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Fuzzy Logic-based automatic Energy Efficient Irrigation Management

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Abstract - Traditional farming is time-consuming, and farmers may find the need to constantly monitor crops to be a hardship. Wireless Sensor Networks (WSN), and Internet of Things (IoT) technology and. Furthermore, in real-life situations, using timers to manage the pumps in a traditional irrigation system is not persistently viable. This study provides a framework for using advanced fuzzy logic to manage an irrigation time based on various real-time soil and ambient variables, with sensors serving as the system's major component and contributor. The output of the irrigation system depends upon the various sensor's output, thus an optimized node placement strategy based on Energy Efficient Coverage Aware Particle Swarm Optimization (EECA-PSO) algorithm is suggested for the deployment of the sensor nodes over the agriculture field. The effectiveness of the proposed node placement scheme is compared with conventional node placement scenarios which indicate that the proposed node placement strategy provides superior network lifetime, reduced delay and optimal selection of nodes for the irrigation management.
Keywords - Agricultural Field Monitoring, Irrigation Management, Fuzzy Logic, Precision Agriculture, Internet of Things.

INTRODUCTION

The tremendous growth in the global population leads to needing for ample food sources. The agriculture sector is the prominent source of food. The elevation in food demand causes various issues regarding agriculture such as air and water pollution; global warming; greenhouse gas emission; degradation in quality and nutrients in food; etc. Agriculture sector is the focal source of raw material needed for numerous industrial products. Thus, the economical, cultural, and social growth of any country majorly depends upon the prosperity of the agriculture sector [1-3].
The WSN is a collection of sensor nodes distributed over the surface in a structured or unstructured way. Each sensor module includes a transducer, signal conditioning unit, central processing unit, transmitter, receiver, and battery. As the sensor modules are battery-operated devices, the lifetime of the network is limited. Depending upon the deployment surface, the WSNs are categorized into terrestrial, underwater, underwater, and aerial/mobile WSNs. WSNs plays important role in precision agriculture for various activities such as irrigation management, crop monitoring, agriculture land protection, crop disease detection, soil analysis, etc [4-5]. The deployment of the sensor nodes over the agriculture field is challenging because of various parameters such as soil type, environmental factors, wild animals, swarms, intruders, etc. the agriculture productivity and quality depend upon proper watering, fertilizers, and pesticides. There is a need for efficient irrigation management due to the decline of underground water levels and uncertainty in rain. the automatic irrigation system helps to minimize human efforts and to save water. However, efficient node placement will help to minimize the deployment cost of the network and select the potential positions that can cover the maximum agriculture field with minimum energy requirement [6-7].
The IoT devices can collect the different agriculture field conditions such as humidity, moisture, and temperature for irrigation management to improve crop productivity and water conservation. The IoT is becoming more popular in many industrial, commercial and agricultural monitoring systems. Currently, many farmers require manual labor for the intensive monitoring and control of the agricultural/crop activities and cattle monitoring which leads to wastage of resources and time. These disadvantages can be overcome by implementing the automatic agriculture monitoring using the combination of WSN, IoT, and soft computing algorithms such as irrigation management, node placement, cattle monitoring crop disease monitoring, etc [8-10].
The proposed scheme provides an energy-efficient node placement strategy for sensor node deployment and irrigation management to improve agriculture productivity. The contributions of the proposed work are summarized as follows:

- Implementation of energy-efficient and coverage-aware node placement scheme using Particle Swarm Optimization for the deployment of sensor nodes over the agricultural field.
- To investigate the irrigation management based on Fuzzy logic for agriculture productivity improvement and water conservation.

The rest of the article is arranged as follows: Section 2 provides a brief discussion of the various strategies employed for agricultural automation. Section 3 gives detailed information regarding the proposed PSO-based node placement strategy and Fuzzy logic-based irrigation management scheme. Further, section 4 provides various simulation results and experimental evidence for the performance evaluation of the proposed schemes. Lastly, section 5 depicts the crisp conclusions and shows the future direction for enhancement of the proposed research work.

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RELATED WORK

In past, many researchers have presented the use of IoT and Artificial Intelligence-based techniques for agriculture automation. The fuzzy-based irrigation system has been presented based on color, soil texture, and slope of the field using IoT for the botanical garden. The fuzzy-based systems have shown simple, reliable, and low-cost solutions for irrigation management based on data collected from the agricultural field [8]. Fuzzy-based irrigation management schemes can emphasize smart agricultural systems that rely on data collection and analysis to make better decisions, lowering costs and improving environmentally-friendly practices. The intricacy of the issues given by the natural intricacy in agricultural monitoring and control is well-suited to fuzzy logic, which employs linguistic variables [9]. The fuzzy-based systems have been successfully employed for the leaf disease grading [11], estimation of stem water potential [12], irrigation control for the water conservation [13-14], herbicides applications [15], etc. In [16] the researchers used various virtual platforms for sensors, data loggers, and LabVIEW for the fuzzy logic irrigation management to develop the interaction application. The fuzzy-based irrigation system has been successfully employed for the irrigation control of crops based on the pattern of the agricultural data obtained from the sensors [17]. Various irrigation systems use moisture, temperature, and humidity parameters for the soil and ambient data collection for irrigation management [18-21]. WSNs and IoT have shown a crucial role in data collection, data analysis, transmission, storage, and building automation systems for precision agriculture [22-27]. A study of different methods suggests that there is a need for efficient sensor node placement so that cost of the system can be reduced, the lifetime of the network can be improved, and maximum targets (crops) can be covered for irrigation management.

PROPOSED METHODOLOGY

The proposed system is split into two phases as node placement phase and the irrigation management phase as given in Figure 1. In the node placement, the EECA-PSO algorithm is employed for the energy-efficient node placement that considers the coverage of the maximum target and requires minimum energy for the communication. The second phase includes the irrigation management based on the agricultural field and environmental data acquired from the sensor node such as humidity, temperature, and moisture using a fuzzy logic algorithm.

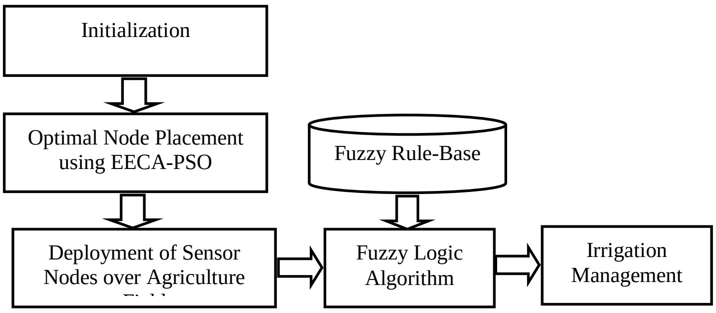

FIGURE 1
OVERALL ARCHITECTURE OF THE PROPOSED SYSTEM

I. Node Placement based on Energy Efficient Coverage Aware Particle Swarm Optimization (EECA-PSO)

PSO is a stochastic optimization method based on the natural phenomenon of birds' navigation for food/shelter searching. It can be used to find the optimum solution while maximizing or minimizing function value. PSO mimics navigation logic followed by a flock of birds. A bird's population is represented by particles. Particles move in the problem space following a set of rules. Each particle has a different direction and must start in different directions. Every particle updates its position and velocity for the next iteration, based on the particle best and the global best value obtained So far.

Every particle in the proposed scheme consists of the k random potential positions for the sensor node placement over the agriculture field. The maximum value of k is considered up to ½ times the total potential positions for the sensor node placement.

$$P_i = \{p_1, p_2, p_2, p_2, p_2, \dots\dots p_k\} \tag{1}$$

The target points T represent the position of the crop in the agriculture field.

For every particle, the proposed node placement scheme is applied and the fitness of the particle solution is computed using equation 2.

$$Fitness_{P_i} = w_1 Eres + w_2\, Cov + w_3 AvgDist \tag{2}$$

The fitness function is dependent on the residual energy of the node (Eres), coverage of the sensor node (Cov), and the average distance of covered targets by sensor nodes (AvgDist). If the fitness of the respective particle is greater than the global fitness value, then the particle is retained. If the fitness of the particle is less than the updated global fitness then the position and velocities of the particles are updated using equations 3 and 4. Following equations are used to update position and velocity for the next iteration itr+1. Each particle has position and velocity.

$$x_i^{itr+1} = x_i^{itr} + v_i^{itr+1} \tag{3}$$

$$v_i^{t+1} = wv_i^{itr} + c1r1(Pbest_i^{itr} - x_i^{it}) + c2r2(Gbest_i^{itr} - x_i^{it}) \tag{4}$$

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Where c1, c2: Acceleration coefficient
It: the number of iterations the particles would undergo
r1, r2: random numbers used to set the initial values of tuning parameters.

The PSO algorithm is executed for several iterations and the final optimized solution is used for node placement that covers a larger area and needs minimum energy. The algorithm for the proposed PSO based node placement is given as follows:

```
Particle swarm optimization algorithm:
Step 1: Initialization of algorithm parameters
        num_particles:   No of particles
        αi: high-frequency coefficient shrinkage factor for i th particle
        βi: Threshold function curvature setting parameter for i  th  particle
        K:  used to set the threshold to preserve useful details from filtering out.
        C1 and C2:   Acceleration parameters are set between  0 to 1.
        Itr: No of iterations  each particle will go through
Step 2: For  j= 1 to itr
        For i 1 to   num_particles
        fitPi = fitness(p)=PSNRPi
        If  Fitp> fit Gbest  then
            Gbest= fitpi
        Else
           Update position of particle using    equation 3.
           Update velocity of particle using    equation 4.
        End
        End
        End
```

II. Irrigation Management using Fuzzy Logic

The agriculture field is divided into four monitoring regions for the irrigation controller. Each region consists of the random deployment of the 5 temperature sensors, five PH sensors, and five moisture sensors for the soil and ambient conditions monitoring. The target indicates the crop positions which are arranged in a structured grid format like the traditional Indian farming system. The targets varied from 50 to 500 over the agricultural field (simulation area) of 50m×50m, 75m×75m, and 100m×100m. The fuzzy logic is implemented using Mamdani fuzzy rule base system using three input variables such as humidity, temperature, and moisture; and one output variable such as watering time. The fuzzy-based agriculture field monitoring is simulated using the MATLAB fuzzy logic toolbox which is shown in Figure 2.

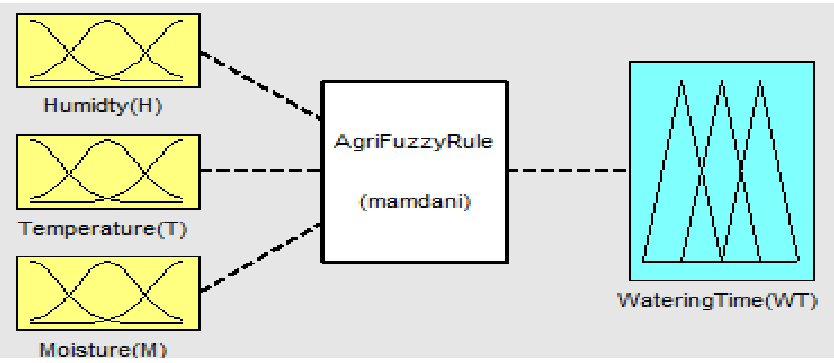

FIGURE 2
FUZZY LOGIC BASED AGRICULTURE FIELD MONITORING SYSTEM

$$Humidity_{Low}(x) = \begin{cases} 1 & 50 \le x \le 60 \\ \dfrac{70-x}{10} & 60 \le x \le 70 \end{cases} \quad (5)$$

$$Humidity_{Medium}(x) = \begin{cases} \dfrac{x-75}{10} & 65 < x \le 75 \\ \dfrac{85-x}{10} & 75 \le x \le 85 \end{cases} \quad (6)$$

$$Humidity_{High}(x) = \begin{cases} \dfrac{x-80}{10} & 80 < x \le 90 \\ 1 & 90 \le x \le 100 \end{cases} \quad (7)$$

$$Moisture_{Dry}(x) = \begin{cases} 1 & 0 \le x \le 15 \\ \dfrac{25-x}{10} & 15 \le x \le 25 \end{cases} \quad (8)$$

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$$Moisture_{Moderate}(x) = \begin{cases} \frac{x-25}{10} & 15 \le x \le 25 \\ 1 & 25 \le x \le 35 \\ \frac{45-x}{10} & 35 \le x \le 45 \end{cases} \quad (9)$$

$$Moisture_{Wet}(x) = \begin{cases} \frac{x-50}{15} & 35 \le x \le 50 \\ 1 & 50 \le x \le 60 \end{cases} \quad (10)$$

$$Temperature_{VeryCool}(x) = \begin{cases} 1 & 0 \le x \le 10 \\ \frac{20-x}{10} & 10 \le x \le 20 \end{cases} \quad (11)$$

$$Temperature_{Cool}(x) = \begin{cases} \frac{x-15}{7} & 15 < x \le 22 \\ \frac{30-x}{8} & 22 \le x \le 30 \end{cases} \quad (12)$$

$$Temperature_{Hot}(x) = \begin{cases} \frac{x-30}{7} & 30 < x \le 38 \\ \frac{45-x}{15} & 30 \le x \le 45 \end{cases} \quad (13)$$

$$Temperature_{VeryHot}(x) = \begin{cases} \frac{x-40}{7} & 40 < x \le 45 \\ 1 & 45 \le x \le 55 \end{cases} \quad (14)$$

$$Temperature_{Medium}(x) = \begin{cases} \frac{x-25}{7} & 25 < x \le 30 \\ \frac{35-x}{5} & 30 \le x \le 35 \end{cases} \quad (15)$$

$$WT_{VeryShort}(x) = \begin{cases} 1 & 0 \le x \le 0.5 \\ \frac{3-x}{2.5} & 0.5 \le x \le 3 \end{cases} \quad (16)$$

$$WT_{Short}(x) = \begin{cases} \frac{x-0.5}{1.5} & 0.5 \le x \le 2 \\ \frac{5-x}{1.5} & 3.5 \le x \le 5 \\ 1 & 2 \le x \le 3.5 \end{cases} \quad (17)$$

$$WT_{Average}(x) = \begin{cases} \frac{x-3.5}{2.5} & 3.5 \le x \le 6 \\ 1 & 6 \le x \le 8.5 \\ \frac{11-x}{2.5} & 8.5 \le x \le 11 \end{cases} \quad (18)$$

$$WT_{Long}(x) = \begin{cases} \frac{x-9}{1.5} & 9 \le x \le 10.5 \\ 1 & 10.5 \le x \le 11.5 \\ \frac{13-x}{2.5} & 11.5 \le x \le 13 \end{cases} \quad (19)$$

$$WT_{VeryLong}(x) = \begin{cases} \frac{x-11.5}{1.5} & 11.5 \le x \le 13 \\ 1 & 13 \le x \le 15 \end{cases} \quad (20)$$

The input and output variables along with their range are given in Table I. The trapezoidal membership function is selected for every input and output variable to improve the sensitivity of the variable and enhance the logic description capability.

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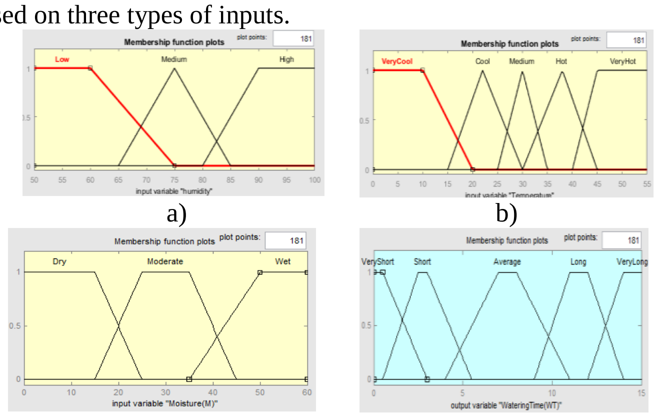
TABLE 1
INPUT AND OUTPUT VARIABLES FOR FUZZY LOGIC

Variables	Input	Level	Range	Membership Function
Input Variable	Humidity (H)	Low	50-70 %	Trapezoidal
		Medium	65-85 %	Triangular
		High	80-100 %	Trapezoidal
	Temperature	Very Cool	0 to 20 (Degree)	Trapezoidal
		Cool	15-30 (Degree)	Trapezoidal
		Medium	25-35 (Degree)	Trapezoidal
		Hot	30-45 (Degree)	Trapezoidal
		Very Hot	40-55 (Degree)	Trapezoidal
	Moisture (M)	Dry	0-25	Trapezoidal
		Moderate	15-45	Trapezoidal
		Wet	35-60	Trapezoidal
Output Variable	Watering Time (WT)	Very Short	0-3 (sec)	Trapezoidal
		Short	0.5–5.1 (sec)	Trapezoidal
		Average	4.5– 11 (sec)	Trapezoidal
		Long	9-13 (sec)	Trapezoidal
		Very Long	12-15 (sec)	Trapezoidal

The input variable humidity (H) consists of two levels such as low and high; temperature (T) consists of two levels such as cool and hot; and moisture (M) consists of three levels as dry, moderate, and wet. The field is considered wet when moisture is high. Figure 3 shows the fuzzy membership function for humidity, temperature, and moisture. The output variable watering time consists of five levels very short, short, average, long, and very long watering time. The fuzzy logic algorithm generates any one level of these output variables based on three types of inputs.



c) d)

FIGURE 3
FUZZY MEMBERSHIP FUNCTION FOR INPUT VARIABLE A) HUMIDITY (H) B) TEMPERATURE (T) C) MOISTURE (M) AND D) WATERING TIME (WT)

Total of twelve rules are designed using the "AND" based rule design method. The various rules designed using fuzzy logic controllers are given in Table II.

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TABLE II
DEVELOPMENT OF FUZZY RULES

Humidity	Temperature	Moisture	Watering Time
Low	Very Cool	Wet	Very Short
Low	Cool	Wet	Short
Low	Medium	Wet	Average
Low	Hot	Wet	Long
Low	Very Hot	Wet	Long
Low	Very Cool	Moderate	Short
Low	Cool	Moderate	Short
Low	Medium	Moderate	Long
Low	Hot	Moderate	Long
Low	Very Hot	Moderate	Very Long
Low	Very Cool	Dry	Short
Low	Cool	Dry	Average
Low	Medium	Dry	Long
Low	Hot	Dry	Very Long
Low	Very Hot	Dry	Very Long
Medium	Very Cool	Wet	Very Short
Medium	Cool	Wet	Very Short
Medium	Medium	Wet	Short
Medium	Hot	Wet	Average
Medium	Very Hot	Wet	Long
Medium	Very Cool	Moderate	Very Short
Medium	Cool	Moderate	Short
Medium	Medium	Moderate	Average
Medium	Hot	Moderate	Average
Medium	Very Hot	Moderate	Long
Medium	Very Cool	Dry	Average
Medium	Cool	Dry	Average
Medium	Medium	Dry	Long
Medium	Hot	Dry	Very Long
Medium	Very Hot	Dry	Very Long
High	Very Cool	Wet	Very Short
High	Cool	Wet	Very Short
High	Medium	Wet	Very Short
High	Hot	Wet	Short
High	Very Hot	Wet	Average
High	Very Cool	Moderate	Very Short
High	Cool	Moderate	Short
High	Medium	Moderate	Average
High	Hot	Moderate	Average
High	Very Hot	Moderate	Long
High	Very Cool	Dry	Long
High	Cool	Dry	Average
High	Medium	Dry	Long
High	Hot	Dry	Very Long
High	Very Hot	Dry	Very long

The rule base is designed using AND rule which gives equal importance to all input variables to decide the output variable. The output variable generates the watering time variable in the variable which is further used to control the watering system of the agriculture motor pump to irrigate the field. The watering time is kept small to cope with the sudden environmental changes such as rainfall, heat, fire, and flood. Figure 4 shows a fuzzy rule viewer for very long watering time (14 sec) for input variables Low Humidity (57.5%), Hot Temperature (35.8oC), and dry moisture (11.9%).

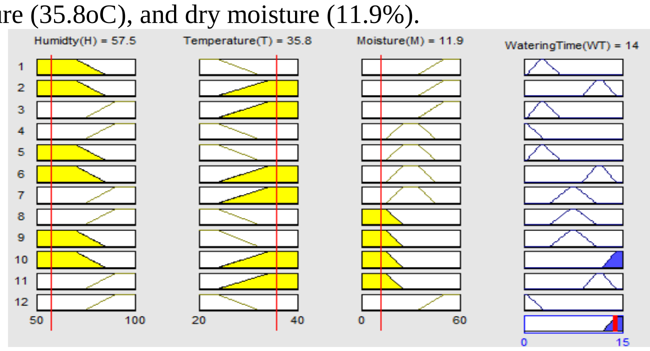

FIGURE 4
FUZZY RULE VIEWER FOR VERY LONG WATERING TIME (14 SEC) FOR INPUT VARIABLES HUMIDITY=57.5%, TEMPERATURE=35.8OC, MOISTURE=11.9%

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Figure 5 shows a fuzzy rule viewer for very short watering time (14 sec) for input variables high Humidity (95.5%), Cool Temperature (23.5oC), and Wet moisture (37.70 %). Figure 6 shows a fuzzy rule viewer for average watering time (14 sec) for input variables high Humidity (95.5%), Cool Temperature (23.5oC), and average moisture (30.70 %).

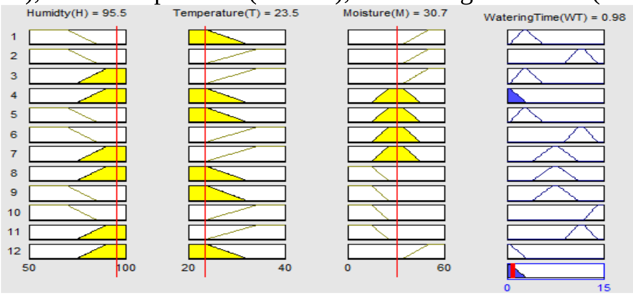

FIGURE 5

FUZZY RULE VIEWER FOR VERY SHORT WATERING TIME (0.98 SEC) FOR INPUT VARIABLES HUMIDITY=95.5%, TEMPERATURE=23.5OC, MOISTURE=37.7%

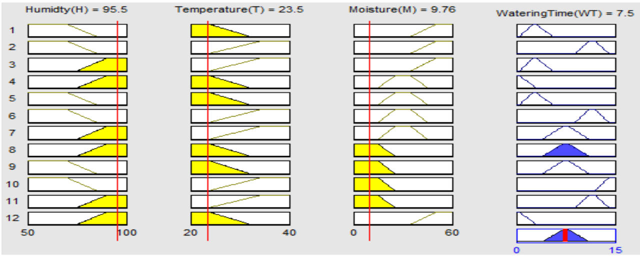

FIGURE 6

FUZZY RULE VIEWER FOR AVERAGE WATERING TIME (7.5 SEC) FOR INPUT VARIABLES HUMIDITY=95.5%, TEMPERATURE=23.5OC, MOISTURE=9.75%

EXPERIMENTAL RESULTS AND DISCUSSIONS

The proposed system is simulated using MATLAB R2018b on a personal computer. The various parameters of the network are mentioned in Table III. The base station is located in the center east position to monitor and control the agricultural activities.

TABLE III
NETWORK PARAMETERS SPECIFICATIONS

Parameter	Value
Number of sensor node	100
Number of Targets	50 - 100
Communication range	70m
Sensing range	40m
Initial Energy of node	0.2J
E_{elect}	50 nJ/bit
E_{fs}	10 pJ/bi/m2
E_{mp}	0.0013 pJ/bi/m4
Packet length	4000 bits
Massage size	500 bit

a) b)

FIGURE 7

A) INITIAL NETWORK SCENARIO B) NODE PLACEMENT SCENARIO

The performance of the proposed EECA-PSO-based node placement scheme provides the optimal node placement compared with the traditional Genetic Algorithm (GA) and Differential Evolution (DE) Algorithm given in [27] for the current scenario. The PSO provides superior results for the node placement compared with GA and DE. The comparative results for the proposed system are validated using live nodes, dead nodes, residual energy, and packet to the base station. The proposed EECA-PSO provides a better network lifetime, and higher packet delivery to the base station with the help of optimal node selection that covers all the targets.

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Figure 8 shows increasing the simulation area of the network increases the number of nodes for covering the complete targets. The node placement scheme is simulated for the varying no of targets between 50 to 500 that represents the crop positions.

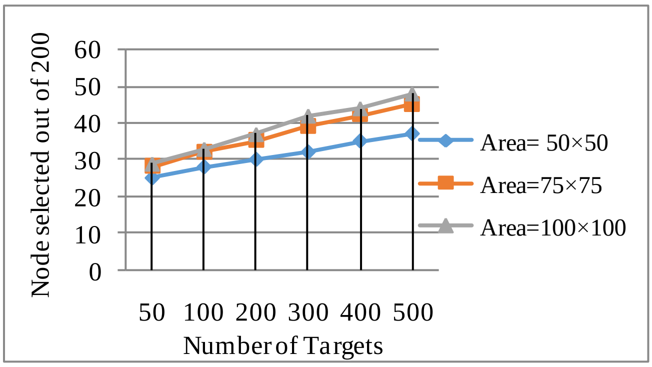

FIGURE 8
COMPARISON OF NODE SELECTION FOR DIFFERENT AREA

Figure 9 illustrates the comparative analysis of the potential node position selection of proposed EECA-PSO, GA, and DE for the 100m×100m simulation area for a different number of targets and 100 initial potential positions. The EECA-PSO helps to minimize the number of sensor nodes that can be deployed in the agriculture field with maximum coverage and higher network lifetime.

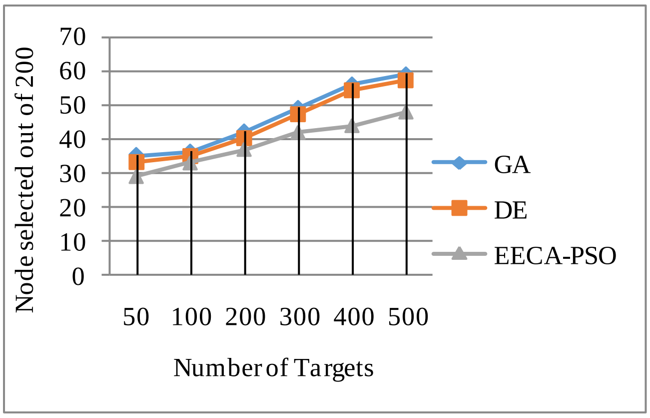

FIGURE 9
COMPARISON OF NODE SELECTION WITH GA AND DE (100M×100M)

Conclusion and Future Scope

Thus, this paper presents agriculture irrigation management using a fuzzy logic algorithm based on different parameters such as moisture, humidity, and temperature. Further, energy-efficient node placement is employed for covering a larger agriculture field area with the least number of sensor nodes and reduced energy. The performance of the system is evaluated for different target counts and area sizes, and it is observed that the proposed scheme provides scalable and energy-efficient solutions for the node placement strategy. The proposed scheme provides a better packet delivery ratio, enhanced network lifetime, reduced energy consumption, and throughput for various conditions. In the future, the performance of the system can be improved by considering unsupervised soft computing techniques to automate the irrigation system. The steady node placement can be replaced by mobile WSN to collect the soil and ambient parameters for real-time irrigation and crop monitoring to minimize the cost and complexity of the WSN.

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