10.48047/jocaaa.2024.33.08.267

Intelligent Energy-efficient Soil Monitoring and Water Conservation using Fuzzy C-Means Clustering and A* Algorithm in WSNs

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Abstract: One of the empathetic factors is Agriculture in the Indian economy. The associated concern is, it consumes excessive water, with lots of wastage due to inefficient irrigation techniques. Traditional agriculture practices face challenges such as inefficient irrigation methods and lack of real-time monitoring, leading to water wastage and reduced crop yield. This paper presents an intelligent, energy-efficient soil monitoring and water conservation system based on Fuzzy C-Means (FCM) clustering and the A* algorithm. Several challenges exist, such as those based on Wi-Fi, Bluetooth, and 4G/5G cellular technology; but also encounter difficulties such as large volumes of real-time data, maintenance or replacement of sensors due to limited battery power, network coverage area etc. Taking care of all these aspects, Soil sensors collect data parameters such as moisture, temperature and humidity, which are clustered using FCM. This classifies soil into 3 categories as Dry, Moderate, and Wet. The A* algorithm then determines optimal irrigation routes and schedules to minimize water usage and energy consumption. The system also enables remote monitoring and control, ensuring adaptability for irrigating fields. Experimental results show improved yield efficiency, reduced water wastage, and prolonged network lifetime compared to existing methods.

Keywords: Clustering, Fuzzy C-Means, Intelligent irrigation, intelligent agriculture, Energy- aware routing

1. INTRODUCTION

Agriculture is a cornerstone of the Indian economy, supporting livelihoods and ensuring food security, but it is also the largest consumer of water resources, using nearly 70% of global water. Increasing climate variability, population growth, and over-extraction of water have made water scarcity a pressing challenge, with the United Nations warning that by 2025 nearly two-thirds of the world's population could face water stress [1-3]. Although traditional irrigation methods—such as surface irrigation, sprinklers, and drip systems—have improved productivity, they remain inefficient because they operate on fixed schedules or manual control, ignoring real-time soil and climate conditions. This leads to over- or under-irrigation, causing water waste, reduced yields, and soil degradation. While smart, sensor-based irrigation systems have emerged as a promising solution, they still face critical challenges in soil classification, energy efficiency of wireless sensor networks, and optimal routing of water distribution [4,5].To overcome these challenges, this paper introduces an intelligent, energy-efficient soil monitoring and irrigation system that integrates Fuzzy C-Means (FCM) clustering with the A* algorithm. FCM clustering analyzes soil parameters such as moisture, temperature, humidity, and pH to classify conditions more adaptively than fixed thresholds, while the A* algorithm optimizes irrigation routes and schedules to ensure efficient water delivery and reduced energy consumption in wireless sensor networks. The proposed framework not only enhances irrigation precision and conserves water but also extends network lifetime, making it suitable for varied agricultural environments, including farms and greenhouses. The major contributions include the development of an adaptive soil monitoring system using FCM, energy-aware routing with A*, and the

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design of a cost-effective, portable, and scalable WSN irrigation solution that demonstrates improved efficiency compared with existing methods.

Section2 presents literature review, Section3 illustrates proposed methodology, Section4 demonstrate experimental setup, Section5 describes results and discussion with performance analysis and last section discusses conclusion and future scope.

2. LITERATURE REVIEW

WSN-based smart irrigation systems have gained significant attention for their ability to optimize water use by collecting real-time data from soil and climate sensors [6-7]. While these systems improve water efficiency, many still rely on fixed thresholds for soil moisture, which fail to account for environmental variability. To address this, fuzzy logic has been widely adopted in irrigation scheduling due to its ability to handle uncertainty and imprecision in sensor data [8-9]. However, traditional fuzzy rule-based systems often depend on manually designed rules, limiting adaptability in diverse agricultural conditions. Clustering techniques such as K-Means and Fuzzy C-Means (FCM) have been applied to soil classification, with FCM proving more effective as it allows soil samples to belong to multiple clusters with varying degrees of membership, making it highly suitable for uncertain and dynamic soil conditions [10-11]. Meanwhile, energy efficiency in Wireless Sensor Networks (WSNs) remains a critical concern, with protocols such as LEACH, IVC-LEACH and WOA proposed to extend network lifetime [12-15]. Recent studies have also applied heuristic and metaheuristic methods for routing optimization, but many approaches struggle to balance energy savings with real-time responsiveness [16]. These gaps highlight the need for an integrated solution that can adaptively classify soil conditions while ensuring energy-efficient routing. To address this, the proposed system combines Fuzzy C-Means clustering with the A* algorithm, thereby improving soil classification accuracy and enabling optimal routing for energy-aware irrigation management.

3. PROPOSED METHODOLOGY

In general, WSNs are effective for irrigation management and water conservation. WSNs consist of interconnected sensor nodes that interact directly with the environment, providing real-time data to identify specific farm areas requiring attention. These networks serve as both data collection tools and decision-making systems for remote and online monitoring. In most studies, WSNs gather data that is transmitted for decision-making, often based on predefined thresholds. For instance, irrigation may be triggered when soil moisture falls below a certain level or to prevent frost damage when temperatures drop below a threshold. In contrast, this study utilizes a FCM for clustering and A* algorithm for routing instead of threshold-based methods. This approach effectively handles sudden and complex environmental changes. A typical irrigation system comprises methods (e.g., manual, drip, or sprinkler irrigation), water sources (e.g., rivers or groundwater), carriers (e.g., pipelines), actuators (e.g., on/ off mechanisms), and valves (e.g., water flow control). Conventional systems rely on fuzzy logic and threshold parameters—such as temperature, moisture, humidity—for decision-making as shown in Figure 1. However, these parameters often fail to provide simple relationships for irrigation decisions. Addressing their complexity requires FCM based analysis for more precise irrigation management.

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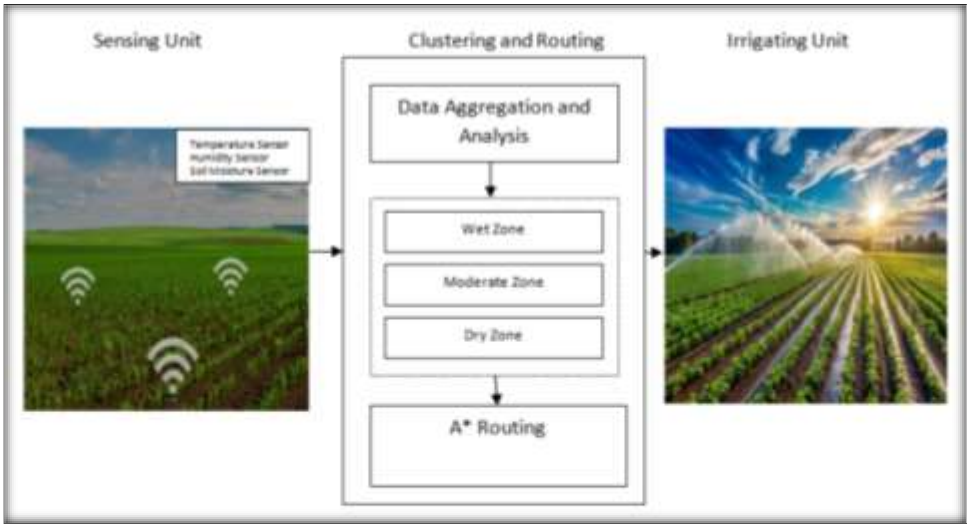

Figure 1: Intelligent Soil Monitoring and Irrigation Framework

The proposed system integrates real-time soil sensing, intelligent clustering, and energy-aware routing to optimize irrigation management in agricultural fields. The methodology is structured into three main modules: data acquisition and sensing, clustering and routing, and irrigation control.

- **Module1: Data Acquisition and Sensing**

The agricultural field is divided into zones. One set of Soil Moisture (S_m), Temperature(T), and Humidity (H) sensors per zone is deployed across the agriculture field to capture real-time environmental parameters such as soil moisture, temperature and evapotranspiration and all the sensors are connected in a network via gateways. An input vector X_i is taken for data acquisition and sensing as: $X_i=\{S_m, T, H\}$. After collecting data from all the zones, it is transmitted wirelessly to the processing node for analysis. To ensure accuracy, preprocessing techniques such as noise reduction and normalization are applied, eliminating redundant or faulty readings. The aggregated data is then forwarded for clustering and decision-making.

- **Module 2: Fuzzy C-Means (FCM) Clustering for Soil Classification**

To effectively categorize soil conditions, the Fuzzy C-Means (FCM) algorithm is applied on the input vectors taken from all the zones to classify the current state. Unlike hard clustering, which assigns each data point to a single group, FCM allows soil samples to belong to multiple clusters with varying membership degrees. This is particularly advantageous in agriculture, where soil properties often exhibit uncertainty and overlapping characteristics. FCM process calculates the membership of X_i to each cluster.

The FCM algorithm minimizes the following objective function: $J_m = \sum_{i=1}^{N} \sum_{j=1}^{C} u_{ij}^{m} \left\| x_i - c_j \right\|^2$ (1)

where N denotes the number of soil data points, C is the number of clusters (here, three: Wet Zone, Moderate Zone, Dry Zone), u_{ij} is the membership degree of data point x_i in cluster j, $m > 1$ is the fuzzification parameter, and c_j represents the centroid of cluster j.

The cluster centroid is updated as: $c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$ (2)

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while the membership update rule is: $u_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\|x_i - c_j\|}{\|x_i - c_k\|}\right)^{\frac{2}{m-1}}}$ (3)

Through this iterative optimization, all the zones are assigned to which clusters they belong as Wet, Moderate, and Dry, which guide irrigation requirements.Once soil clusters are determined, the corresponding irrigation commands must be transmitted to the irrigation unit via the Wireless Sensor Network (WSN). Efficient communication is critical to avoid excessive energy consumption, which can reduce the network lifetime. Now the task is to find the most efficient sequence to irrigate the 'Dry zones'. To achieve this, the A* routing algorithm is employed, which selects the most energy-efficient communication path.

The A* evaluation function is defined as: $f(n) = g(n) + h(n)$ (4)

where $g(n)$ is the actual cost from the source to node n (e.g., energy consumption) and is defined as:

$$\sum(Water\ Volume\ \times Energy\ Cost) + \ Time\ Delay \quad (5)$$

and $h(n)$ is the heuristic estimate of the cost from node n to the destination (e.g., residual energy or distance). The optimal routing path is determined as:

$$P^* = \arg\min f(n) \quad (6)$$

This ensures that the chosen path balances shortest distance and energy efficiency, thereby extending WSN lifetime.

- **Module 3: Irrigation Control and Execution**

The irrigation unit executes these commands using pumps or sprinklers, ensuring adaptive water allocation. The system sends the commands to open the solenoid valves for the duration required to bring their soil moisture upto the threshold value. During irrigation, the sensor shows the soil moisture is rising faster than the predicted due to a recent, unforecasted cloud cover that reduced ET. The system continuously feeds this rising S_m back to A* process. A* dynamically terminates the irrigation when soil moisture level reaches the threshold value to save water. This integration of FCM clustering with A* routing not only ensures accurate soil condition classification but also minimizes energy consumption in data transmission, thereby achieving sustainable and intelligent water management in agriculture as shown in Algorithm 1.

Algorithm 1: Intelligent Soil Monitoring and Irrigation using FCM and A*

Module1: Initial Set-up

1) **Sensor Deployment:** Deploy N sensor nodes in a 100×100 field, each equipped with soil and environmental sensors.Each node is aware of its residual energy and position.
2) **Data Acquisition:** Each node periodically measures soil moisture, temperature, humidity, pH, and soil type.
3) **Feature Vector Formation:** Represent node data as

   x_i = [moisture, temperature, humidity, pH, soil type,...]

4) **Normalization:** Normalize all features for uniform scaling.

Module2: Clustering and Routing

5) **Clustering Initialization:** Set number of clusters C=3 (Dry, Moderate, Wet) and initialize cluster centers c_j.

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6) **Membership Update:** Compute membership values using

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

7) **Centroid Update:** Recalculate $c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} x_i}{\sum_{i=1}^{N} u_{ij}^{m}}$; repeat Steps 7–8 until convergence.
8) **Zone Identification:** Assign clusters:
lowest moisture centroid → Dry, medium → Moderate, highest → Wet.
Each node belongs to a zone with a membership valueu_{ij}.

9) **Priority Calculation:** For each node, Priority Index can be calculated as:

$$P_i = w_1 . u_{i,Dry} + w_2 . (1 - Moisture_i) + w_3 . CropRequirement_i$$

- Nodes in Dry Zone generally get higher Pi, but exact value depends on other factors (crop type, temperature, rainfall, energy).
- Nodes in Moderate Zone may get medium priorities depending on their soil deficit.
- Nodes in Wet Zone often have low or zero priority (since irrigation is not needed).

10) **Zone-level Irrigation Decision:**
- Compute average priority score per zone:

$$P_{zone} = \frac{1}{N_z} \sum_{i \in zone} P_i$$

Where N_z is the number of nodes in that zone.
- Define thresholds for irrigation:
  If $P_{zone} \geq 0.6$ → Irrigate immediately (Dry Zone).
  If $0.4 \leq P_{zone} < 0.6$ → Partial or scheduled irrigation (Moderate Zone).
  If $P_{zone} < 0.4$ → No irrigation required (Wet Zone).
- If $P_i \geq$ threshold, mark node for irrigation.

11) **Scenario generation as a graph for A* routing**
- Model network as a graph with nodes as vertices and wireless links as edges.
- For link (u, v), define

$$Cost(u, v) = \alpha . E_{tx}(u, v) + \beta . d(u, v) + \gamma . \frac{1}{E_v}$$

- **A* Routing:** Use A* to find the least-cost path from sensor node to sink while avoiding low-energy nodes.

Module3: Irrigation Control and Execution

12) **Irrigation Execution**
- Controller sends irrigation commands through optimal paths; actuators (pumps/valves) irrigate identified zones.

13) **Energy Update & Iteration:** Deduct communication energy; reconfigure if energy < threshold. Repeat Steps 3–13 periodically until network lifetime ends.

4. EXPERIMENTAL SETUP

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The simulation environment for this study emulates a wireless sensor network deployed in an agricultural field for irrigation management. The simulation area spans 100 × 100 m², representing a typical farmland, where ($N = 100$) sensor nodes are randomly and uniformly distributed. Each node has a communication range (d_0) of 30 m, ensuring effective coverage and connectivity across the network. Python programming is used as the primary simulation tool due to their capability in modeling network protocols, sensor behavior, and energy consumption. The experiments are designed to assess the proposed system's performance in terms of energy efficiency, routing reliability, and irrigation decision-making accuracy. The simulation parameters, including energy consumption models, are summarized in Table 2. Each node is initialized with 5 Joules of energy and consumes power during transmission, reception, sensing, and processing. Energy parameters include electronics energy consumption (E_{elec}), amplifier energy consumption (ε_{fs} and ε_{mp}) for free-space and multipath fading, and the path-loss exponent (α) for realistic propagation. Additionally, sensing power, processing power, and their respective durations are incorporated to capture the overall energy dynamics. Transmission distance varies based on routing outcomes, making the energy model reflective of real deployment scenarios. These parameters collectively ensure a robust simulation framework to evaluate the proposed irrigation management system.

The simulation workflow proceeds in distinct phases. In the initialization phase, sensor nodes are deployed, and their parameters such as energy levels and communication ranges are set. During the data collection phase, nodes sense environmental parameters such as soil moisture, temperature and humidity, and transmit this information to the Sink/Intelligent Unit (SIU).

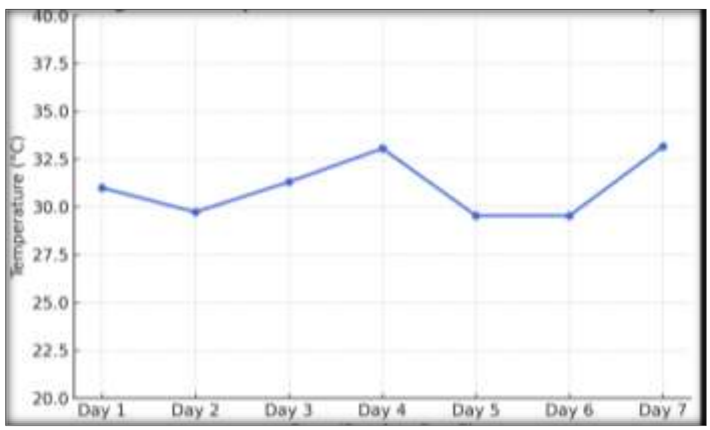

Figure 2: Temperature Fluctuations

Temperature fluctuations have been displayed in Figure 2 over a period of seven days (Day1 to Day7). The vertical axis represents temperature values ranging from 20°C to 40°C, while the horizontal axis marks the time span in daily intervals. The data exhibits high-frequency variations, indicating that the temperature changes rapidly and frequently throughout each day. This suggests a dynamic environment with significant short-term temperature variability, possibly due to factors like weather conditions or sensor noise.

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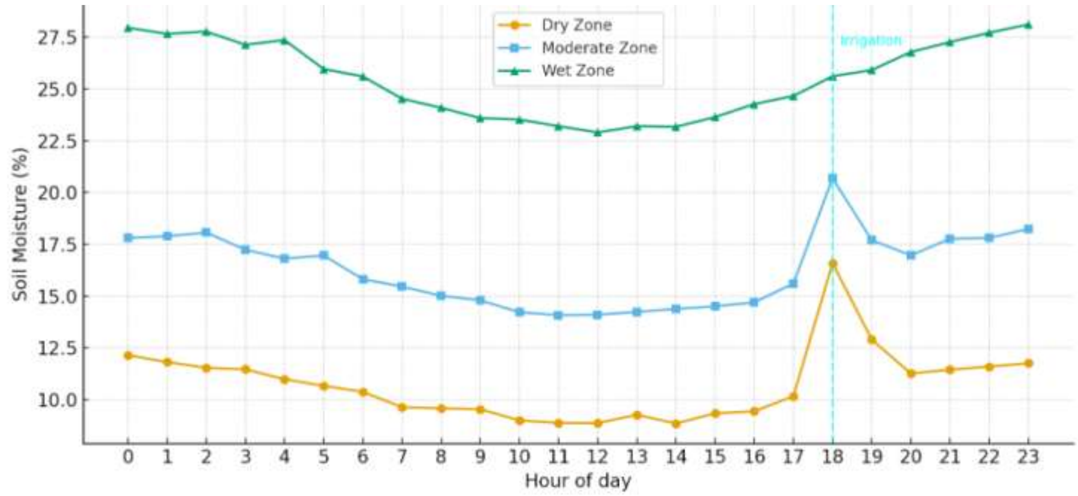

Figure 3: Soil Fluctuations

Figure 3 illustrates soil moisture fluctuations across three zones—Dry Zone**,** Moderate Zone, and Wet Zone**—**measured hourly over a 24-hour period. All zones show a gradual decline in moisture during the day, when a sharp spike in moisture occurs due to an irrigation event, marked by a vertical dashed line. Post-irrigation, soil moisture levels quickly drop back and then stabilize. The Wet Zone consistently maintains the highest moisture levels (above 25%), while the Dry Zone stays below 13%, showing the lowest values. This graph effectively demonstrates how irrigation impacts different soil zones, with the Moderate Zone showing the most prominent response.

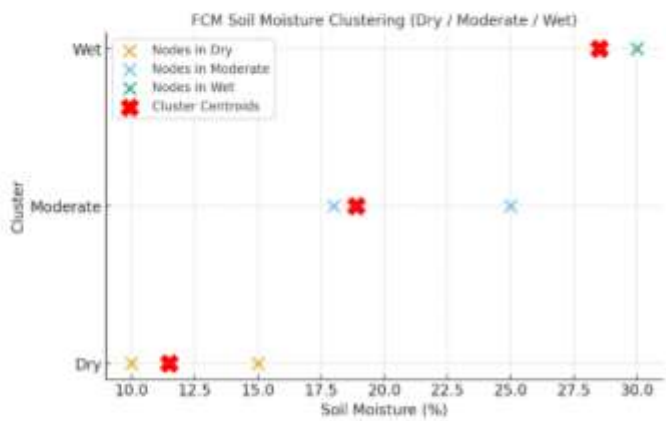

Figure 4: Division of Field region according to soil moisture levels

In the decision-making phase, Fuzzy C-Means (FCM) clustering is applied to group soil conditions (e.g., dry, moderate, wet), providing a more adaptive basis for irrigation scheduling compared to fixed threshold systems as shown in Figure 4. In the routing phase, the A* algorithm computes optimal routes for data transmission, minimizing energy consumption while ensuring reliable communication within the WSN. Finally, the system's performance is evaluated using key metrics, including energy efficiency, network lifetime, packet delivery ratio (PDR), routing latency, and irrigation accuracy. Multiple simulation runs are conducted under varying environmental conditions to validate the robustness of the proposed FCMA* based irrigation framework.

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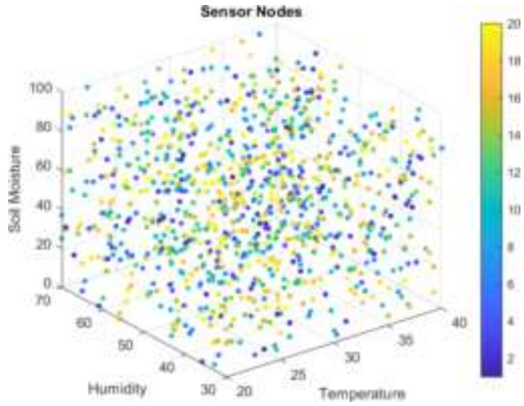

Figure 5: 3D Visualization of Sensor Node Distribution Based on Soil Moisture, Humidity, and Temperature

Figure 5 illustrates the spatial distribution of sensor nodes in a wireless sensor network, where each node measures soil moisture**,** humidity, and temperature parameters. The color gradient represents varying data values across the network, with lighter shades indicating higher readings and darker shades indicating lower ones. This visualization shows how sensor nodes capture diverse environmental conditions across the monitored field. The dense and well-dispersed node placement ensures comprehensive environmental monitoring, allowing accurate detection of variations in soil and climate conditions essential for smart irrigation and agricultural decision-making.

Table 2: Simulation Parameters

Parameter	Symbol	Value	Unit	Description
Number of sensor nodes	N	100	–	Total number of sensor nodes deployed in the WSN.
Simulation area	M × M	100 × 100	meters	Dimensions of the agricultural field.
Initial energy per node	E_0	5.0	joules	Initial energy allocated to each sensor node.
Radio range	d_0	30	meters	Maximum communication range for each node.
Data packet size	k	512	bits	Size of the data packet transmitted/received.
Electronics energy	E_{elec}	50×10^{-9}	joules/bit	Energy consumed for signal processing.
Amplifier energy	ε_{fs}, ε_{mp}	100×10^{-12}	joules/bit/m²	Energy consumed by amplifier for free space and multipath models.
Path-loss exponent	–	2 and 4	–	Path-loss exponent for free-space (2) and multipath fading (4).
Sensing power	P_{sense}	0.5	watts	Power consumed by sensors during operation.
Sensing duration	T_{sense}	1	seconds	Time required to sense soil/environment parameters.
Processing power	P_{proc}	0.3	watts	Power consumed during data processing.
Processing duration	T_{proc}	1	seconds	Time required for data processing.

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Parameter	Symbol	Value	Unit	Description
Transmission distance	d	Variable	meters	Distance between transmitter and receiver, computed dynamically by A*.
Update interval for routing	t	10	seconds	Interval for updating routing decisions in the A* algorithm.
Soil classification method	–	FCM	–	Fuzzy C-Means clustering applied for adaptive soil condition grouping.
Routing algorithm	–	A*	–	Used for optimal and energy-efficient routing in WSN.

FCM parameters: C = 3 clusters, fuzziness m = 2.0, convergence ε = 1e-5

Priority weights: w_1 (membership) = 0.5, w_2 (moisture deficit) = 0.3, w_3 (crop requirement) = 0.2 *(adjustable)*

- **Baseline Methods**

To advance precision irrigation beyond baseline clustering and optimization techniques such as LEACH**,** IVC-LEACH**,** and WOA, a novel system employs Fuzzy C-Means (FCM) integrated with the A* search algorithm (FCMA*). In this intelligent approach, FCM adaptively clusters real-time soil sensor data (e.g., moisture, temperature, pH, and nutrient levels) into irrigation zones (Dry, Moderate, Wet), effectively capturing the fuzzy membership of each field region to specific water requirement classes. Unlike LEACH, which randomly selects cluster heads and often leads to uneven energy depletion, and IVC-LEACH, which improves cluster head selection but still lacks adaptability to varying soil conditions, FCM provides dynamic and data-driven clustering. Similarly, while WOA applies metaheuristic optimization for efficient cluster head selection, it incurs higher computational complexity. The proposed FCMA* framework goes further by combining fuzzy clustering with heuristic path optimization: once zones are identified through FCM, the A* algorithm models the irrigation infrastructure as a graph and computes the most cost-effective route to deliver water. Its heuristic function considers transmission energy, distance, and residual energy of nodes, ensuring energy-aware routing and precise irrigation execution. This integration enhances throughput, packet delivery, and network lifetime compared to LEACH, IVC-LEACH, and WOA, while achieving highly granular irrigation control and resource efficiency.

- **Metrics Used**

The performance evaluation of the proposed FCMA* algorithm across key metrics—Packet Delivery Ratio (PDR)**,** Dead Nodes**,** Network Lifetime**,** and Delay—demonstrates its superiority over traditional approaches. The PDR remains consistently high, indicating reliable data transmission and effective handling of communication errors through optimized routing. The number of Dead Nodes is significantly lower in FCMA*, as its energy-efficient clustering and adaptive routing minimize power depletion across sensor nodes. Consequently, the Network Lifetime is extended, showcasing the system's ability to sustain long-term operations under varying field conditions. Additionally, the Delay is considerably reduced due to A*'s intelligent path selection, which ensures faster data delivery by avoiding congested or energy-drained nodes. Collectively, these results confirm that FCMA* achieves an optimal balance between energy efficiency, reliability, and responsiveness, making it highly suitable for precision irrigation and sustainable agricultural monitoring.

5. RESULTS AND DISCUSSION

The proposed method is evaluated against LEACH, IVC-LEACH and WOA in terms of residual network energy, which represents the total remaining energy of all nodes in the network at the end of each routing cycle. The results of this comparison are presented in Figure 6.

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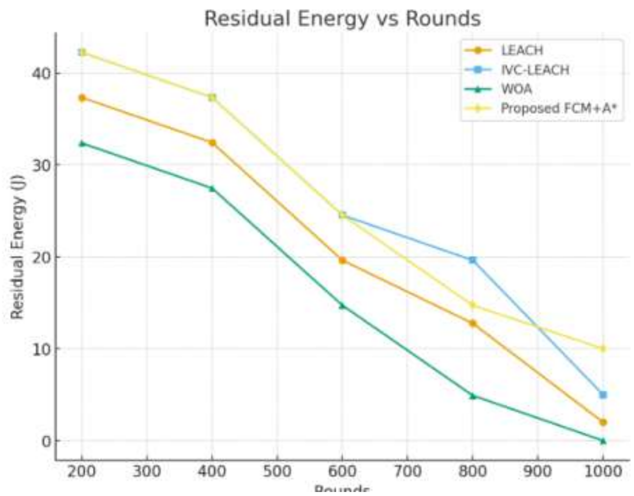

Figure 6: Residual Energy Comparison w.r.t rounds

Starting with an initial energy of 500 Joules (5 Joules per node for 100 nodes), the network's energy decreases progressively over time due to operational activities. At the end of 1000 rounds, the proposed method achieves a significantly higher residual energy than LEACH, IVC-LEACH and WOA. This result highlights the superior energy efficiency of the proposed method compared to the baseline approaches. The improved residual energy is a direct outcome of the proposed method's intelligent energy conservation strategies. Unlike LEACH, IVC-LEACH, which may lack fine-grained control over energy consumption across the network, and WOA, which, while effective, still faces localized energy depletion, the proposed method ensures a more uniform energy usage among nodes. This is achieved through optimized routing protocols that minimize unnecessary data transmissions and reduce energy-intensive operations. Furthermore, the proposed method likely prioritizes paths and tasks that balance energy consumption across the network, preventing nodes with critical energy levels from being overutilized. This balanced and energy-aware approach not only preserves network longevity but also ensures that resources are utilized efficiently, maintaining higher energy reserves at the network's conclusion compared to the baseline methods. Network life metric is analyzed for varying numbers of nodes ranging from 20 to 100, as depicted in Figure. 7.

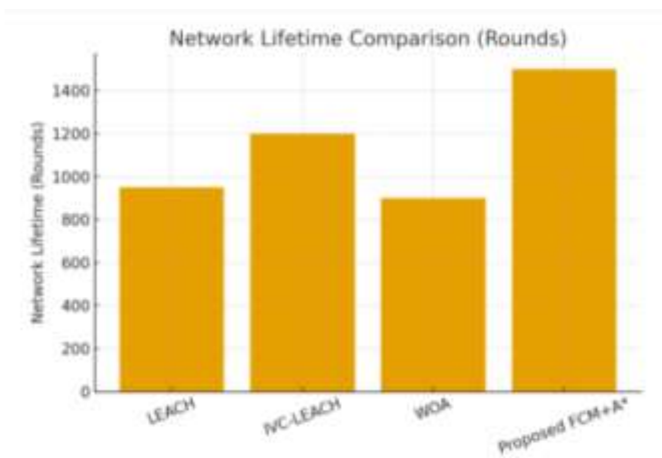

Figure 7: Network Life Comparison (Rounds)

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The results demonstrate that the proposed method consistently achieves better network life compared to LEACH, IVC-LEACH and WOA across all node configurations. This improvement highlights the robustness and adaptability of the proposed method in prolonging network functionality under different scenarios. The superior performance of the proposed method can be attributed to its strategic prioritization of routing paths, which effectively balances energy consumption across the network. By distributing the workload more evenly, the method prevents overuse of nodes with critical energy levels, thereby avoiding premature node failures. Additionally, the proposed approach likely incorporates adaptive energy-aware mechanisms that dynamically adjust routing decisions to optimize energy utilization in real-time. This ensures that no single node is disproportionately burdened, contributing to an extended network lifespan. is shown in Figure 8. This balanced and efficient energy managementstrategy not only enhances the overall durability of the network but also ensures that resources are maximally utilized, outperforming the baseline methods in maintaining network operations over time. The proposed method shows the lowest number of dead nodes in comparison with baseline approaches.

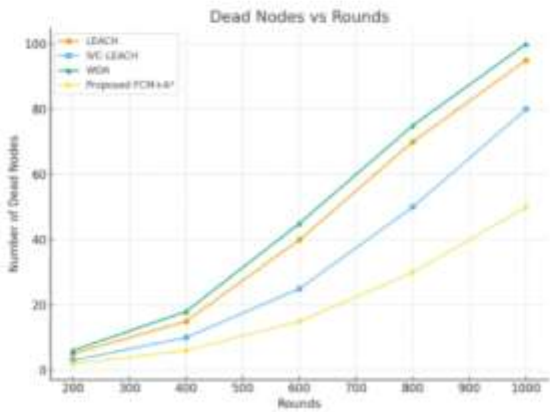

Figure 8: Dead Nodes v/s Rounds

The performance of the proposed method is evaluated against LEACH, IVC-LEACH and WOAin terms of network delay, a critical metric for assessing the responsiveness of routing protocols. The comparison results, as illustrated in Figure 9 indicate that the proposed method consistently achieves lower delay across various scenarios, outperforming the baseline methods. This improvement underscores the method's ability to optimize communication efficiency and reduce latency in data transmission. The reduced delay in the proposed method can be attributed to its intelligent routing and scheduling strategies. Unlike LEACH, IVC-LEACH, which may lack dynamic adaptability to real-time network conditions, or WOA, which may face bottlenecks due to limited prioritization, the proposed method effectively minimizes delays by selecting routes with lower congestion and shorter transmission paths. Additionally, the method likely integrates mechanisms to prioritize critical tasks, ensuring timely data delivery. By optimizing resource allocation and reducing transmission overhead, the proposed approach enhances the responsiveness of the network, enabling faster communication and better overall performance compared to the existing methods.

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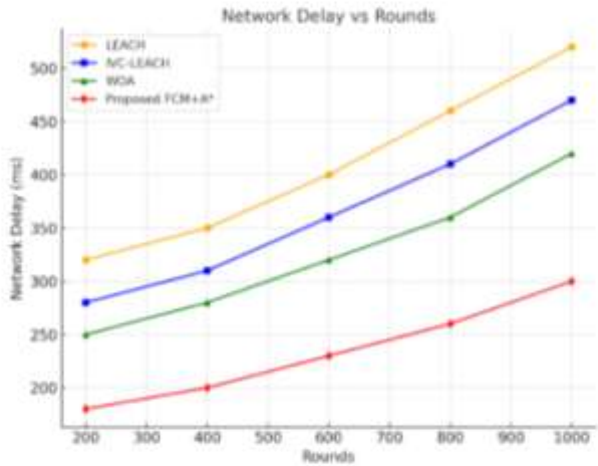

Figure 9: Network Delay Comparison

The performance of the proposed method is assessed as compared to LEACH, IVC-LEACH and WOAin terms of PDR, a key metric for evaluating the reliability of data transmission in the network. The results depicted in Figure 10 show that the proposed method consistently achieves a higher PDR under various network conditions, demonstrating its robustness in maintaining reliable communication even in dynamic environments. The superior PDR of the proposed method can be attributed to its efficient routing and error-handling mechanisms. Unlike LEACH and IVC-LEACH, which may experience packet losses due to congestion or suboptimal path selection, or WOA, which might face reliability issues under high traffic loads, the proposed method ensures reliable delivery by selecting stable and low-error paths. Furthermore, the method likely employs adaptive retransmission techniques and real-time congestion management to minimize packet drops.

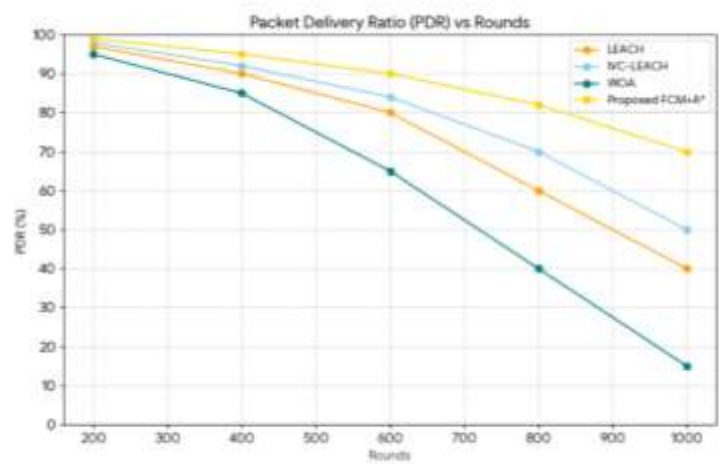

Figure 10: PDR comparison

These strategies not only enhance the reliability of data delivery but also maintain consistent network performance, ensuring that a higher proportion of packets successfully reach their intended destinations compared to the baseline methods. The average results for the evaluated metrics, including residual energy, network life, delay, and PDR, are summarized in Table 3. These averages were calculated across multiple simulation runs to ensure the reliability and consistency of the reported outcomes. The table highlights the comparative performance of the proposed method against the baseline methods (LEACH, IVC-LEACH

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and WOA), providing a comprehensive overview of its advantages across various scenarios and metrics. The results clearly confirm the superiority of the proposed method in all metrics. The many current systems lack the ability to scale effectively in large agricultural areas, leading to inefficiencies in water management. Additionally, some approaches are cost-prohibitive for small-scale farmers, which limits their widespread adoption. Furthermore, while accuracy is crucial in determining optimal irrigation schedules, many existing systems do not achieve the necessary precision in real-time conditions due to their reliance on simplistic models or outdated technologies. In contrast, the proposed method addresses these limitations by integrating FCM for clustering, A* for decision-making and an energy-efficient routing approach, ensuring scalability, affordability, and higher accuracy. To validate the effectiveness of our approach, extensive simulations were conducted to compare the proposed method against three baseline algorithms (LEACH, IVC-LEACH and WOA) using key performance metrics, including residual network energy, network lifetime, delay, and PDR. The results demonstrated that our method significantly outperforms existing approaches in terms of energy efficiency and network longevity. According to performance analysis results in Table 3, our approach maintained more residual energy, and improved PDR as compared to the best-performing baseline method. Furthermore, the proposed system reduced network delay, ensuring faster data transmission for realtime irrigation control. These results confirm the robustness and practicality of our approach for scalable and efficient smart irrigation management.

- **Performance Analysis**

The comparative performance table clearly demonstrates that the proposed FCMA* algorithm significantly outperforms the baseline techniques — LEACH, IVC-LEACH, and WOA — across all key network performance metrics. The average energy consumption of FCMA* is the lowest at 0.52 J, indicating more efficient energy utilization during data transmission and routing, whereas LEACH, IVC-LEACH, and WOA consume higher energy levels of 0.82 J, 0.74 J, and 0.68 J, respectively. Furthermore, after 800 rounds, FCMA* retains the highest residual energy (24.53 J), showing that nodes in the proposed method conserve more power and remain active longer. The death node rate for FCMA* is also the lowest at 28%, compared to 60% in LEACH, 45% in IVC-LEACH, and 50% in WOA, confirming improved network stability and reduced node mortality. Most importantly, FCMA* achieves the longest network lifetime of 1500 rounds, outperforming all other methods, which range between 950 and 1200 rounds. Overall, these results highlight that the proposed FCMA* algorithm provides a more energy-efficient, reliable, and long-lasting WSN operation, making it superior to existing clustering and routing approaches.

Table 3: Comparative Performance Analysis

Metric	LEACH	IVC-LEACH	WOA	Proposed FCMA*
Avg. Energy Consumption (J)	0.82	0.74	0.68	0.52
Avg. Residual Energy after 800 rounds (J)	12.76	19.62	14.72	24.53
Death Node Rate at 1000 rounds (%)	60%	45%	50%	28%
Network Lifetime (rounds)	950	1200	1150	1500
PDR(%)	74.6	87.2	63.6	91.9
Delay	450	380	330	270

6. CONCLUSION

The proposed Fuzzy C-Means (FCM) with A* algorithm demonstrates a robust and intelligent framework for precision irrigation in Wireless Sensor Networks (WSN), effectively addressing energy efficiency, reliability, and real-time decision-making challenges in smart agriculture. Through extensive simulations and comparisons with baseline protocols such as LEACH, IVC-LEACH, and WOA, the FCMA* approach consistently outperforms existing methods in terms of residual energy, packet delivery ratio (PDR), network delay, and network lifetime. The fuzzy clustering mechanism efficiently classifies soil zones based on

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environmental attributes such as soil moisture, temperature, and pH, ensuring adaptive and context-aware irrigation decisions. Simultaneously, the A* routing algorithm identifies the most energy-efficient and congestion-free communication paths, thereby minimizing transmission delay and extending network longevity. The synergistic combination of these techniques results in a system capable of intelligent water distribution and optimized resource utilization, supporting sustainable irrigation practices. Experimental results validate that the proposed method achieves higher PDR and lower energy depletion compared to traditional algorithms, confirming its suitability for dynamic agricultural conditions. Looking forward, the system can be enhanced by integrating hybrid optimization algorithms such as PSO, ACO, or WOA for adaptive cluster formation and route optimization. Moreover, incorporating machine learning-based prediction models for crop water demand, block-chain for secure data handling, and edge computing for low-latency decision support can further strengthen scalability and practical implementation. Thus, the FCMA* framework establishes a solid foundation for developing AI-driven, resource-efficient, and sustainable smart irrigation systems in the future.

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