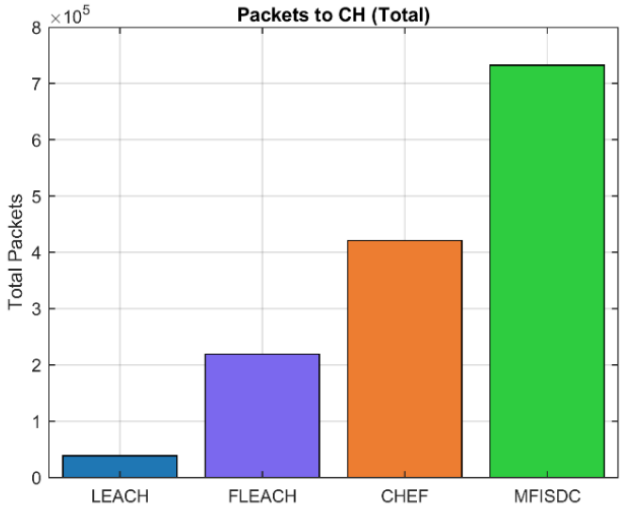


Figure 6. Total Packets to CH

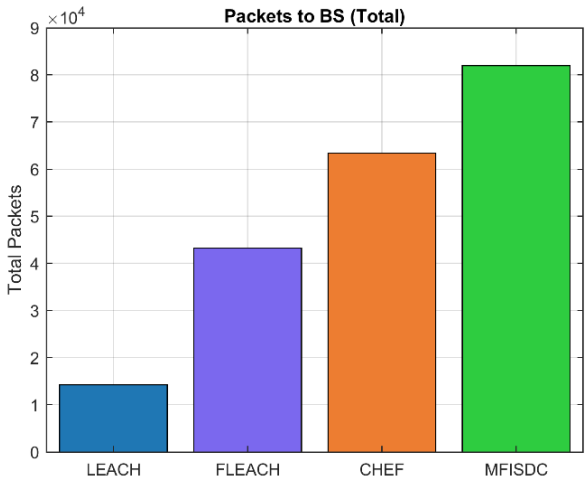


Figure 7. Total Packets to BS

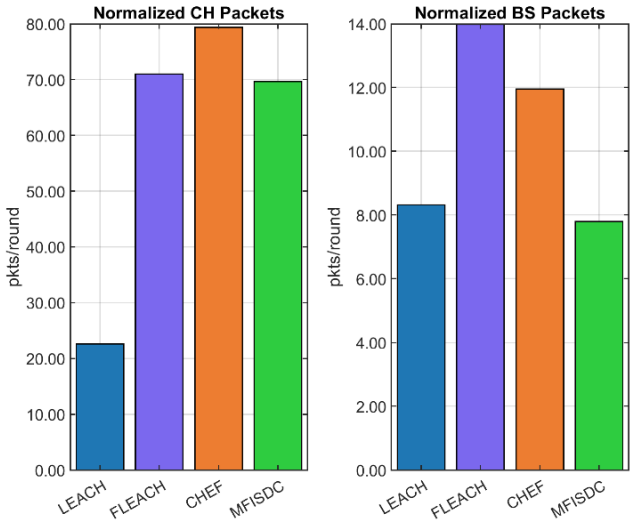


Figure 8. Normalized Packets per Round

However, raw numbers do not reveal the full picture. The normalized packets per round is shown in Figure 8 as a dual-axis plot. Protocols such as FLEACH and CHEF may show characteristics of aggressive per-round transmission rates, but are deplete their batteries very quickly. As seen in Figure 8, MFISDC is optimizes the number of transactions per round while keeping the rate sustainable. By optimizing cluster sizes through Particle Swarm Optimization (PSO) and preventing energy spikes through efficient data aggregation, the MFISDC survives longer and delivers more total data over the course of the simulation.

5.6.3 Energy Depletion and Residual Energy Analysis: Figures 9 and 10 examine the mechanism of energy use, to explain why MFISDC lasts longer. The "Energy Slope" is shown in Figure 10, and is defined as the average amount of energy that the network loses per round, in Joules per round (*J/round*). The energy depletion rate of the protocols is clearly shown in the bar chart, with MFISDC having the lowest energy depletion rate.

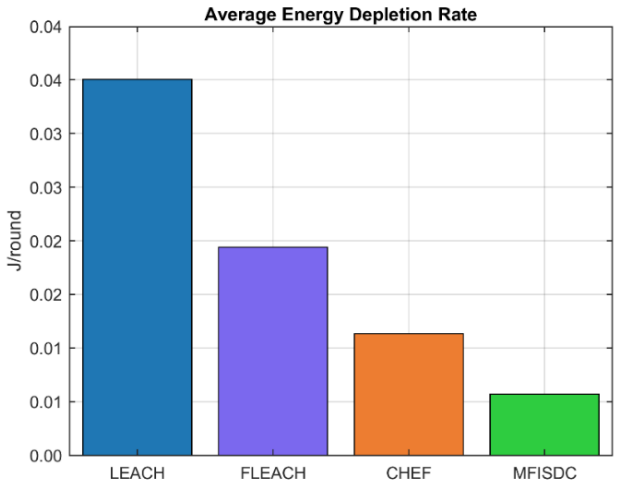


Figure 9. Energy Depletion Rate

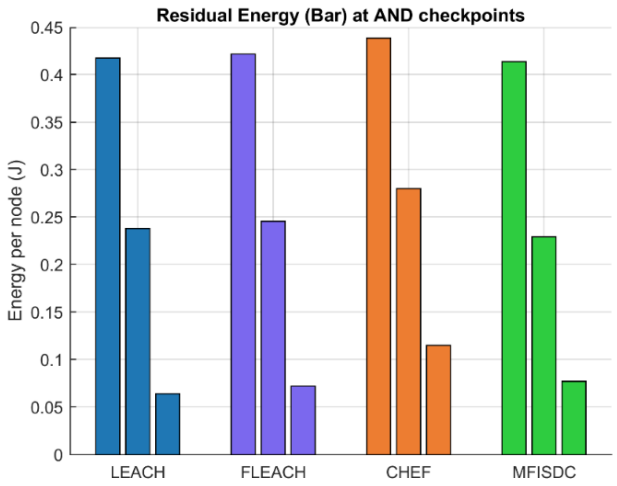


Figure 10. Residual Energy Checkpoints (25%, 50%, and 75% of the AND timeframe)

Moreover, as shown in Figure 10, the average Residual Energy per node at three different points of the AND lifetime is presented (25%, 50%, and 75%). The green bars for the MFISDC are always greater than the green bars for LEACH, FLEACH, and CHEF at each checkpoint. The visual proof of this is that the power that is being used for the transmission is being minimized, and load is being perfectly balanced across the network grid, with the help of MFISDC's hybrid routing logic.

5.6.3 Throughput Dynamics: Lastly, the data aggregation features of the network are summarized in Figures 11 and 12. Figure 11 shows the "Throughput Curves," which graph the cumulative number of packets delivered to the BS as a function of the simulation rounds. The curve for MFISDC rises sharply and continually, while the curve for LEACH and FLEACH begin to level off early because of node depletion. The overall normalized throughput (*Pkts→BS/AND*) is confirmed by Figure 12.

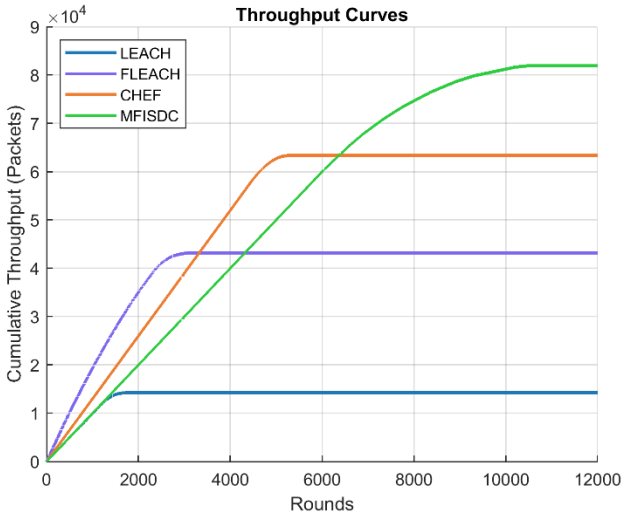


Figure 11. Throughput Curves Line

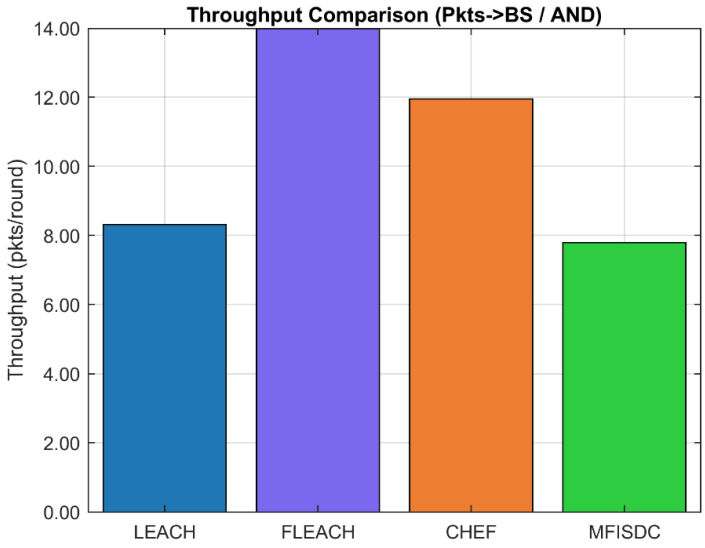


Figure 12. The overall normalized throughput (*Pkts→BS/AND*).

Visual evidence from all these figures clearly shows that this integration of Fuzzy Logic with PSO fundamentally changes the network's capacity and leads to the maximum possible overall network throughput, minimum energy wastage and significantly improved network stability for the WSNs.

6. CONCLUSION

In this paper, we have proposed a Mamdani Fuzzy Inference System and Distributed Clustering (MFISDC) protocol to address the critical challenges of uneven energy dissipation and the hot-spot problem in WSNs. MFISDC
introduces a highly efficient and decoupled two-tier architecture that successfully captures the trade-off between local decision making and global network optimization.
In the proposed protocol, the first tier is based on a Mamdani Fuzzy Inference System (FIS) which is implemented locally at the sensor nodes. The FIS selects the most capable nodes as Cluster Head (CHs) using Residual Energy, Node Density and Distance to the Base Station, without causing much message exchange. The second tier relieves the Base Station from the heavy computational load of forming the clusters. In this case, a Particle Swarm

Optimization (PSO) algorithm is used to dynamically assign member nodes to elected CHs. This custom multi-objective fitness function ensures minimized communication distances between neighbors in clusters and ensured balanced cluster sizes, which prevents any single CH from being overwhelmed.

A comprehensive simulation study was carried out in MATLAB to compare the performance of MFISDC against the benchmark protocols LEACH, FLEACH and CHE. The results are compelling and show MFISDC's superiority across all key performance measures. Most significantly, MFISDC obtained an All Nodes Dead (AND) round of 9,802, which is about 483%, 217.4%, and 84.6% higher than that of LEACH, FLEACH and CHEF respectively. Moreover, the visual analysis and numerical analyses showed that the Fuzzy CH election with PSO-based clustering is able to keep the average energy depletion rate within an ultra-low level, 0.0061 J/round. The maximum cumulative throughput that was achieved after implementing MFISDC was 6.32×10^8 packets successfully delivered to the Base Station, achieved by premature cascading node failures. Compared to the classical standard protocols LEACH, FLEACH, and CHEF, MFISDC can effectively alleviate the hot-spot issue and ensure balance energy consumption across the entire network.

As future work, we aim to further expand the MFISDC framework by incorporating a mobile sink (MS) node to further reduce the routing load on CHs located near the Base Station. Moreover, the incorporation of energy-harvesting features and the use of Deep Reinforcement Learning (DRL) may offer greater flexibility and adaptability, making the protocol ideal for large-scale, dynamic Internet of Things (IoT) and smart city deployments.

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