Cureus Journal of Engineering

Open Access Original Article

# Orchestrating a Smart Agriculture System with Optimized Sensor Allocations and Heterogeneous Wireless Coverage

**Received** 02/28/2025
**Review began** 03/10/2025
**Review ended** 04/18/2025
**Published** 05/29/2025



**DOI:** https://doi.org/10.7759/s44388-025-03470-x

Mohamed H. Naeem [1] , Mohamed A. El-Khoreby [2] , Hussein M. ELAttar [2] , Mohamed Aboul-Dahab [2]

1. Computer Networks and Data Center, Arab Academy for Science, Technology and Maritime Transport, Cairo, EGY 2. Department of Electronics and Communications Engineering, Arab Academy for Science, Technology and Maritime Transport, Cairo, EGY

**Corresponding author:** Mohamed H. Naeem, mohamed.hamdy@aast.edu

## Abstract

Smart agricultural systems are essential in increasing production rates and reducing losses, while poor connectivity hinders their capabilities. Ensuring robust connectivity among its components within a systematic agricultural field remains a significant challenge. Issues related to sensor allocation and wireless coverage further complicate this landscape. A practical solution lies in adopting an orchestrated wireless sensor network (WSN) design that addresses these research gaps in tandem. The orchestrated design provides a novel connectivity solution that improves connectivity development within two approaches. The first approach utilizes a hybrid method for sensor allocation. The second approach concerns maintaining more robust wireless coverage for those allocated sensors. This paper proposes an orchestrated design that employs a hybrid approach to incorporate area clustering using the rapidly exploring random trees method for efficient spatial sampling. Additionally, it introduces an improved allocation method for agricultural sensors based on a mathematical variable length distance technique combined with the Voronoi algorithm. To further enhance wireless coverage, the design targets the interoperability of wireless transmission via the Fuzzy Analytical Hierarchical Process method. This is complemented by the k-nearest neighbors method for planning wireless sensor communication pathways. Overall, the proposed orchestrated design demonstrates significant advancements. It provides economic implementation by allocating only 13 nodes, achieving minimal power consumption rates and optimal coverage. Furthermore, it has 86% WSN coverage and a performance score that surpasses Particle Swarm Optimization by 1.13%.

**Categories:** Agricultural Machinery and Automation, Embedded Systems and IoT, Wireless Communication Systems
**Keywords:** hybrid algorithm, pso algorithm, mathematical methods, wireless sensor networks (wsn), agriculture iot, sensor distribution, binar knn, smart agriculture, voronoi diagram, things wireless sensor network

## Introduction

The world is facing a severe food crisis, with only 60% of the population projected to have a secure food supply by 2050 [1]. In response, the United Nations, governments, and non governmental organizations (NGOs) have launched a series of initiatives to enhance food production, transportation, and storage. One of the most crucial initiatives is the development of innovative agriculture solutions to maximize agricultural production and minimize loss rates [2]. Smart agriculture systems, which have recently embraced the Internet of Things (IoT) and emerging technologies such as artificial intelligence AI, cloud, and edge computing, are at the forefront of this effort. These systems are adopting the precision agriculture (PA) system, which includes sensors, actuators, controllers, gateway, fog computing, edge computing, and cloud computing [3].

While the PA system suffers several challenges, connectivity remains the most important [4]. Connectivity is essential for the PA system to maintain its sustainability of monitoring, supervising, and automating the agriculture process autonomously [5]. Dependency on human factors provided several challenges that led to adopting a sustainable PA system for effectively sensing, controlling, and activating the agricultural process [6]. Data acquisition in agriculture is essential for effectively monitoring plant, soil, climate, and water conditions [7]. Recent interest in sensor data acquisition increased interest in maintaining a sustainable PA system. Agriculture sensors are the PA system's main element and require a wireless sensor network (WSN). The availability of the WSN depends mainly on the communication technologies through which it seeks to maintain stable connectivity [8]. Several communication technologies are employed in different forms [9] to achieve this connection stability. Since the first adoption of IoT as a PA system, some standard small-range wireless communications have been adopted, such as Zigbee, wireless fidelity (Wi-Fi), Bluetooth, Z-wave, and near field communication. Multiple or large agricultural areas regularly use a moderate range of wireless technologies. Large areas require a wide range of wireless technologies such as SigFox, low power area network (LoRa), narrowband IoT, and low power wireless wide area network. Furthermore, an extended range of wireless communication technologies is necessary for remote and

**How to cite this article**
Naeem M H, El-Khoreby M A, ELAttar H M, et al. (May 29, 2025) Orchestrating a Smart Agriculture System with Optimized Sensor Allocations and Heterogeneous Wireless Coverage. Cureus J Eng 2 : es44388-025-03470-x. DOI https://doi.org/10.7759/s44388-025-03470-x

internet connectivity. Internet connectivity for sensors and actuators is usually maintained using cellular data communication and satellite communication. Assessing the most relevant connectivity technologies is essential for designing a robust WSN. Later on, an efficient design of the sensor allocation should be maintained. Combining both to maintain an efficient sensor distribution and communication through the agricultural fields. Another issue is maintaining sensor deployment and localization through the farm field [10]. That is a challenging point for retaining the data acquisition with adequate density, wise cost, coverage, and energy considerations. There are two main categories of sensor distribution: mobile (robotic, Unmanned Aerial Vehicle (UAV), and drone) and stationary (based on fixed locations) [11]. The mobile sensor deployment has some advantages, like surfing the agriculture field effectively, but disadvantages, like cost, soil sensor management, and energy limitations.

On the other hand, stationary sensing nodes provide lower costs and better operational energy. The most crucial point is the localization of the stationary sensing nodes and deployment of the nodes based on a fixed length or trial and error method [12]. The first method provides faster deployment but has some errors compared to the second method. Another mission is to design the deployed sensing node as a hierarchical or plane deployment. At the same time, hierarchical deployment is preferred based on the anchor and salve sensing node scenario. It is difficult for the precision agriculture system to maintain those vast numbers of devices for large agricultural areas as delays may halt the system's operation. So, it is also essential to cluster the farm system to solve such a huge capacity, which is a serious challenge. It is commonly implemented to overcome the constraints of delay and limitation of the system scalability [13]. There is plenty of research interest in sensor allocations and communication; however, there are still some issues related to the capacity, interoperability, cost, and power consumption. Better optimization techniques than the Particle Swarm Optimization (PSO) and Gaussian methods should be utilized to minimize the number of allocated nodes, provide better sensing coverage, better capacity planning, and minimum cost and power consumption. The connectivity problem within the smart agriculture system requires better allocation of the sensors and wise wireless coverage. The sensor allocation is meant to provide better sensing coverage, while the coverage is to provide relevant wireless coverage to the sensor's location.

This paper aims to provide an orchestrated design of the WSN in the systematic agriculture field by providing better allocation of the sensor nodes and sustainable coverage. The paper structure has five main sections, and it is a literature review that lists recent efforts in sensor allocation and wireless coverage. The methodology section provides a shade of the methodology used to orchestrate wireless coverage and sensor deployment. The simulation section outlines the simulation process used in investigating the wireless technologies, the wireless coverage mechanism, and the sensor deployment strategy. The results and analysis section discusses the simulation results with a smart link to illustrate the orchestration process. The conclusion summarizes the effort exerted to reach the outcome and the most challenging issues in achieving the orchestration principle.

## Related work

Maintaining an orchestrated design of the WSN by jointly maintaining effective sensor allocation, coverage, and connectivity is a long waiting objective. In contrast, it is a challenging problem, requiring a profound study of the objective elements, methods, and gaps to contribute to a great solution.

## Wireless technologies in WSN

Connectivity through the smart agriculture field has some significant challenges, especially interoperability. The heterogeneity of the sensors and actuators connectivity requires a heterogeneous wireless infrastructure. That is to support the multi-access edge computing (MEC) communication capability within the availability of the heterogeneous multiple radio access networks (Het-MRAN) infrastructure. This heterogeneity requires assessing the wireless to a gateway solution for designing a resilient Het-MRAN. Widely implemented as a practical solution, as shown in [14], supplying LoRa and wifi. In [15], it provided better coverage by offering Bluetooth and Wi-Fi. Moreover, the solution in [16] gives Long Term-Evolution (LTE) and ZigBee as a Het-MRAN solution. However, those solutions provided a Het-MRAN solution that they lack, considering scalability and delay as constraints through the design. The solution in [17] provided a good practice for this by giving a clustering technique. From another perspective, sensor allocation through the field is essential to gather the agricultural data necessary for decision-making. Heterogeneous wireless coverage contributes to achieving the resilient coverage objective.

## Sensor allocation methods

However, the sensor that connects to those Het-MRAN has some concerns. They should have a better allocation method that guarantees better sensing of the agriculture field and minimizes the number of deployed units. Several efforts, such as uniform distribution of the agriculture sensors [18], provide high reliability while having some drawbacks, such as cost, delay, and power consumption. Those challenges motivated researchers around the globe to work on designing the sensor deployment based on a deterministic approach. Some deterministic sensor deployments include square sensor allocation as in

[19], triangular allocation as found in [20], hexagon grid as in [21], and tri-hexagon tiling as in [22]. However, there are methods used to effectively provide a deterministic allocation of sensor nodes, like fixed distance as in [23], k-coverage as found in [24], and an algorithm as in [25]. Clustering the agricultural area may require area segmentation and sensing or communication technology, as in [26]. However, the design of the wireless coverage passes by several techniques to provide adequate coverage for the allocated sensors. Some coverage solutions adopt chicken swarms, as in [27], which utilize optimization by placing the wireless propagating nodes to cover the area. At the same time, others utilized particle swarms, as in [28], to cover most of the agricultural area with minimum overlap. Utilizing K-nearest neighbors (KNN) for better clustering and allocation of WSN propagating nodes is beneficial for dual coverage and sensor allocation, as in [29]. The summarized taxonomy of the literature related methods is shown in Figure *1*.

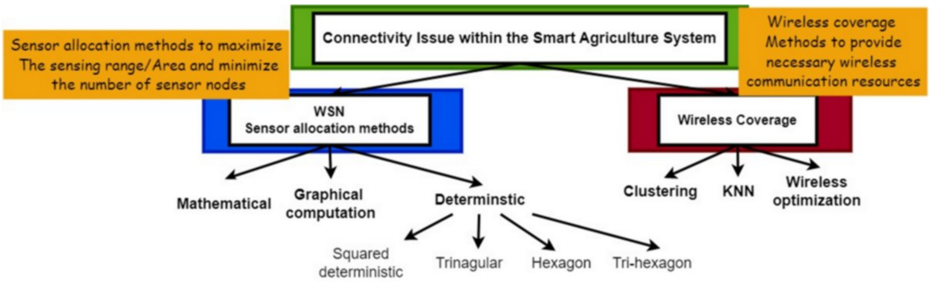



**FIGURE 1: Taxonomy for the methods used to solve the connectivity issue within the WSN**

WSN, wireless sensor network

The connectivity solution methods are summarized in a taxonomy of two main related issues:

· WSN sensor allocation

· Wireless coverage

There is an interesting need to provide a solution that addresses both the sensor allocation and its relevant wireless coverage. This paper investigates the design of an orchestrated WSN for better coverage and sensing, and minimizes drawbacks related to capacity, delay, power consumption, and deployment cost.

## Materials And Methods

The methodology passes through several stages to achieve the orchestration in designing the WSN coverage and sensor allocation. Those stages are illustrated briefly in the flow chart shown in Figure *2* and comprise several stages.

The first stage (wireless tech selection): aims to investigate the interoperability of sensors and their supportive communication technologies. The hypnosis investigates a suitable quantitative method to design a heterogeneous network. Those heterogeneous WSNs provide connectivity for the smart agriculture system elements and determine the sensing range for better allocations of sensors.

The second stage (area clustering): is to cluster the agricultural land based on the area and supportive wireless technology capacity, power consumption, and delay constraints.

The third stage (sensor allocation): provides the allocation of sensors based on an area of interest process as a cluster sub-area, path of interest, and distance-aided Voronoi algorithm. The proposed heterogeneous WSN is then utilized as a dynamic connection based on sensing type using the KNN algorithm.

Finally, the research evaluates the proposed orchestrated design against the PSO design, which has dominated research in recent years.

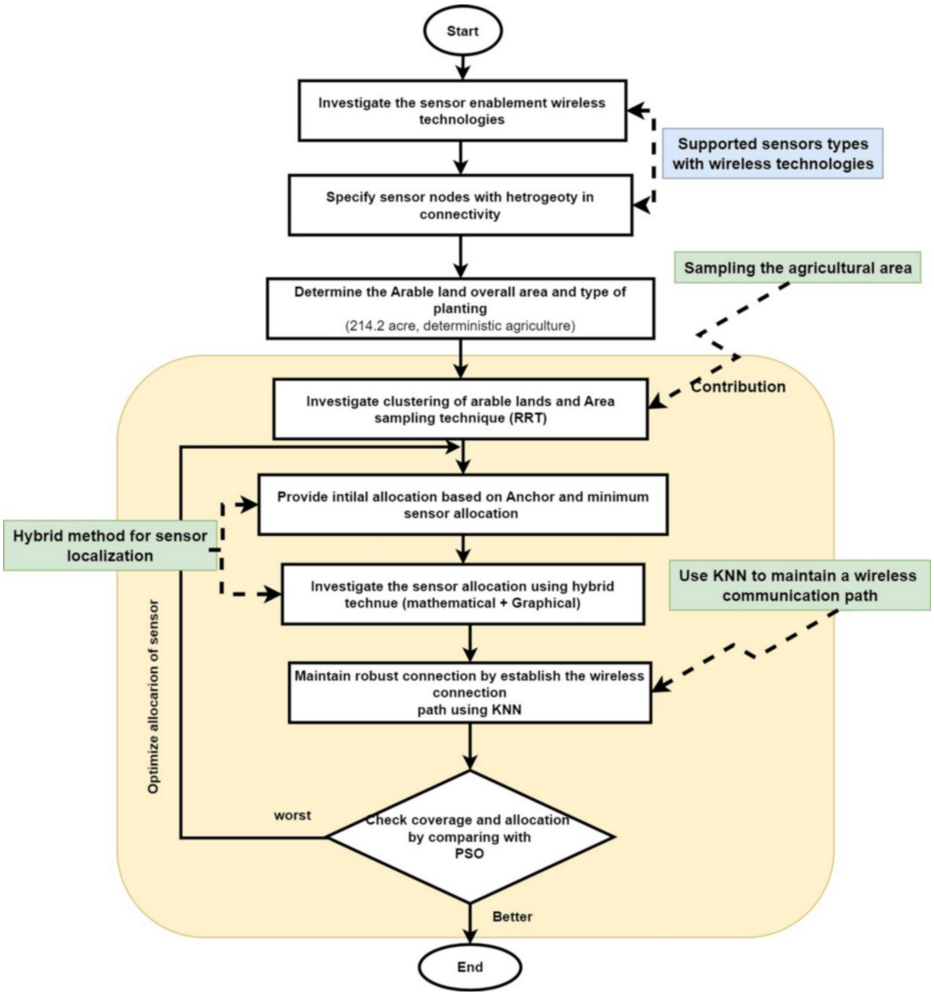



**FIGURE 2: Methodology flow chart**

KNN, k-nearest neighbors; RRT, random trees; PSO, Particle Swarm Optimization

## Methods for sensors

This subsystem illustrates the different actions of the innovative agriculture system that need to be monitored and controlled. The relevant sensors and possible heterogeneity within most supported wireless communication technologies are identified and assessed. There are four main agriculture processes upon which the innovative agriculture system elements:

(a) Irrigation process (actuating and sensing)

(b) Planting process (sensing)

(c) Fertilization process (actuating and sensing)

(d) Harvesting process (sensors, machinery, and robotics)

## Sensing stations

The agricultural process requires several sensing stations to sense all relevant physical parameters within the farm field. Moreover, the necessary data can be acquired within the innovative agriculture system.

A. Weather sensing station

B. Soil sensing station

C. Water sensing stations

D. Plant health and pest control sensing station

Those four listed sensing stations require wise classifications concerning their applicable sensing area into two main categories:

(a) High Area of Interest Sensors (HAIS): An anchor node

The anchor node is a sensing node with more powerful resources, making it capable of controlling all other nodes within the clustered area. The anchor node should provide two main functions: sensing and control. The sensing function within the cluster at its allocated point is like other sensing nodes. Moreover, it provides control and management for all other sensing nodes within the cluster. The sensors have a sensing range usually within a large area of 15 to 20 acres (Rain, pH sensor, salinity sensor, air pressure sensor, wind speed, ultraviolet (UV) index, Temperature, Humidity, and water salinity sensors). This sensor requires low data rate communication.

(b) Low Area of Interest Sensors (LAIS): Resource-constrained sensor

The sensing range of sensors usually has a minimum of 20 meters and a maximum of 50 meters [30,31]. This sensor requires high data rate communication.

## Wireless technologies for sensors

Bluetooth, LoRa, Wi-Fi, and LTE are wireless technologies frequently used in WSN deployments [32]. Table *1* shows the relevant parameter values for coverage, data rates, power consumption, delay, and capacity.

| HWNs | Bluetooth | LoRa-WAN | Wi-Fi | LTE |
|---|---|---|---|---|
| Coverage (km) | 0.002-0.01 | 15-102 | 0.1 | 3-55 |
| Data rates (Kbps) | 1000 | 50 | 54000 | 25000-75000 |
| Power consumption (W) | 0.5 | 0.2 | 2 | 5 |
| Delay (ms) | 150 | 1000 | 12 | 100 |
| Capacity (number of sensor nodes) | 10 | 10,000 | 32 | 1000 |

### TABLE 1: Het-MRAN wireless technologies

Het-MRAN, heterogeneous multiple radio access network; LTE, Long Term-Evolution; HWN, Heterogeneous Wireless Network; loRa-WAN, low power area network-wide area network; Wi-Fi, wireless fidelity

Those quantitative parameters illustrated in Table *1* have uncertainty when evaluating and ranking them for prioritization in heterogeneous infrastructure coverage. The analytical hierarchy process (AHP) is a decision-making process that solves uncertainty. However, it mainly judges using expertise knowledge with a scaled relative value.

## Heterogeneous wireless network ranking with FAHP

Ranking requires a quantitative process to help find a tie, such as the Fuzzy-Analytical Hierarchy Process (FAHP) [33]. Fuzzy provides a quantitative comparison matrix utilizing a hierarchical relationship between the wireless technologies and their parameters, as illustrated in Figure *3*. The ranking process retains its process flow by performing the FAHP process, as illustrated in Figure *4*.

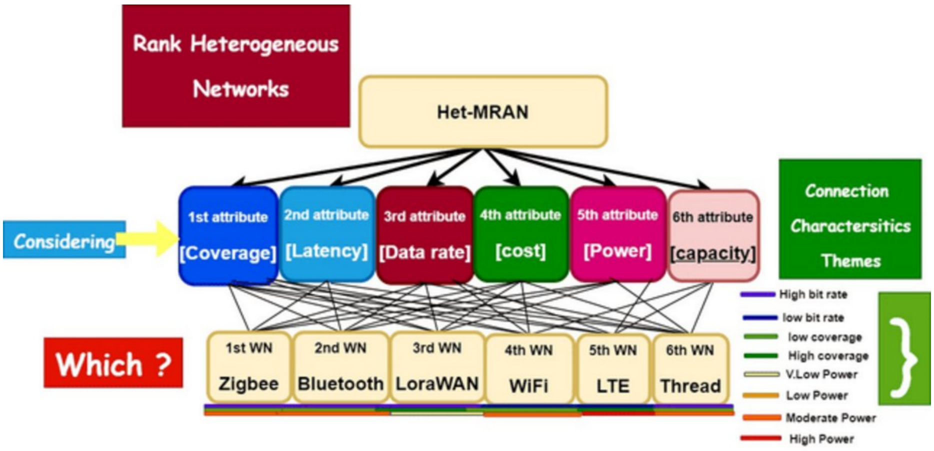



**FIGURE 3: FAHP wireless ranking based on the technology's hierarchical relationship with their parameters**

Het-MRAN, heterogeneous multiple radio access network; LTE, Long Term-Evolution; FAHP, Fuzzy Analytical Hierarchical Process; LoRaWAN, low power area network wide area network; Wi-Fi, wireless fidelity

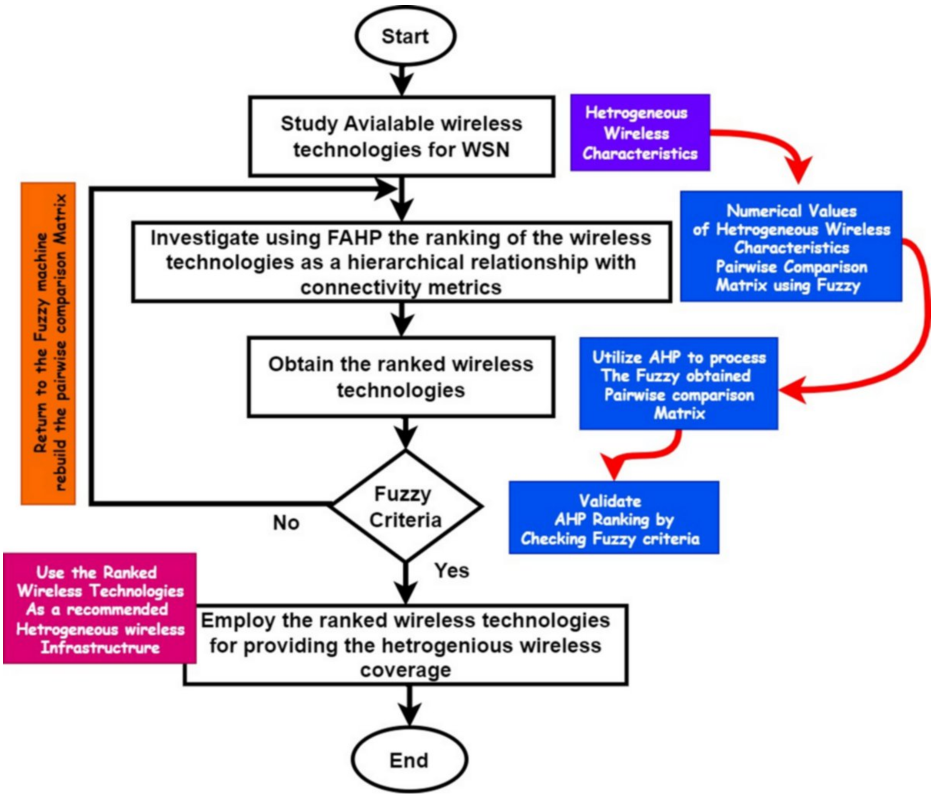



**FIGURE 4: FAHP process flow chart for ranking wireless technologies**

FAHP, Fuzzy Analytical Hierarchical Process; WSN, wireless sensor network; AHP, analytical hierarchy process

Furthermore, the communication infrastructure utilizes a hybrid technique to provide a robust Het-MRAN infrastructure solution. The FAHP uses quantitative ranking for the four best wireless technologies to maintain the Het-MRAN. However, a tradeoff between the coverage and bit rate requires an extra switch technique. The additional selection for the wireless coverage is based on the uncertainty of coverage and bit rate, as illustrated in Figure *5*. The selected four wireless technologies form a confusion matrix for the sensor node to switch between the Het-MRAN.

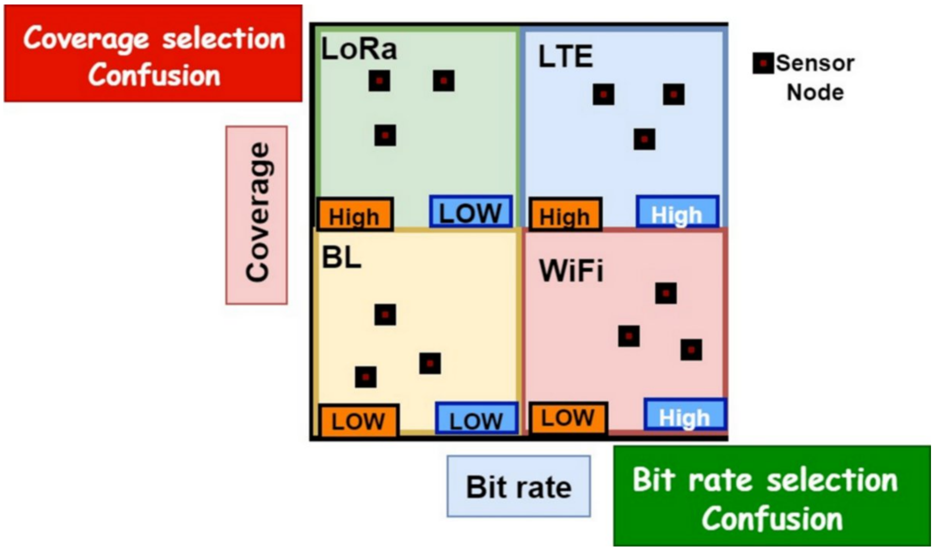



**FIGURE 5: Confusion matrix for selecting for both coverage and bit rate**

LTE, Long Term-Evolution; LoRa, low power area network; Wi-Fi, wireless fidelity

## Wireless connectivity using KNN

The sensor device is a constrained resource, making it challenging to implement a complex algorithm [34]. This paper addresses this limitation by utilizing a binary KNN algorithm with a K value of 2, which leverages the selection of wireless technology as a binary decision. The KNN algorithm facilitates the establishment of a complete path setup between the resource-constrained sensor node and the anchor node. It starts by classifying the sensor nodes into two categories based on their sensing data rates: category A (low bit rates, such as Bluetooth and ZigBee) and category B (high bit rates, such as Wi-Fi and LTE), as shown in Figure 6. Sensor A is located in agricultural area D (X, Y) with coordinates SA ($x_a$, $y_a$) with an omnidirectional radiation pattern as a circle with a radius $R_A$. Sensor B is also situated in agricultural area D (X, Y) with coordinates SB ($x_b$, $y_b$) and with an omnidirectional radiation pattern as a circle with a radius $R_B$, while the newly placed sensor, SN, has coordinates SN ($x_n$, $y_n$) and with an omnidirectional radiation pattern as a circle with a radius $R_N$.

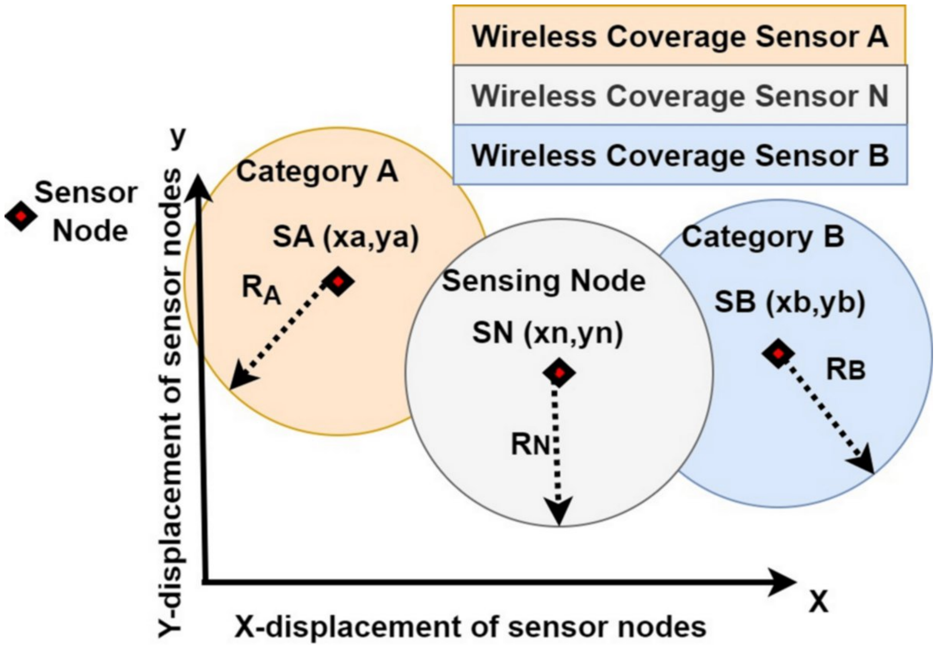



**FIGURE 6: Wireless coverage of sensor node distribution through agricultural field D (X, Y)**

The sensing node offers various heterogeneous wireless connection possibilities as a MEC communication device. The KNN algorithm evaluates the wireless network switching decisions of the sensor node by determining its classification as either category A or B, along with avoiding interference and jamming of signals between adjacent sensors [35]. Category A employs low data-rate wireless technology, while category B utilizes high wireless connectivity. Dynamic switching is guided by the physical parameters of the sensing object; nearly all sensing objects rely on low data rates, except for the plant photo, which requires a high data rate. The KNN method facilitates this dynamic switching throughout the communication path from the resource-constrained sensor to the anchor node. Switching is based on the sensing parameter size. For a heterogeneous network (Wi-Fi and Bluetooth) the small-size sensing parameters are sent over the Bluetooth connection, and large-size sensing parameters are sent over the Wi-Fi connection. The switching is done in real time through the anchor node or the controller.

## The proposed orchestrated WSN system design

The proposed orchestrated WSN system design is an object that maintains an economical sensor distribution for achieving better sensing, coverage, latency, and power consumption. The proposed system design implementation plan requires three main stages, as shown in Figure 7.

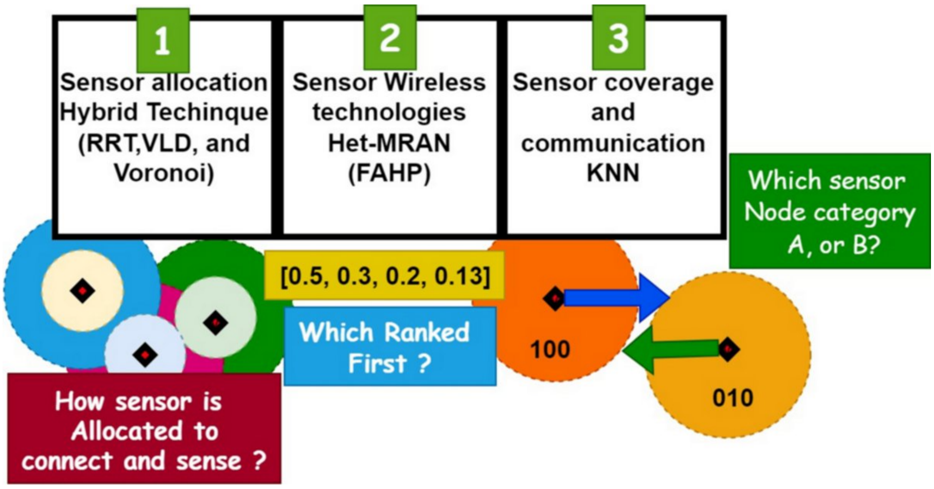



**FIGURE 7: WSN orchestrated design methodology**

WSN, wireless sensor network; RRT, random trees; VLD, variable length distance; Het-MRAN, heterogeneous multiple radio access network; FAHP, Fuzzy Analytical Hierarchical Process; KNN, k-nearest neighbors

The proposed design methodology for the orchestrated WSN system consists of three key stages, as shown in the block diagram in Figure 7. The first stage involves allocating sensors using the proposed hybrid technique. The second stage evaluates the most commonly used heterogeneous wireless technologies to assess the sensors' communication heterogeneity. Finally, the third stage ensures sensor coverage through Het-MRAN and establishes a wireless communication path for the MEC capable sensor nodes using KNN.

## Sensor allocation methods

The sensor allocation methodology examines a 214.2-acre agricultural farm [14]. This agricultural system enables systematically planting 60 rows of trees 5 meters apart in 60 columns perpendicular to the main irrigation channel. The farm features both central and sub-irrigation gates. A key objective is implementing an innovative sensor allocation and coverage strategy throughout the area. The approach employs a clustering technique to streamline the design process by dividing the total agricultural area into sub-areas. This is done based on various attributes about the types of sensor nodes, whether they are HIAS or LAIS, as well as considerations regarding deployment and communication processes, which include aspects like capacity, coverage, latency, and power consumption. The methodology posits that the 214.2 acres will be organized into 10 sub-areas, each measuring 300 by 300 meters, as illustrated in Figure 8.

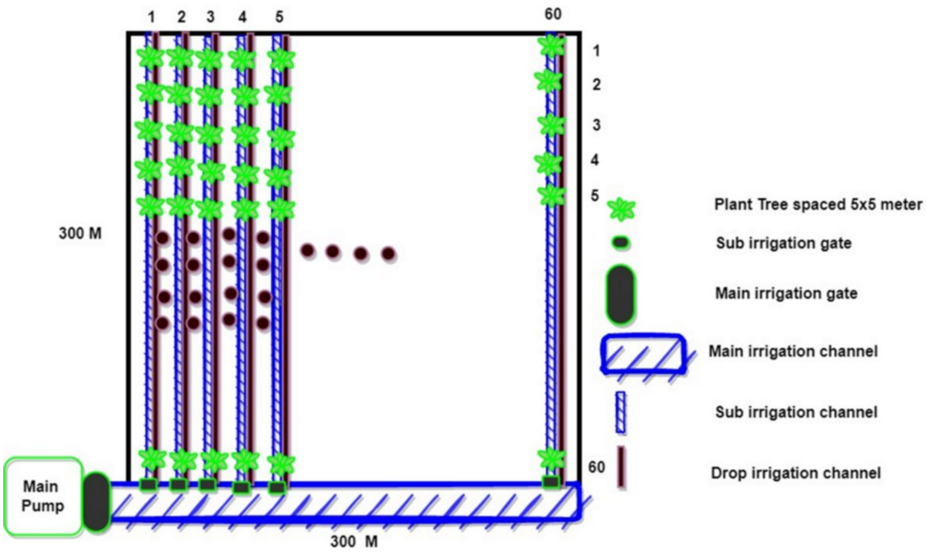



**FIGURE 8: Agriculture plot cluster**

As depicted in Figure 8, the pedestrian agriculture plot is meticulously designed with a network of 60 drop irrigation channels, complemented by several flood irrigation sub-channels. Each channel nurtures 60 thriving tree plants, resulting in 3,600 sensing objects dedicated to monitoring plant health. This intricate setup optimizes water usage and ensures that each plant receives the attention it needs for robust growth and vitality. This uniform distribution of sensor nodes is costly as it requires a big budget for sensor node devices and wireless coverage devices.

## The proposed hybrid sensor allocation method

The proposed allocation method adopts a hybrid solution [36] of mathematical and graphical methods to determine the minimum number of sensors and maximize the sensing coverage area. The proposed hybrid method relies on the following:

· Sensing path or determination of the effective sensing area

· Mathematical distribution based on Manhattan distance

· Range-free allocation technique.

## Area sampling technique

The total sensing pass using a rapidly exploring RRT is adopted to determine the area of interest for deploying sensor nodes [37]. Decreasing the area or determination of a sensing path aids in reducing the total number of sensors and allocating the sensor effectively. The method plans the path taken by the autonomous vehicle (UAV, drone, robot, and car) through a continuous closed-loop path [38]. The vehicle traces a tunnel as a path of a constant conical shape trajectory. The trajectory of the conical shape uses a series of trigonometry vertices to guide the movement through the path, as illustrated in Figure 9.

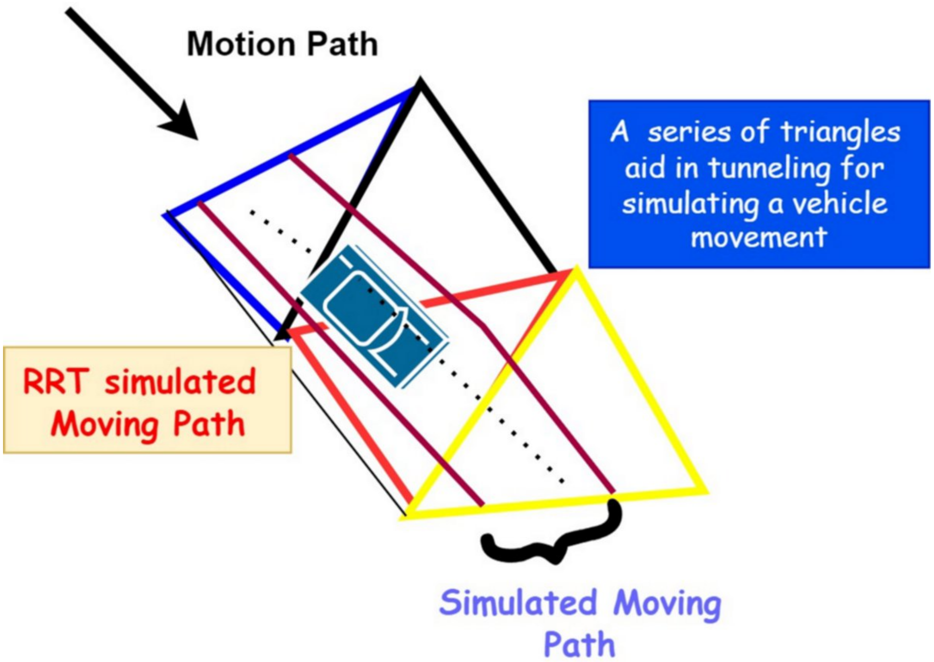



**FIGURE 9: Triangulation method used with RRT to develop a closed loop path**

RRT, random trees

This moving path is vital for determining the interesting sensing area, which minimizes the required node number for the total area. The RRT method develops a graphical solution of the sampling area to reduce the number of sensor allocations. However, a mathematical method ensures the graphical solution and provides a better tie of the final number of sensors.

## Mathematical solution: VLD

To our knowledge, the hybrid algorithm combines graphical and mathematical solutions to provide the best solution. However, the proposed mathematical solution, the VLD technique, employs the Manhattan distance to minimize the number of sensors. It estimates the allocation of nodes using the long edge distance of the cluster area, which is 150 m. Sensor node allocation is maintained based on bounding conditions. This condition limits the sensing distance spacing between nodes dsi, as given in equation (1).

$$20 \leq dsi \leq 50 \ (1)$$

The mathematical solutions consider the physical distance constraint in designing the wireless coverage, as given in equation (1). The maximum limit of the Wi-Fi is the wireless coverage limit of 50 m, and the minimum limit is the Bluetooth wireless coverage limit of 20 m. The interspacing sensor distance should maintain a considerable value between the maximum and minimum values. The Manhattan distance determines the localization distance based on the right-angle distance rule, as given by:

$$D = |P1 - q1| + |P2 - q2| \ (2)$$

Equation (2) illustrates the allocation of Manhattan distance utilizing proper right-angle distance measures between two points with different coordinates. This distance allocation framework employs the coordinates of the category A anchor nodes, designated as ($P_1$, $P_2$), to determine the position of the category B sensor node, represented by ($q_1$, $q_2$). The relationship and calculation are visually depicted in Figure *10*, which clarifies how the anchor nodes facilitate the measurement of the distance to the sensor node within a defined two-dimensional space.

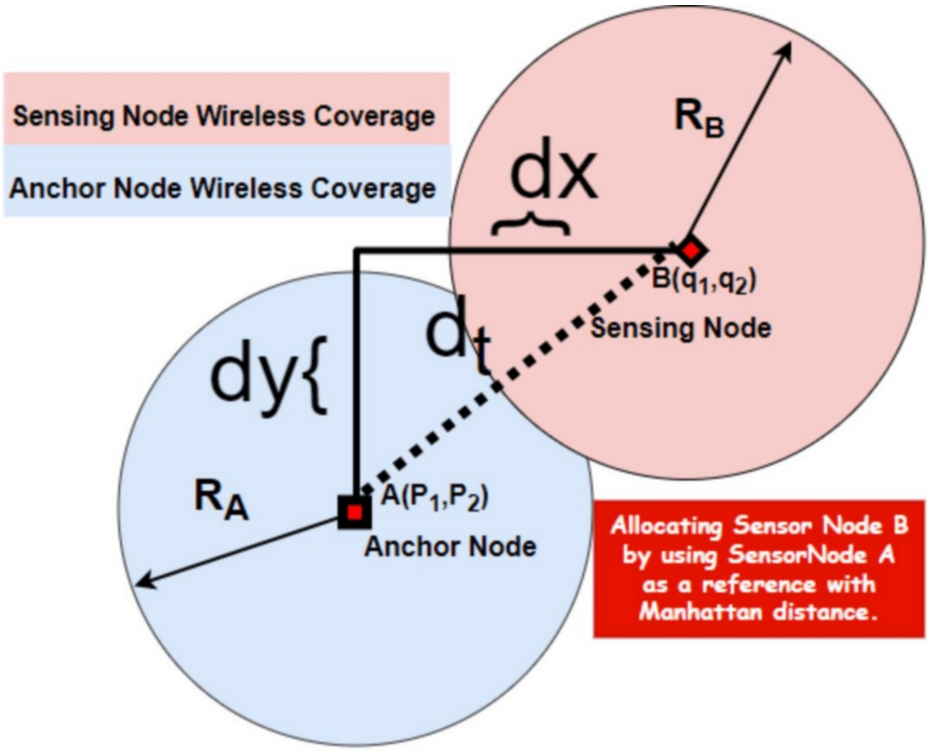



**FIGURE 10: Sensor distance localization using Manhattan distance**

Evaluating the distance requires using the Manhattan equation as represented in equation (2), which also satisfies the trigonometry equation given in equation (3).

$$dt = (\sqrt{(dy)^2 + (dx)^2})(3)$$

Rather than employing a generalized method to distribute the sensor across the entire environment, utilizing a designated, unique sensor is more effective. The anchor node is the pivotal extended area sensing component within its cluster and is utilized only once. This node plays a crucial role in collecting and consolidating data from the various sensor nodes, establishing a star topology connection. This structured approach allows for efficient data aggregation, as depicted in Figure *11*, enhancing the sensing process's reliability and accuracy.

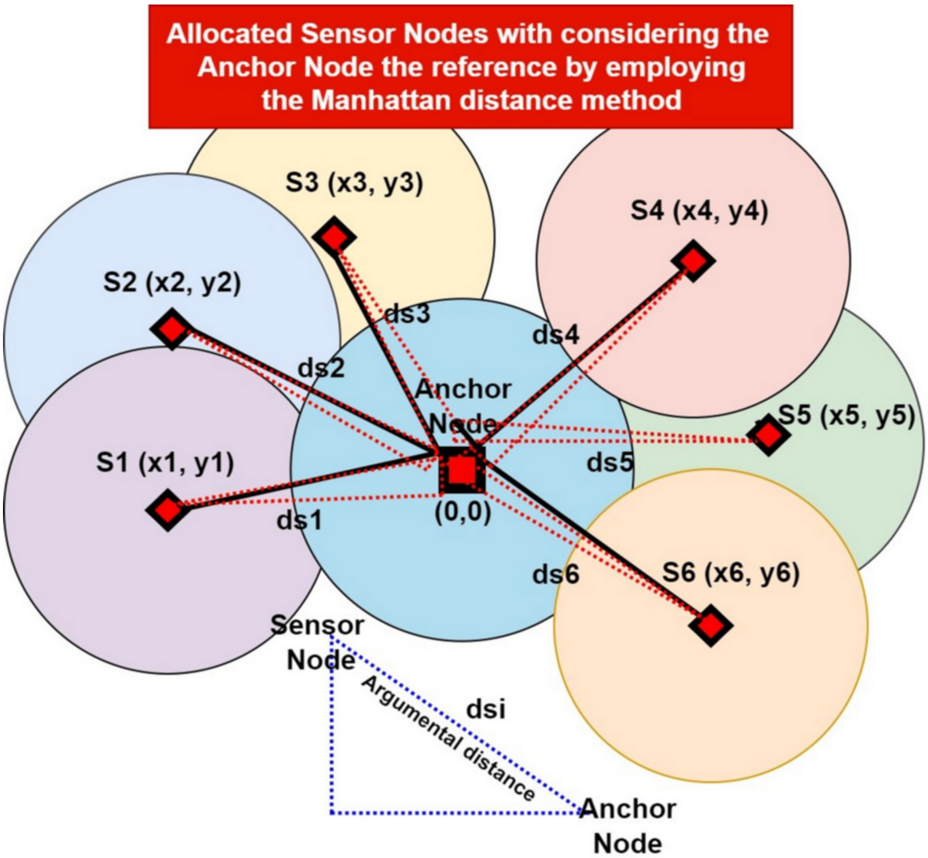



**FIGURE 11: Connecting anchor to other sensor nodes in a star topology connection**

Star topology vividly represents dynamic relationships within a network, centering around an anchor node that functions like the core hub of a wheel. In contrast, the other sensing nodes radiate outward like the spokes. In this configuration, the coordinates of the anchor node serve as the central reference point for all surrounding sensing nodes, which are designated as (0,0) for simplicity. Interestingly, even though the anchor node's coordinates are labeled as (0,0), it is strategically positioned at point D, with actual coordinates of (150,150). This indicates that the anchor node is situated 150 meters horizontally from the nearest edge and 150 meters vertically from the top boundary of the designated area, effectively creating a pivotal point for the entire network's functionality. All six other nodes coordinate Si ($x_i$, $y_i$), where i = 1:6 is an outcome of a variable argument according to the Manhattan distance rule from the anchor node. This distance rule must adhere to the sensing and minimum wireless coverage ranges.

## Computation graphic solution (Voronoi)

Followed by sensing range allocation based on a nonuniform pattern graphical solution using the Voronoi algorithm as a range-free method. Voronoi is the nonuniform pattern, considered a more realistic representation of the omnidirectional antenna and directional pattern deformation. Deformation is possible based on the multipath transmission and environmental effects on wireless communication, so the node pattern allocation is more relevant when using Voronoi. Voronoi simulates the heat map of the wireless signals within an area of nodes. Voronoi partitions the area based on polygons to aid in heterogeneous sensors for more realistic connectivity solutions, as illustrated in Figure 12.

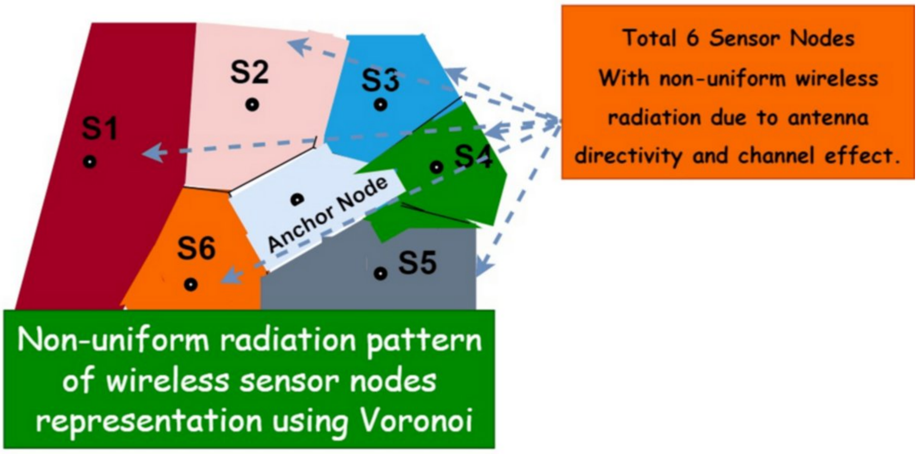
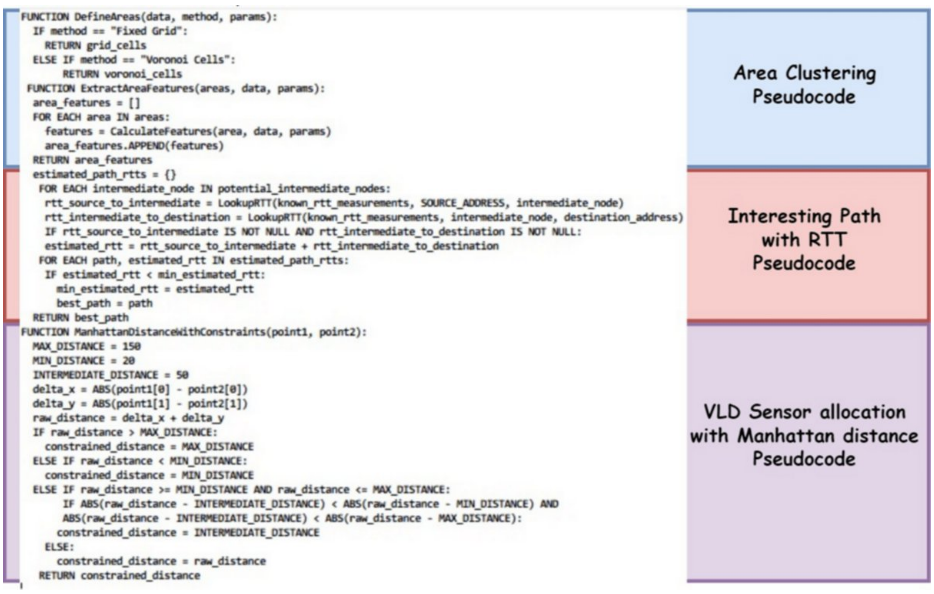



**FIGURE 12: Sensor wireless signal radiation formation using Voronoi**

The proposed sensor allocation is depicted in Figure *12*, highlighting a strategically positioned anchor node at the center of the designated area. This anchor node, marked as point P, has specific coordinates represented by (P1, P2). Surrounding the anchor, various sensor nodes-Q nodes-are deployed at distinct coordinates indicated by ($q_n$, $q_m$). Here, "n" denotes the starting coordinate, while "m" indicates the ending coordinate for each sensor node. These sensor nodes are arranged around the anchor node in diverse, nonuniform deployment patterns shaped by factors such as their signal strength, the characteristics of the environment, and the level of interference present. This thoughtful arrangement is crucial for optimizing sensor performance and maintaining effective communication within the sensor network. Moreover, the novelty of combining Manhattan distance with Voronoi is to provide a near-reality distribution of frequencies within the sensor allocation points. The real-world deployment is also highlighted to make use of this method by mitigating interference, overlapping, and jamming. The proposed design provides robust connectivity, economic, scalable, and reliable. A pseudo-code for the proposed hybrid algorithm is shown in Figure *13*.



```
FUNCTION DefineAreas(data, method, params):
  IF method == "Fixed Grid":
    RETURN grid_cells
  ELSE IF method == "Voronoi Cells":
       RETURN voronoi_cells
 FUNCTION ExtractAreaFeatures(areas, data, params):
  area_features = []
  FOR EACH area IN areas:
    features = CalculateFeatures(area, data, params)
    area_features.APPEND(features)
  RETURN area_features
  estimated_path_rtts = {}
   FOR EACH intermediate_node IN potential_intermediate_nodes:
    rtt_source_to_intermediate = LookupRTT(known_rtt_measurements, SOURCE_ADDRESS, intermediate_node)
    rtt_intermediate_to_destination = LookupRTT(known_rtt_measurements, intermediate_node, destination_address)
    IF rtt_source_to_intermediate IS NOT NULL AND rtt_intermediate_to_destination IS NOT NULL:
    estimated_rtt = rtt_source_to_intermediate + rtt_intermediate_to_destination
   FOR EACH path, estimated_rtt IN estimated_path_rtts:
    IF estimated_rtt < min_estimated_rtt:
      min_estimated_rtt = estimated_rtt
      best_path = path
  RETURN best_path
FUNCTION ManhattanDistanceWithConstraints(point1, point2):
  MAX_DISTANCE = 150
  MIN_DISTANCE = 20
  INTERMEDIATE_DISTANCE = 50
  delta_x = ABS(point1[0] - point2[0])
  delta_y = ABS(point1[1] - point2[1])
  raw_distance = delta_x + delta_y
  IF raw_distance > MAX_DISTANCE:
    constrained_distance = MAX_DISTANCE
  ELSE IF raw_distance < MIN_DISTANCE:
    constrained_distance = MIN_DISTANCE
  ELSE IF raw_distance >= MIN_DISTANCE AND raw_distance <= MAX_DISTANCE:
       IF ABS(raw_distance - INTERMEDIATE_DISTANCE) < ABS(raw_distance - MIN_DISTANCE) AND
       ABS(raw_distance - INTERMEDIATE_DISTANCE) < ABS(raw_distance - MAX_DISTANCE):
      constrained_distance = INTERMEDIATE_DISTANCE
    ELSE:
      constrained_distance = raw_distance
   RETURN constrained_distance
```



**FIGURE 13: The proposed hybrid algorithm pseudo-code**

As illustrated in Figure *13*, the proposed hybrid algorithm consists of three main phases:

Area clustering.

Interesting path for allocating sensor nodes.

VLD method using Manhattan distance for determining the accurate allocation points.

Those stages are executed in sequence as illustrated in the hybrid algorithm pseudo-code and yield a better allocation of sensor node with minimum number of nodes, maximum sensing range/coverage, lowest latency, and better scalability.

## Results

The agricultural area under investigation is a deterministic agrarian area with a dimension of 300 × 300 meters squared. The sensors are of two types: a resource-constrained sensor (LAIS), which is required to spread through the area, and the anchor sensor node (HAIS), which requires only one unit within the cluster. The simulation uses a MATLAB 2024 simulator and a laptop with a hardware configuration such as Dell latitude E7250, an Intel core i7 VPRO processor with a clock speed of 2.59 Gigahertz (GHz), 16 Gigabyte (GB) random access memory (RAM), and 250 Gigabyte (GB) Solid State Drive (SSD) storage.

### Sensor localization and deployment results

As stated in the methodology section, deploying (the LAIS) sensor type with uniform distribution through the 300 × 300 meter squared equals 3600 as a 60 × 60 sensor node. The uniform distribution has high-density sensors within the uniform grid clustered area, as shown in Figure 14.

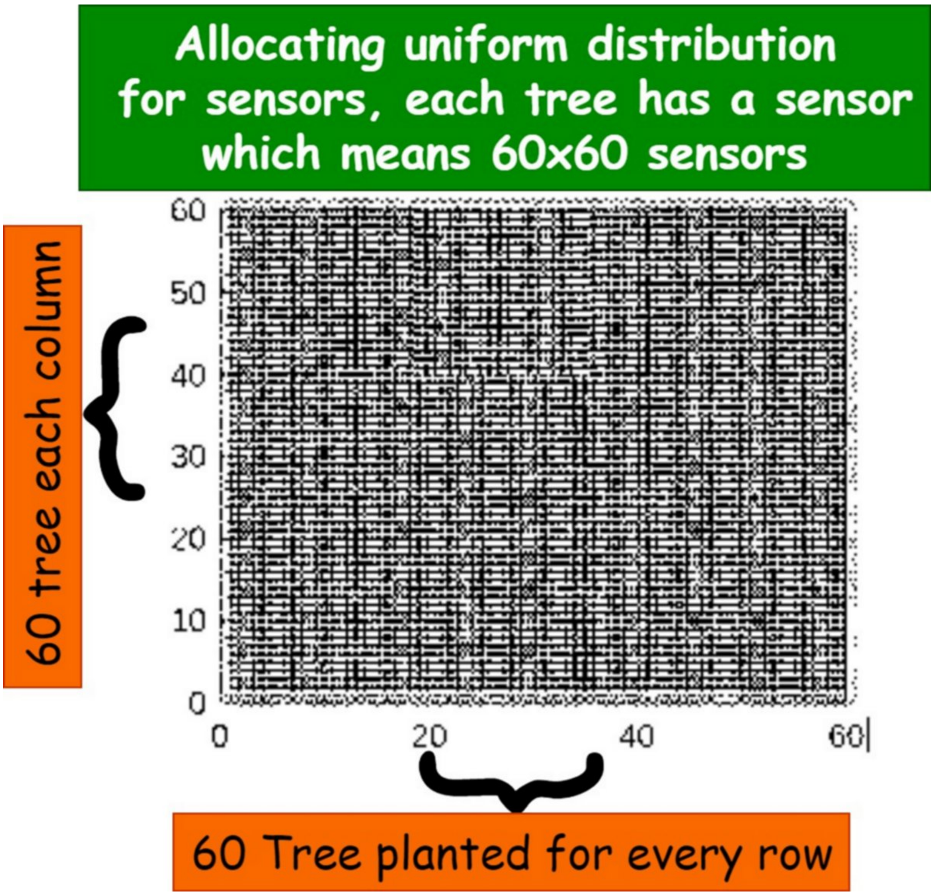



**FIGURE 14: Uniform distribution of sensor nodes through the agriculture plot cluster**

The distribution of 3600 nodes has a high implementation cost, power consumption, and delay. Moreover, it has zero sensor allocation error and highly efficient sensing of the agricultural field parameters. However, the implementation cost and power consumption demands prevent its deployment. Utilizing the Gaussian distribution of sensor nodes through the examined agricultural field cluster, as illustrated in Figure 15, provides more centralized sensing coverage.

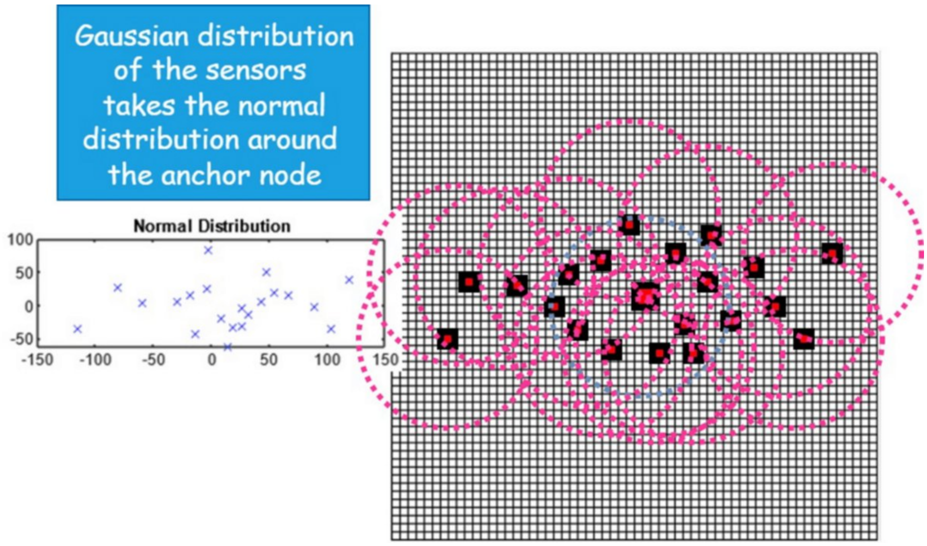



**FIGURE 15: Gaussian distribution of sensor nodes through the agriculture plot cluster**

The Gaussian distribution of sensor nodes through the examined agriculture plot cluster achieved a sensing coverage of 65%, necessitating the deployment of 21 sensor nodes. The sensor distribution used the Gaussian function and the sensing coverage of the agriculture field cluster is obtained using the area function within the MATLAB simulator. While this method was effective in ensuring good coverage with a relatively small number of nodes, it ultimately resulted in a less efficient sensing area, as the nodes were primarily clustered around the central anchor node. In contrast, when analyzing the widely adopted PSO technique, 36 nodes were strategically deployed. As illustrated in Figure *16*, these nodes, referred to as 36 PSO, enhanced the sensing coverage to an impressive 76%. The sensor nodes are distributed using the PSO algorithm within the MATLAB simulator, employing the area function to determine the sensing coverage of the 36 distributed sensor nodes. This optimization not only improved coverage but also expanded the effective sensing area, offering a more balanced distribution of nodes across the operational space.

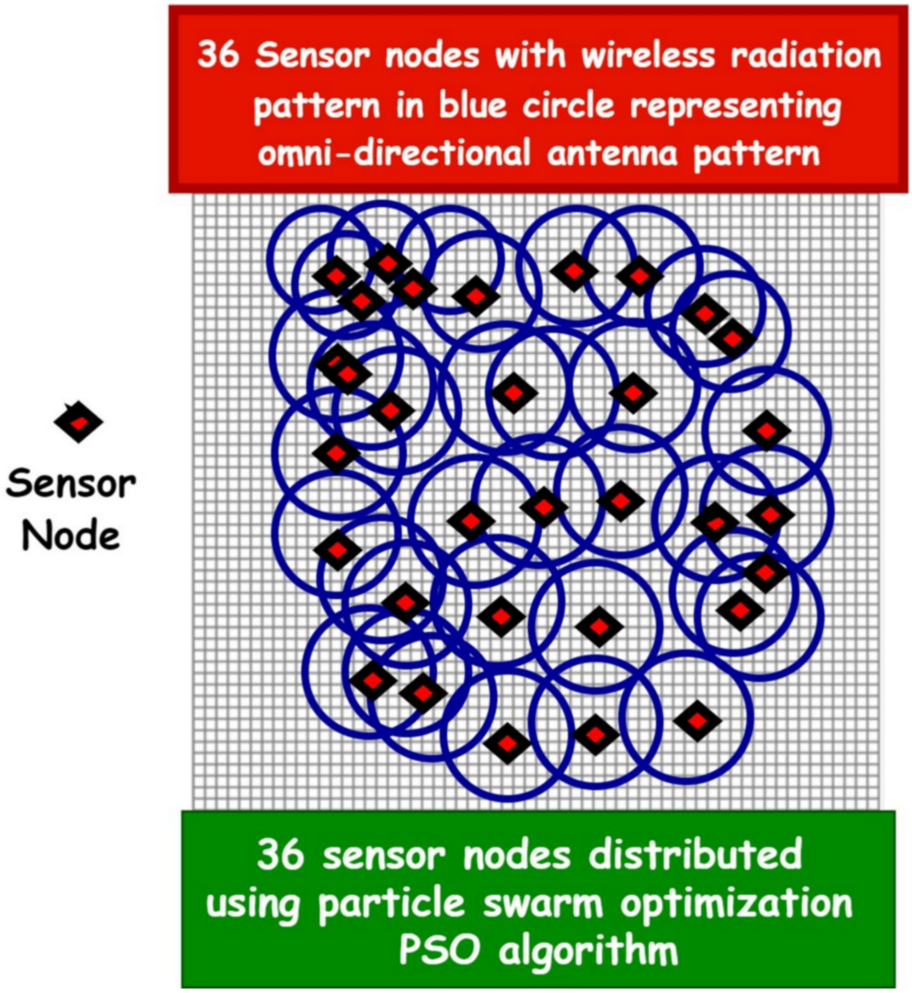



**FIGURE 16: PSO distribution of sensor nodes through the agriculture plot cluster**

PSO, Particle Swarm Optimization

The PSO, while providing more efficient sensing coverage, demanded more sensor nodes and presented challenges in controlling the capacity of the WSN. The proposed hybrid allocation algorithm, on the other hand, demonstrated an optimization between the effective sensing area and the minimum allocated sensor nodes. This algorithm, which used the mathematical process to investigate the minimum number of nodes while using the graphical solution method minimum area, proved to be a promising solution. The graphical solution used in the RRT and Triangulation method investigated the formation of a closed loop sample area from the total area, as illustrated in Figure *17*. This graphical solution optimized the agriculture plot cluster area and further validated the efficiency of the proposed hybrid algorithm.

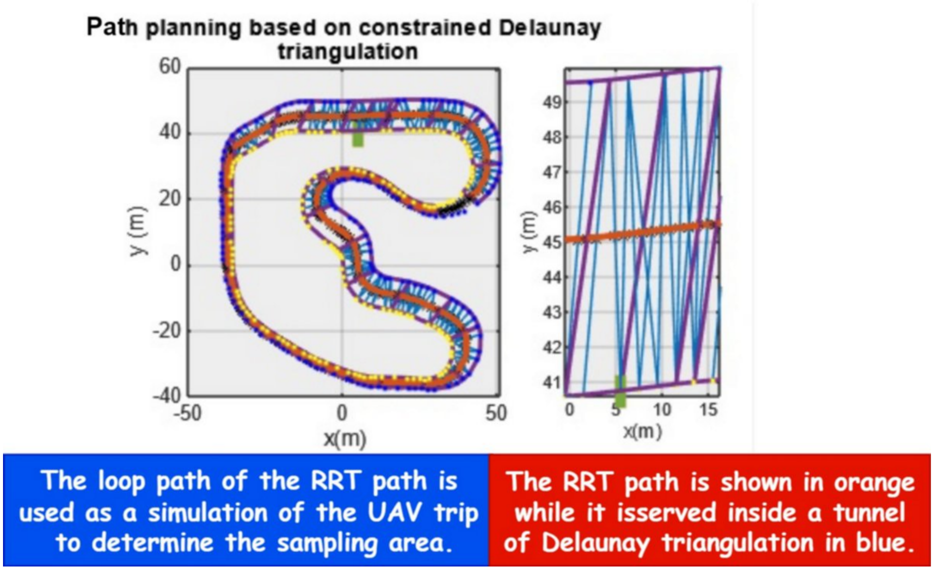



**FIGURE 17: Optimized agriculture plot cluster area obtained using RRT and Triangulation method**

RRT, random trees; UAV, Unmanned Aerial Vehicle

The optimized agriculture plot cluster area appeared to be an efficient graphical solution for minimizing the overall cluster area. It offered a promising solution to minimize the number of nodes and improve sensing coverage. However, the mathematical method's rule is to determine the number of nodes and its allocation precisely. The hypothesis uses the Manhattan distance, which has a maximum right-angle distance $D_{max}$ of 150 m, a minimum sensing range of 20 m, and a maximum sensing range of 50 m. This limitation within the Manhattan distance provided a VLD solution that was interesting or localized within the sample area. The proposed VLD solution deployed 12 nodes, as illustrated in Figure *18*.

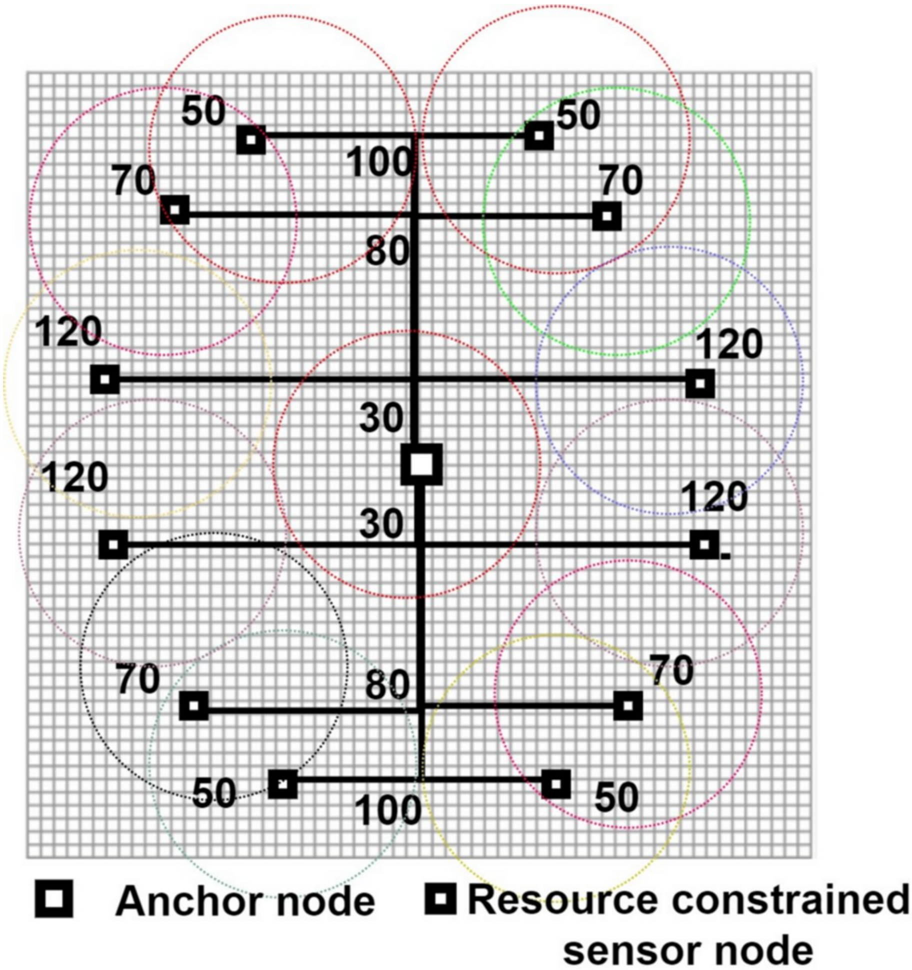



**FIGURE 18: VLD as a mathematical solution to distribute the sensor nodes through the agriculture plot cluster**

VLD, variable length distance

As illustrated in Figure 18, the sensor nodes deployment process started by allocating the anchor node at the center of the agriculture plot cluster. The anchor node, a key component in our proposed algorithm, is a reference point for the sensor nodes deployment process. It plays a crucial role in determining the optimal allocation of sensor nodes. At the same time, sensors are allocated starting with the anchor node and using the VLD method to allocate the sensor nodes, as given in equation (2). The VLD method validates only 12 sensor nodes and a single anchor node per cluster. The coordinates of those nodes are listed in Table 2.

| Node ID | X coordinates | Y coordinates |
|---|---|---|
| 1st node | 120 | 30 |
| 2nd node | 70 | 80 |
| 3rd node | 50 | 100 |
| 4th node | -120 | 30 |
| 5th node | -70 | 80 |
| 6th node | -50 | 100 |
| 7th node | 120 | -30 |
| 8th node | 70 | -80 |
| 9th node | 50 | -100 |
| 10th node | -120 | -30 |
| 11th node | -70 | -80 |
| 12th node | -50 | -100 |

**TABLE 2: Sensor nodes final coordinates**

The total nodes presented satisfy the mathematical criteria of the proposed VLD method. The localization of the sensor nodes is achieved by integrating the VLD method with the sample area generated by RRT, as illustrated in Figure *15*. By combining Figures *17* and 18, we achieved a more effective allocation of the nodes, as shown in Figure *19*.

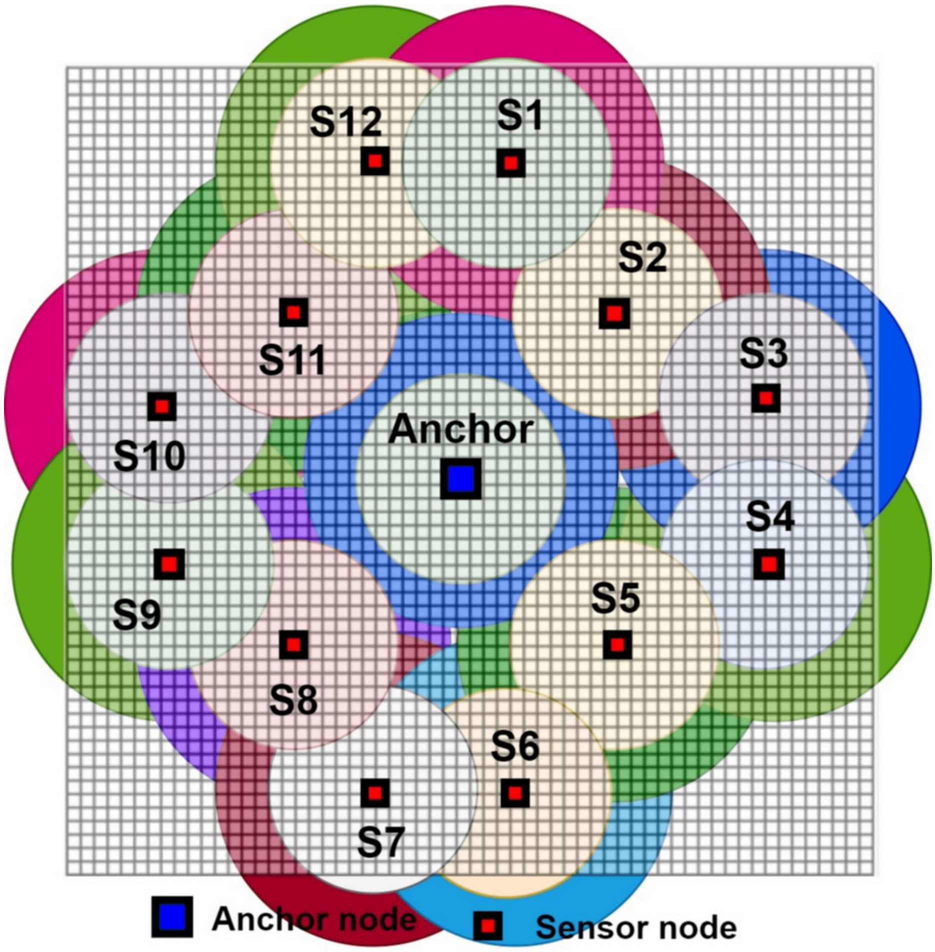



**FIGURE 19: The proposed hybrid method distribution of sensor nodes through the agriculture plot cluster**

Our proposed algorithm utilizes a streamlined network composed of 13 nodes, including 12 sensor nodes and one controller or anchor node, to achieve near-optimal sensing coverage. Remarkably, the algorithm reached a coverage rate of 86% of the monitored area, highlighting its outstanding performance. This significant Figure not only demonstrates the effectiveness of the algorithm but also guarantees its reliability in practical applications.

The allocation of the sensor nodes which may vary concerning the deviation of the sensor node from the planned location to the actual placement points. Assuming the ideal case of a plain surface, the error is approximately zero in value; however, for variation of surface levels, the error range may be from 0 to 0.05. The study is based on previous technical studies, as in [14], and builds the assumptions upon its limitations in deploying the sensor nodes. In addition to that, Manhattan distance depends on the right-angle rule for allocating the sensor nodes within the maximum distance value lower than the maximum edge distance to the cluster edge. However, the cluster edge distance was given as 150 meters from the center. Changing the cluster dimension and area for sure will result in changing the maximum right-angle distance. On the other hand, assuming the Wi-Fi and Bluetooth networks limitation with 50 meters and 20 meters as given in [23]. Those may also change based on the wireless technologies used and their corresponding limitation in connectivity.

## Comparing the proposed hybrid allocation method against the PSO method

The comparison evaluates the proposed hybrid sensor nodes deployment method found in Figure *19* against the PSO sensor nodes deployment method results in Figure *16* using the MATLAB heatmap method. Figure *20* illustrates the comparison results between the proposed sensor deployment and the PSO using their MATLAB heat maps.

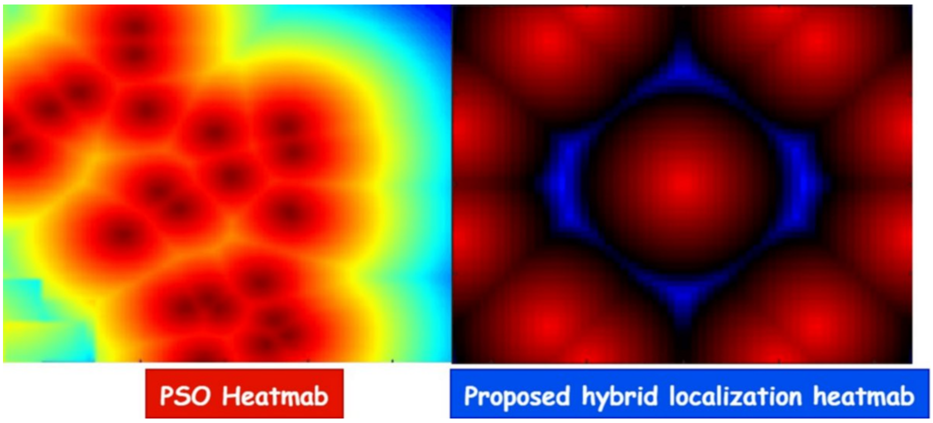



**FIGURE 20: Heatmap comparison of PSO against the proposed hybrid method**

PSO, Particle Swarm Optimization

The results illustrated in Figure *20* reveal a striking contrast in sensing coverage between the proposed hybrid method and the PSO method. On the left side, the PSO heatmap showcases its performance, achieving a mere 76% sensing coverage despite deploying a greater number of sensor nodes. This highlights a limitation in efficiency, as a larger quantity of nodes does not translate to better coverage.

In stark contrast, the heatmap on the right depicts the performance of the proposed hybrid method, which boasts an impressive 86% sensing coverage while employing fewer sensor nodes. This notable enhancement not only underscores the effectiveness of the hybrid approach but also emphasizes its ability to optimize resource utilization. By maximizing efficiency and significantly improving overall sensing capabilities, the hybrid method presents a more robust and effective solution for achieving comprehensive coverage in sensor networks.

## Wireless coverage results

Ensuring wireless coverage for those allocated sensors requires robust heterogeneous wireless infrastructure. The proposed wireless coverage methods apply fuzzy to quantify and rank the wireless technologies with the AHP method, as shown in Figure *21*.

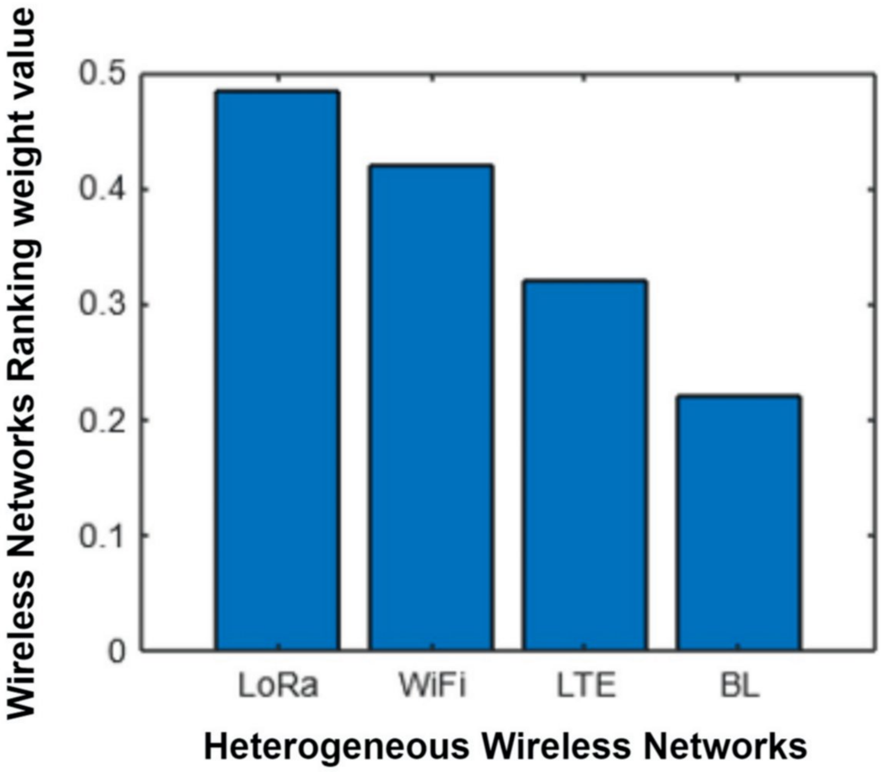



**FIGURE 21: Ranking of wireless technologies using FAHP**

FAHP, Fuzzy Analytical Hierarchical Process; LoRa, low power area network; LTE, Long Term-Evolution

However, according to the data transmission requirements of the sensing object, the sensors are transmitting at a low and high data rate. The heterogeneity of the wireless infrastructure provides connectivity sustainability. Maintaining the sensor transmission according to the sensing object requires switching between the heterogeneous wireless networks based on the ranking, as shown in Figure *20*. The KNN method, a key part of our proposed algorithm, is a machine-learning technique that helps in the binary selection of wireless networks based on sensing objects. The KNN method selects between two Het-MRAN groups according to the sensing objects. The first group contains LoRa and Wi-Fi (high coverage-low bit rate, low coverage-high bit rate), and the second group is LTE and BL (high coverage-high bit rate, low coverage, low bit rate). Switching between wireless connectivity is maintained by the anchor node controller and executed by the constrained resources node, a critical component that manages the network resources and ensures the smooth operation of the network. As illustrated in Table *3*, the binary KNN wireless network switching truth table is maintained based on the sensing object demands.

| Case | Sensor A | Sensor B | Chosen | |
|---|---|---|---|---|
| | | | Tech A | Tech **B** |
| 1 | Low data | High data | BL | Wi-Fi |
| 2 | Low data | Low data | BL | BL |
| 3 | High data | Low data | Wi-Fi | BL |
| 4 | High data | High data | Wi-Fi | Wi-Fi |

**TABLE 3: KNN truth table**

KNN, K-nearest neighbors

The proposed solution perform switching based on the sensing object data size. The low data rate connection satisfies the transmission of the low data size sensing object parameter. On the other hand, the high data rates offer a transmission needs for the large data size as a sensing object parameter. As an instance, the low data size sensing object is the temperature, and the high data size sensing object is the plant photo.

(1) The sensor captures a plant photo and is required to transmit it to the anchor node for analysis. The anchor node is sensing a soil parameter with a low data rate. So, the KNN switches Sensor A to BL and Sensor B to Wi-Fi. At the same time, a Wi-Fi communication path between Sensor A and Sensor B must be maintained.

(2) The sensor senses the weather parameters and is required to transmit it to the anchor node for analysis. The anchor node is sensing a water parameter with a low data rate. So, the KNN switches Sensor A and Sensor B to use BL, and a BL communication path between Sensor A and Sensor B is established.

(3) The sensor senses the soil salinity parameters and is required to transmit it to the anchor node for analysis. The anchor node captures plant photos to analyze the infection, which has a high data rate. So, the KNN switches Sensor A to a Wi-Fi communication while Sensor B uses BL, establishing a BL communication path between Sensor A and Sensor B.

(4) The sensor captures the plant photo for leave analysis and is required to transmit it to the anchor node for analysis. Also, the anchor node captures the plant photo for weed analysis, which has a high data rate. So, the KNN switches Sensor A and Sensor B to use Wi-Fi and establishes a Wi-Fi path of communication between Sensor A and Sensor B.

# Discussion

## Energy calculation for wireless coverage and performance estimation

Four scenarios are based on the KNN path establishment and sensor wireless communication with the Het-MRAN coverage. The four scenarios of sensor wireless path within the four shortlisted Het-RAN coverage provide the following possibilities:

(1) High bit rate wireless transmission with low coverage (Wi-Fi) and Low bit rate wireless transmission with Low coverage (BL). Economic wireless coverage provides low coverage with a low implementation cost.

(2) High bit rate with high wireless coverage (LTE) and Low bit rate with High Wireless Coverage (LoRa). This is the highest-cost wireless coverage implementation but provides the best coverage solution. Moreover, it depends on enterprise infrastructure unavailable in rural areas.

(3) High bit rate with low wireless coverage (Wi-Fi) and Low bit rate with High Wireless Coverage (LoRa). This moderate solution provides an economical solution within the high bit rate transmission but is most costly within the low bit rate transmission.

(4) High bit rate with high wireless coverage (LTE) and Low bit rate with Low coverage (BL). This advanced-moderate solution provides a tradeoff between cost and wireless coverage. The high bit rate provides the best coverage with a high implementation cost. Despite the low bit rate, transmission has a low coverage and implementation cost.

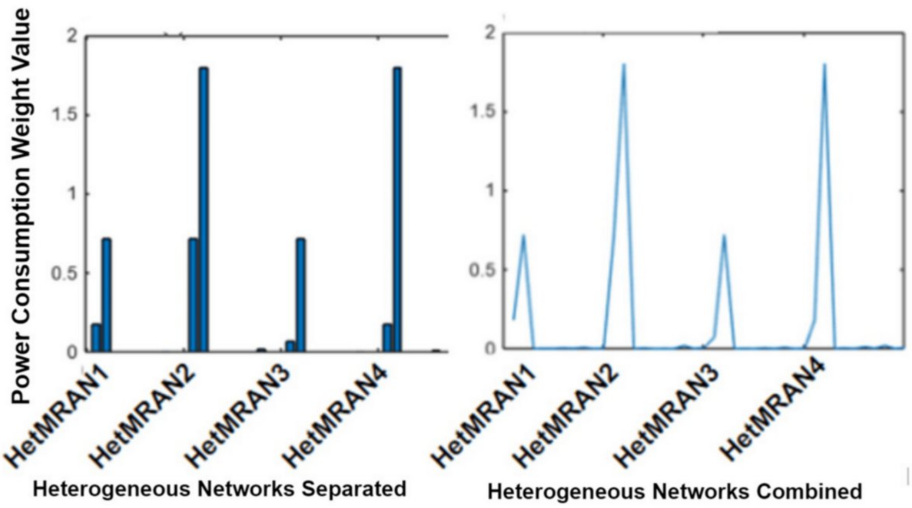
Based on those scenarios, performance estimation for power consumption and coverage is investigated. Table *4* outlines the total power consumption per cluster based on the implemented sensor localization solution and the power consumption rate found in Table *1* relevant to the wireless characteristics.

| localization Solution | Het-MRAN [1] | | Het-MRAN [2] | | Het-MRAN [3] | | Het-MRAN [4] | |
|---|---|---|---|---|---|---|---|---|
| | BL (W) | Wi-Fi (W) | LoRa (W) | LTE (W) | LoRa (W) | Wi-Fi (W) | BL (W) | LTE (W) |
| Uniform sensor distribution (3600 nodes) | 1800 | 7200 | 720 | 18000 | 720 | 7200 | 1800 | 18000 |
| Gaussian (21 nodes) | 10.5 | 42 | 4.2 | 105 | 4.2 | 42 | 10.5 | 105 |
| PSO (36 nodes) | 18 | 72 | 7.2 | 180 | 7.2 | 72 | 18 | 180 |
| Hybrid-Proposed (13 nodes) | 6.5 | 26 | 2.6 | 65 | 2.6 | 26 | 6.5 | 65 |

### TABLE 4: Het-MRAN four scenarios and relevant power consumption

Het-MRAN, heterogeneous multiple radio access network; PSO, Particle Swarm Optimization; LTE, Long Term-Evolution; LoRa, low power area network; Wi-Fi, wireless fidelity

Table *4* provides a detailed analysis of the power consumption patterns observed across different wireless networks, highlighting the significant impact of sensor localization on energy usage. The data presented offer insights into how various configurations and positioning of sensors influence overall network efficiency and power demands. These data illustrate that the proposed hybrid sensor distribution has the lowest power consumption rates, as shown in Figure *22*.




### FIGURE 22: Power consumption rates

As depicted in Figure *22*, the power consumption for the third HetMRAN3 model is notably efficient, demonstrating a commendable balance between performance and energy use. In contrast, the HetMRAN4 model shows a significantly higher power consumption level, indicating a greater energy demand that may impact operational costs and sustainability considerations. By comparing the proposed heterogeneous wireless solution against the practical solution found in [14], the proposed solution guarantees a better connection possibility with two wireless technologies in opposed to only one type. Moreover, the proposed solution offered better power saving by adapting the wireless connection based on the sensing parameter for the observed object. As well, the proposed solution provides better sustainable connectivity for a scalable smart agriculture system in large farms by utilizing a clustering controller approach. The plot of the wireless network Het-MRAN energy consumption vector as a function of the wireless technology is illustrated in Figure *23*.

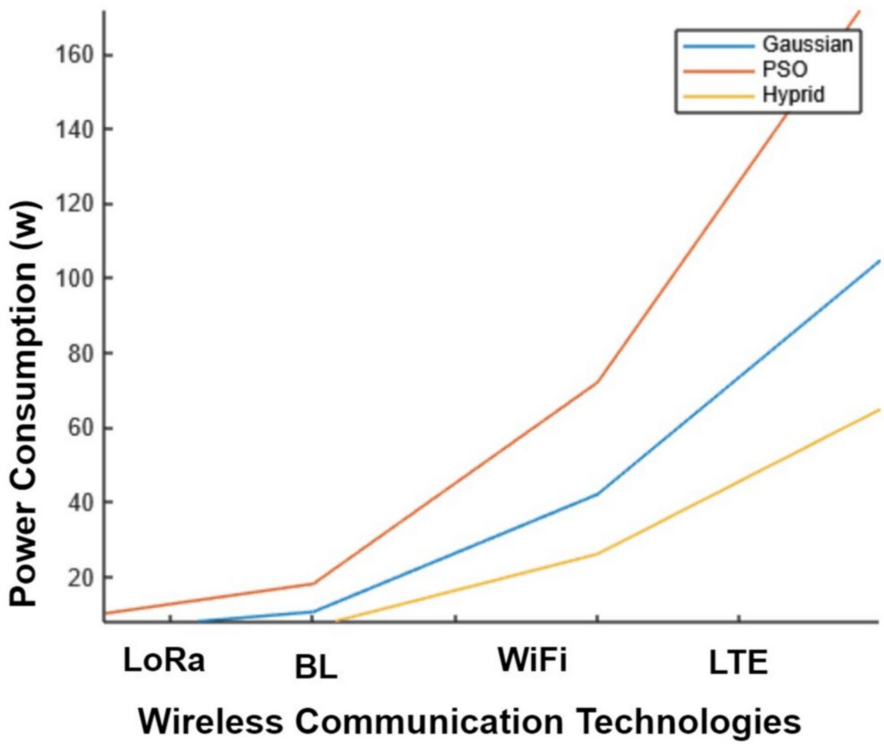



**FIGURE 23: Power consumption per localization method and wireless technologies**

LoRa, low power area network; LTE, Long Term-Evolution; Wi-Fi, wireless fidelity

Figure *21* presents a detailed comparison of the localization methods employed in the simulation for deploying wireless sensor networks. The graph illustrates that the proposed hybrid algorithm exhibits the lowest power consumption rates among the methods analyzed. This is followed by the Gaussian sensor distribution, which ranks as the second most power-efficient approach. In contrast, the PSO-based sensor localization method stands out as the least efficient, exhibiting the highest levels of power consumption. This clear differentiation among the algorithms emphasizes the effectiveness of the hybrid approach in minimizing energy use in wireless sensor network deployments.

## Performance evaluation for wireless coverage

In the meantime, Figure *24* illustrates the performance estimation from a coverage perspective, derived from the deployment of wireless sensors using commonly applied methods in agricultural systems. The proposed hybrid method is expected to deliver enhanced deployment of wireless sensors when compared to widely accepted deployment algorithms. Additionally, it guarantees sustainable connectivity through the Het-MRAN wireless coverage provided by localized sensors.

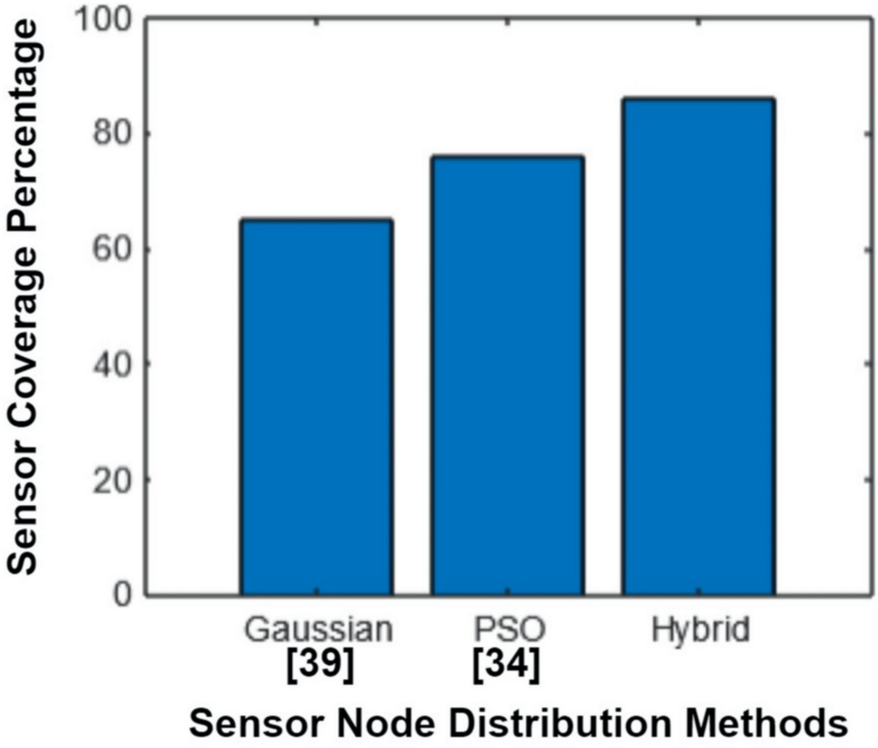



**FIGURE 24: Sensing coverage percentage vs localization method**

PSO, Particle Swarm Optimization

The results, as depicted in Figure 24, demonstrate that the proposed Hybrid method significantly outperformed the other methods in terms of sensing coverage. Specifically, the hybrid approach achieved an impressive 86% sensing coverage, while the PSO distribution method [34] achieved 76%, and the Gaussian distribution method [39] lagged behind at 65%. Compared to its closest competitor, the proposed hybrid approach achieved a score of 1.13 better results, as indicated in the sensing coverage ratio equation (4):

Sensing Coverage Ratio (SCR) = Proposed sensing coverage (0.86)/PSO sensing coverage (0.76) (4)

Remarkably, the proposed method utilized only 13 sensor nodes yet managed to deliver superior sensing coverage while maintaining a minimal power consumption profile. This efficiency underscores the method's effectiveness in optimizing resource usage. Furthermore, Figure 25 illustrates the final sensing coverage achieved by the proposed hybrid algorithm within the designated sample area, highlighting its capability to maximize coverage effectively in the area of interest.

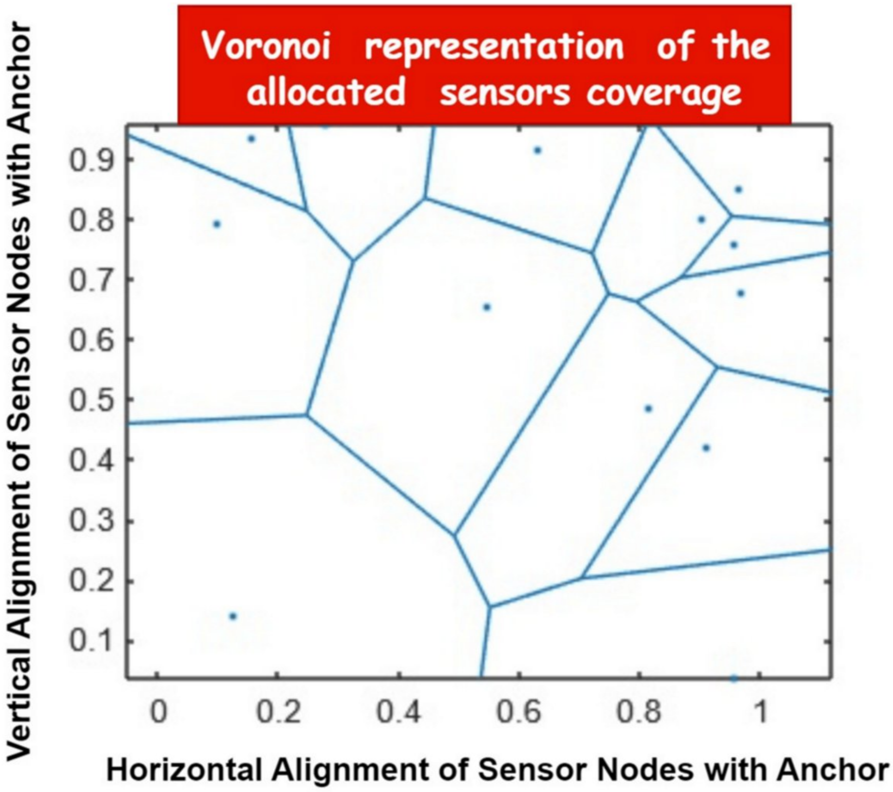



**FIGURE 25: Voronoi diagram of the localized sensors**

As shown in Figure 25, the Voronoi diagram developed in this study illustrates the complex intersection of the nonuniform radiation patterns emitted by the communicating sensor nodes. The deployment strategy involves positioning the anchor sensor node at coordinates p(p1, p2) at the very center of the designated sample area, while strategically placing 12 additional sensing nodes, denoted as $q_i(q_{i1}, q_{i2})$ for i ranging from 1 to 12. Together, these 13 sensor nodes work collaboratively to effectively sense and cover the entire target cluster area, successfully achieving the design objective of comprehensive wireless coverage. Furthermore, the selected number of sensor nodes is carefully determined to ensure a scalable design that promotes interoperable wireless connectivity, minimizes latency, and reduces power consumption to optimize overall system performance.

As a summarized performance metrics a comparison is illustrated in Table 5

| Sensor allocation type | Coverage percentage | Power consumption Wi-Fi-(W) | Allocated nodes | Cost per sensing unit | Scalability (Wi-Fi limitation) | Latency |
|---|---|---|---|---|---|---|
| Gaussian | 65 | 42 | 21 | 21 | low | Low |
| PSO | 76 | 72 | 36 | 36 | lower | High |
| Proposed Hybrid Method | 85 | 26 | 13 | 13 | High | Lowest |

**TABLE 5: Summarized performance metrics**

PSO, Particle Swarm Optimization; Wi-Fi, wireless fidelity

The summarized performance metrics illustrate the achievements of the proposed solution as compared to the Gaussian and PSO methods. The proposed solution provides better coverage percentage for the total area with 85%; however, it provided 100% coverage within the clustered and interesting path. The proposed solution has lower power consumption, which provides longer lifetime of the resource-constrained sensor nodes. The allocated nodes of the proposed solution are smaller than both PSO and

Gaussian, which mean less overall cost and lowest latency. With the lowest number of nodes and a controller to control the sensor nodes within the cluster, the proposed solution provided high scalability solution as well.

# Conclusions

The research examined the connectivity challenges within innovative agricultural systems. It contributed to sensor localization and wireless coverage advancements, addressing some of the most significant connectivity issues. The paper proposed a hybrid algorithm that effectively maintains sensor node localization while ensuring adequate wireless coverage. This research's contributions can be summarized in two key areas. First, it introduced a method for sensor localization by determining a sampling area through a graphical computation solution and applying a VLD mathematical approach for precisely determining the sensors' location coordinates. Guaranteed wireless coverage for sensor nodes with resilient heterogeneous wireless infrastructure ensured connectivity and achieved the sustainable MEC needs. The wireless coverage aspect also explored the Het-MRAN design by ranking the most commonly used wireless technologies utilizing FAHP. This was followed by employing KNN to establish a wireless communication path between the sensor and anchor nodes. Furthermore, comparing the proposed solution with frequently used methods demonstrated improvements in coverage, cost-effectiveness, capacity management, and reduced power consumption. The research achieved 86% coverage with 13 nodes, and 70% lower power consumption rates than the PSO. The proposed solution provides a potential solution for large, especially rural farms. The proposed solution also supports agriculture system, which adopts fixed sensing stations with constrained application of the UAV solution. As a direction for future work, the study recommends conducting an empirical study by deploying the proposed orchestrated design.

# Additional Information

## Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

**Concept and design:** Mohamed H. Naeem, Hussein M. ELAttar, Mohamed Aboul-Dahab

**Acquisition, analysis, or interpretation of data:** Mohamed H. Naeem, Mohamed A. El-Khoreby, Hussein M. ELAttar

**Drafting of the manuscript:** Mohamed H. Naeem, Mohamed A. El-Khoreby

**Critical review of the manuscript for important intellectual content:** Mohamed H. Naeem, Mohamed A. El-Khoreby, Hussein M. ELAttar, Mohamed Aboul-Dahab

**Supervision:** Mohamed Aboul-Dahab

## Disclosures

**Human subjects:** All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

# References

1. Xia L, Robock A, Scherrer K, et al.: Global food insecurity and famine from reduced crop, marine fishery and livestock production due to climate disruption from nuclear war soot injection. Nature Food. 2022, 3:586-96. 10.1038/s43016-022-00573-0
2. Elbasi E, Zaki C, Topcu AE, et al.: Crop prediction model using machine learning algorithms. Applied Sciences. 2023, 13:9288. 10.3390/app13169288
3. Senapaty MK, Ray A, Padhy N: IoT-enabled soil nutrient analysis and crop recommendation model for precision agriculture. Computers. 2023, 12:61. 10.3390/computers12030061
4. Mahajan HB, Badarla A, Junnarkar AA: CL-IoT: cross-layer Internet of Things protocol for intelligent manufacturing of smart farming. Journal of Ambient Intelligence and Humanized Computing. 2021, 12:7777-791. 10.1007/s12652-020-02502-0
5. Singh R, Gehlot A, Akram SV, Thakur AK, Buddhi D, Das PK: Forest 4.0: Digitalization of forest using the Internet of Things (IoT). Journal of King Saud University-Computer and Information Sciences. 2022, 34:5587-601. 10.1016/j.jksuci.2021.02.009

6. Medel-Jiménez F, Krexner T, Gronauer A, Kral I: Life cycle assessment of four different precision agriculture technologies and comparison with a conventional scheme. Journal of Cleaner Production. 2024, 434:140198. 10.1016/j.jclepro.2023.140198
7. Presti DL, Tocco JD, Massaroni C, et al.: Current understanding, challenges, and perspective on portable systems applied to plant monitoring and precision agriculture. Biosensors and Bioelectronics. 2023, 222:115005.
8. Behnke I, Austad H: Real-time performance of industrial IoT communication technologies: A review. IEEE Internet of Things Journal. 2023, 11:7399-410. 10.1109/jiot.2023.3332507
9. Kasera RK, Gour S, Acharjee T: A comprehensive survey on IoT and AI-based applications in different pre-harvest, during-harvest and post-harvest activities of smart agriculture. Computers and Electronics in Agriculture. 2024, 216:108522.
10. Prakash C, Singh LP, Gupta A, Lohan SK: Advancements in smart farming: A comprehensive review of IoT, wireless communication, sensors, and hardware for agricultural automation. Sensors and Actuators A: Physical. 2023, 362:114605. 10.1016/j.sna.2023.114605
11. Abdulrab HQA, Hussin FA, Ismail I, Assaad M, Awang A, Shutari H: Hybrid Harris Hawks with sine cosine for optimal node placement and congestion reduction in an industrial wireless mesh network. IEEE Access. 2023, 11:2500-523. 10.1109/access.2023.3234109
12. Ghahroudi MS, Shahrabi A, Ghoreyshi SM, Alfouzan FA: Distributed node deployment algorithms in mobile wireless sensor networks: survey and challenges. ACM Transactions on Sensor Networks. 2023, 19:1-26. 10.1145/3579034
13. Ahmad R, Alhasan W, Wazirali R, Aleisa N: Optimization algorithms for wireless sensor networks node localization: an overview. IEEE Access. 2024, 12:50459-488. 10.1109/access.2024.3385487
14. Taparci E, Olcay K, Akmandor MO, Kabakulak B, Sarioglu B, Gokdel YD: A mathematical programming approach for IoT-enabled, energy-efficient heterogeneous wireless sensor network design and implementation. Sensors. 2024, 24:1457-80. 10.3390/s24051457
15. Effah E, Thiare O, Wyglinski AM: Hardware evaluation of cluster-based agricultural IoT network. IEEE Access. 2024, 12:33628-651. 10.1109/access.2024.3370230
16. Et-taibi B, Abid MR, Boufounas E, Morchid A, Bourhnane S, Hamed TA, Benhaddou D: Enhancing water management in smart agriculture: A cloud and IoT-Based smart irrigation system. Results in Engineering. 2024, 22:102283. 10.1016/j.rineng.2024.102283
17. Essalhi SE, El Fenni MR, Chafnaji H: A new clustering-based optimized energy approach for fog-enabled IoT networks. IET Networks. 2023, 12:155-66. 10.1049/ntw2.12082
18. Shahab H, Iqbal M, Sohaib A, Khan FU, Waqas M: IoT-based agriculture management techniques for sustainable farming: A comprehensive review. Computers and Electronics in Agriculture . 2024, 220:108851. 10.1016/j.compag.2024.108851
19. Yang C, Xia Y: A novel two-step strategy of non-probabilistic multi-objective optimization for load-dependent sensor placement with interval uncertainties. Mechanical Systems and Signal Processing . 2022, 176:109173. 10.1016/j.ymssp.2022.109173
20. Miao J, Rajasekhar D, Mishra S, Nayak SK, Yadav R: A microservice-based smart agriculture system to detect animal intrusion at the edge. Future Internet. 2024, 16:296. 10.3390/fi16080296
21. Tiwari V, Pandey C, Yadav SS, Roy DS, Pandey OJ, Cenkeramaddi LR: Maximizing coverage and energy conservation in B5G networks using hexagonal tiling to deploy FT-S2ES. IEEE Open Journal of the Communications Society. 2024, 5:2541-554. 10.1109/ojcoms.2024.3389591
22. Yinjun Z: An adaptive hexagonal deployment model for resilient wireless sensor networks in precision agriculture. Scientific Reports. 2024, 14:24078. 10.1038/s41598-024-75571-2
23. Liu Y, Chin KW, Yang C, He T: Nodes deployment for coverage in rechargeable wireless sensor networks. IEEE Transactions on Vehicular Technology. 2019, 68:6064-73. 10.1109/tvt.2019.2912188
24. Bucarelli N, El-Gohary N: Sensor deployment configurations for building energy consumption prediction. Energy and Buildings. 2024, 308:113888. 10.1016/j.enbuild.2024.113888
25. Gou P, Guo B, Gou M, Mao S: VKECE-3D: energy-efficient coverage enhancement in three-dimensional heterogeneous wireless sensor networks based on 3D-voronoi and K-means algorithm. Sensors. 2023, 23:573. 10.3390/s23020573
26. Ahmadi F, Abedi O, Emadi S: Enhancing smart agriculture monitoring via connectivity management scheme and dynamic clustering strategy. Inventions. 2024, 9:10-42. 10.3390/inventions9010010
27. Nagarajan B, Santhosh Kumar SVN, M Selvi, Thangaramya K: A fuzzy based chicken swarm optimization algorithm for efficient fault node detection in Wireless Sensor Networks. Scientific Reports. 2024, 14:27532. 10.1038/s41598-024-78646-2
28. Bhargavi KVNA, Varma GPS, Hemalatha I, Dilli R: An enhanced particle swarm optimization-based node deployment and coverage in sensor networks. Sensors. 2024, 24:6238. 10.3390/s24196238
29. Aruna M, Narayana PB, Kumar SN, Walid MAA, Patra JP, Kumar BS: Arithmetic optimization algorithm with machine learning based smart irrigation system in IoT environment. Fifth International Conference on Electrical, Computer and Communication Technologies (ICECCT). IEEE, Erode, India; 2023. 5th:01-05. 10.1109/icecct56650.2023.10179741
30. Lloret J, Sendra S, García-Fernández J, García L, Jimenez JM: A WiFi-based sensor network for flood irrigation control in agriculture. Electronics. 2021, 10:2454. 10.3390/electronics10202454
31. Sun H, Yang S: Range-free localization algorithm based on modified distance and improved black-winged kite algorithm. Computer Networks. 2025, 259:111091. 10.1016/j.comnet.2025.111091
32. ElBeheiry N, Balog RS: Technologies driving the shift to smart farming: A review. IEEE Sensors Journal. 2022, 23:1752-769. 10.1109/jsen.2022.3225183
33. Silva FSD, Lima MPS, Corujo D, Venâncio Neto AJ, Esposito F: A comprehensive step-wise survey of multiple attribute decision-making mobility approaches. IEEE Access. 2024, 12:108616-8656. 10.1109/access.2024.3436074
34. Su S, Yang C, Ju X, Xu C: Deployment optimization of self-powered sensors for coverage enhancement in the internet of things sensing layer. IEEE Sensors Journal. 2022, 23:20773-781. 10.1109/jsen.2022.3204346
35. Tong R, Du Y, Liu H, Chen Y: An improved least-square based jammer localization algorithm. International

Conference on Parallel and Distributed Systems (ICPADS). IEEE, Nanjing, China; 2023. 28th:258-65. 10.1109/icpads56603.2022.00041

36. Omari M, Kaddi M, Salameh K, Alnoman A, Elfatmi K, Baarab F: Enhancing node localization accuracy in wireless sensor networks: a hybrid approach leveraging bounding box and harmony search. IEEE Access. 2024, 12:86752-6781. 10.1109/access.2024.3417227
37. Castro GGD, Berger GS, Cantieri A, Teixeira M, Lima J, Pereira AI, Pinto MF: Adaptive path planning for fusing rapidly exploring random trees and deep reinforcement learning in an agriculture dynamic environment UAVs. Agriculture. 2023, 13:354-78. 10.3390/agriculture13020354
38. Nguyen VH, Tan ND: Voronoi diagrams and tree structures in HRP-EE: Enhancing IoT network lifespan with WSNs. Ad Hoc Networks. 2024, 161:103518. 10.1016/j.adhoc.2024.103518
39. Forbes A, Jagan K, Donlevy J, Sousa JAE: Optimization of sensor distribution using Gaussian processes. Measurement: Sensors. 2021, 18:100128. 10.1016/j.measen.2021.100128