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Hybrid Optimized 3D Localization for WSN-Assisted IoT Networks in Smart Agriculture

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Abstract
Accurate localization of sensor nodes within precision agriculture applications is a critical component in Wireless Sensor Network (WSN)-assisted Internet of Things (IoT) networks. The presence of environmental noise, terrain irregularities, and data anomalies degrades the performance of the existing 3D localization techniques. This article presents a novel hybrid 3D localization scheme that integrates Particle Swarm Optimization (PSO), Random Forest (RF)-based anomaly detection, and trilateration refinement to enhance localization accuracy, energy efficiency, and scalability in smart agriculture (SA) environments. The proposed scheme proceeds in three phases, i.e., initial node position estimation using RSSI-based path-loss modelling, machine learning (ML)-based anomaly detection and filtering of Received Signal Strength Indicator (RSSI) data, and PSO-based global optimization followed by trilateration for fine-tuning. Based on the simulation experiments for several scenarios, the proposed hybrid approach renders a robust and scalable solution for accurate node localization in WSN-assisted IoT (WIoT) networks for smart agriculture. It attains low localization errors at 1.2 meters, with energy consumption abridged to 8–10 J and computation time under 0.5 seconds, outdoing the state-of-the-art.

Keywords- WSN-assisted IoT, Localization, Anomaly detection, PSO, Agriculture.

1. Introduction

The IoT and WSNs have merged to modernize the agriculture sector. These technologies enable humankind to manage resources efficiently and collect real-time data to operate them efficiently. The WIoT networks are built of devices and sensor nodes, which are required to localize for efficient data transmission. Finding the coordinates of the sensor node is called localization. Finding the exact location of the node is challenging because of dynamic environmental conditions, high energy consumption due to inefficient resource usage and the potential for node failure. This impacts efficient decision-making and results in high energy consumption.

By accurately localizing the sensor node, various agricultural applications benefit from and are advanced with technology. Applications like precision farming, pesticide usage and control, irrigation management and automation, crop health monitoring, crop harvesting, and livestock management have become more easily manageable if we apply the correct techniques for sensor node localization (Zhang et al., 2024). Various environmental factors create problems and hindrances in accurately localizing the node's position. These obstacles are sometimes some physical objects and occasionally extreme weather conditions. Such issues impact the signal quality, such as multipath propagation and signal attenuation, resulting in high energy consumption. The exhausted node dies soon and affects the overall performance of the network. Hence, there occurs the requirement for advanced localization methods as conventional localization techniques are not able to deal with the mentioned issues.

Finding the 3D location of sensor nodes in a WIoT network is much more challenging. Because of the adverse environmental conditions, it becomes tough to find the exact distance among the nodes as the obstacles create interference with the signal (Survase et al., 2024). Again, the effectiveness of traditional localization schemes such as trilateration becomes weak when it is used for large-scale deployment, where the noisy data and computation increase (Yinjun, 2024). To solve the mentioned issue, the proposed approach has combined trilateration with an ML-based anomaly detection technique for localization, which uses PSO for location estimation.

Once the data is gathered, it is not always perfect. It contains various anomalies. It is crucial to remove those anomalies (Tan & Wong, 2024) and the RF technique is applied for the same. Further, we must refine the location coordinates as they are initial estimates and lack the required precision. For this refinement, we have used the trilateration technique and PSO algorithm for further enhancement to improve the location estimation.

The proposed work is specifically developed for the 3D scenario of SA. This approach will improve the localization accuracy, computational complexity and efficient usage of the resources for large-scale environments (Wang et al., 2025). The proposed scheme is also capable of real-time monitoring of agricultural resources and crops. The developed system is scalable, reliable, more accurate and energy-efficient for the advanced applications of agriculture practices. This research is broadly oriented to dealing with environmental noise issues in 3D agriculture scenarios and energy-efficient resource management by combining PSO, RF-based anomaly detection, and trilateration techniques (Arjun et al., 2025).

This research introduces a novel localization approach that integrates three complementary methods: PSO for generating initial position estimates, a random forest algorithm to detect and eliminate anomalous RSSI readings, and trilateration for refining positional accuracy. The proposed approach works with a tri-layer framework and effectively handles the noisy and dynamic environment. The designed approach can boost the network's overall performance by enhancing localization accuracy and network reliability and supporting scalability in the WIoT-based SA environment.

1.1 Research Contribution
The notable contribution to WIoT localization in SA is as follows:
(i) The proposed work develops a scheme that utilizes PSO to estimate the node position. We have used RF anomaly detection and trilateration refinement to filter the noisy RSSI values for localization accuracy.
(ii) The proposed work resolves the environmental noise and computational complexity, further enhancing the localization accuracy in the changing environment of SA.
(iii) Combining anomaly detection and optimization techniques collectively ensures energy conservation and computational efficiency for large-scale deployment in resource-constrained environments.
(iv) A hybrid approach that maintains scalability and is suitable for large-scale networks in innovative agriculture applications achieved high localization accuracy.

1.2 Structure of the Article
The sections of the article are as follows: Section 1 is about the introduction of WIoT, localization, ML techniques and, SA and how they all are helpful when collaborated, Section 2 outlines the literature survey for the proposed scheme. Section 3 produces the problem statement, while Section 4 presents the methodology of the proposed scheme. Section 5 is about the mathematical model, followed by Section 6, which discusses the simulation framework and parameters. Section 7 demonstrates the results and discussions. Section 8 provides insight and implications of the proposed work. Section 9 concludes the article along with the future scope.

2. Literature Survey
Integration of IoT with WSNs has completely transformed the world of agriculture by ensuring that the environment is adequately monitored, tracking environmental conditions, collecting real-time data, and making data-driven decisions. The precise location of the sensor nodes is essential here, as it allows other activities to run efficiently within the network. In this work, we examined the methods and techniques related to 3D localization in WIoT applications, which majorly target methods like metaheuristics, trilateration, and ML methods for anomaly detection (Singh & Mittal, 2021).

2.1 Traditional Localization Methods
The localization methods can be classified into two broad categories: range-based and range-free. The range-based method calculates the distance between two nodes using techniques like arrival time, angle of arrival, and signal strength. The range-based method usually uses the trilateration approach, which estimates the node's position by intersection points of spheres that move near the known location of three or more reference nodes (Ahmad et al., 2024). Trilateration is a simple and intuitive method to calculate the node position. Still, the dynamic behaviour of agriculture, noisy data, and physical distraction does not allow the trilateration method to achieve precise location. On top of that, it relies entirely on exact location, which is impossible with a large-scale set-up where distraction is quite possible in any format (Rose et al., 2020).

Multilateration is the next upper version of trilateration, using more reference nodes to improve position accuracy. However, it still suffers from physical distraction and huge computation problems in large-scale areas. Additionally, these conventional methods face limitations with the dynamic behaviour of agriculture, where parameters like soil moisture, rainfall, humidity, and temperature change rapidly, directly impacting signal propagation (Malivert et al., 2023).

2.2 Metaheuristics for Localization
To solve the drawbacks of the old localization methods, we have introduced advanced metaheuristic optimization techniques, which will improve the efficiency and accuracy of the localization algorithm. Metaheuristic methods are most popular because they adequately respond to WIoT networks. They can find suboptimal solutions efficiently and optimize network parameters and complex search spaces (Khalil & Saeed, 2024). PSO is the most popular optimization technique widely used for localization in WIoT networks. PSO is a population-based optimization technique that models the collective behaviour of particles (agents) to identify optimal solutions within a search space (Mohammed et al., 2025).

Generally, PSO is used in localization algorithms for estimating the initial position of nodes, where it tries to mitigate the noisy data and improves the accuracy of estimates (Lee et al., 2023). PSO is found very suitable for reducing localization errors, but to improve accuracy further, it is essential to refine the errors in some real-time scenarios combined with trilateration and PSO techniques, localization accuracy and computational efficiency (Sattibabu et al., 2025).

2.3 Machine Learning for Anomaly Detection
Real-time applications like agriculture suffer from various challenges due to dynamic conditions. As these factors impact the RSSI value, hampering the distance estimation, sole localization techniques are not sufficient (Waqas et al., 2025). Environmental noise increases the localization error and impacts the location accuracy. The ML techniques provide advantages through clustering and classification techniques on anomalous data to reduce localization error (Hassan & Alharbi, 2024). The RF technique is an appropriate technique for anomaly detection in WIoT networks (Hnaien et al., 2025).

The RF technique identifies the underlying patterns by classifying the data points for efficient decision-making. The classification is done by filtering noise from RSSI values. The RF model is trained using historical data and contextual environmental factors. This classification and improvement enhance the accuracy of distance estimation. The incorporation of ML techniques and localization algorithms is highly capable of improving accuracy (Naeem et al., 2025). The integration of optimization techniques with ML and localization techniques provides potential outcomes for localization in 3D environments (Yadav & Sharma, 2023b).

2.4 Challenges in Smart Agriculture
The dynamic nature of the environment gives rise to many challenges to localization in WIoT for Smart SA. Factors such as physical obstructions, including trees, buildings, vegetation, and weather conditions, can create obstacles and degrade the signal strength, leading to localization inaccuracy. Moreover, larger agricultural land requires extensive monitoring, which adds more complexity for localization. Recent research has shown that to resolve these larger-scale issues, multiple goal-driven approaches are designed to work well in a resource-constrained and dynamic environment (Omari et al., 2024).

In a WIoT environment, the "Energy efficiency" parameter is crucial for sensor nodes regarding localization. As IoT devices are battery-operated, energy consumption becomes the primary factor and has become the most considered point for recent studies (Sowmya et al., 2025). A hybrid approach can resolve these issues by combining metaheuristics, ML, and data filtering techniques. This combination can enhance localization accuracy, handle the complexity of a larger network lifespan, and optimize energy usage.

Numerous studies on 3D Localization in WIoT for Smart Agriculture (SA) have incorporated multiple methods that improve scalability, reduce energy consumption, and enhance accuracy (Saqhib & Lakshmikanth, 2025). Earlier methods like trilateration were widely used; however, they were not good enough to handle dynamic behaviour and noisy data. Metaheuristic techniques, such as PSO, have been applied to refine node estimation but struggle to obtain optimal accuracy. Moreover, integrating machine learning methods, particularly random forest-based anomaly detection, can help filter noisy data and strengthen network reliability (Yadav & Sharma, 2023a).

We developed an optimized hybrid 3D scheme incorporating PSO, trilateration, and RF anomaly detection techniques. This work is proposed to face the challenges raised by resource constraints, noise, and large-scale deployment in SA. The fusion of ML with metaheuristics techniques tackles the issues like resource constraints, scalability, and energy efficiency. Also, it enhances localization accuracy, a key requirement for real-world IoT applications in agriculture. **Table 1** overviews various localization techniques for SA in WSN and IoT networks.

Table 1. Survey of hybrid 3D localization techniques for WIoT in smart agriculture.

Method/Technique	Description	Key findings/Contributions	Challenges addressed	Application/Use case
Improved Trilateration with K-Means Clustering (Luo et al., 2022)	A novel trilateration approach enhanced with anchor node combination and K-Means clustering to reduce the positioning errors .	Proposed a trilateration algorithm that utilizes anchor node combinations and K-Means clustering to remove significant errors and improve accuracy in LOS and NLOS environments.	Environmental noise, anchor node uncertainty, optimization of positioning accuracy in diverse environments.	Tested in indoor, outdoor, and hall environments; applicable to agriculture and IoT-based intelligent systems.
Efficient Trilateration Algorithm Based on RSS (Matharu & Buttar, 2016)	A beacon-based distributed algorithm using RSS for 3D localization via trilateration.	Proposed a distributed trilateration algorithm using RSSI value to achieve accuracy in 3D localization.	Environmental noise, efficient computation of 3D positions, reducing localization error.	Accurate localization of blind nodes in WSNs for SA
Trilateration (Paul & Sato, 2017)	A traditional range-based method for location estimation in a 3D scenario using the intersection of spheres centred on known reference nodes.	Trilateration for node localization in WSNs, but highlighted challenges due to environmental noise.	Environmental noise, interference, signal distortion.	Used in general WSNs for various applications for outdoor environments.
Hybrid PSO and FF Algorithms (Arul & Jebaselvi, 2023)	A hybrid approach that combines PSO and Firefly Optimization to reduce localization errors.	Proposed hybrid iterations (PSO + FF, GA + FF) to enhance localization accuracy and efficiency.	localization errors, improving accuracy and efficiency, robustness in complex environments.	Environmental monitoring, surveillance, healthcare, and other real-world WSN applications.
PSO-ELM (Wanqing et al., 2024)	Combines PSO and ELM to optimize RSSI fingerprinting localization with PSO to enhance ELM.	Demonstrated that PSO-ELM reduces localization mean error and improves positioning accuracy.	Noise in RSSI data, improving accuracy of fingerprint matching, computational optimization.	Indoor Localization for high-accuracy positioning in environments like smart homes or warehouses.
PSO (Gopakumar & Jacob, 2008)	A metaheuristic optimization algorithm that simulates particle social behaviour to find optimal positions.	PSO is applied for the initial position, minimizing the impact of noisy measurements.	Noisy measurements, large-scale WSNs, and high computational cost.	Innovative agriculture applications for large-scale WSNs with the need for accurate positioning.
Hybrid PSO and Trilateration (Fute et al., 2022)	A hybrid approach that combines PSO with trilateration to refine initial estimates and improve localization accuracy in WSNs for agriculture.	Demonstrated that combining PSO with trilateration improves the accuracy of 3D localization.	Inaccurate initial estimates are needed for the iterative refinement of positions.	Used in precision agriculture where accurate 3D localization is required for sensor placement.
RF for Anomaly Detection (Pachauri & Sharma, 2015)	A ML technique for detecting anomalies RSSI values to mitigate noisy data.	RF filters noisy RSSI values, improving localization reliability in dynamic environments.	Noisy data, signal distortion, outliers in RSSI values.	Anomaly detection in SA is used to reduce localization errors and environmental disturbances.

Table 1 continued…

Energy-Efficient localization (Jawad et al., 2017)	Focusing on minimizing energy consumption in localization algorithms to enhance the lifespan of WSN nodes.	Proposed energy-efficient localization techniques, ensuring a balance between accuracy and energy consumption in large-scale WSNs.	Energy consumption, battery-powered nodes, resource constraints in SA.	Energy-efficient methods in SA for large-scale deployments of WSNs.
3D localization with Metaheuristic Algorithms (Niranjan et al., 2024)	Use of advanced metaheuristic algorithms to solve the 3D localization problem, optimizing the search space.	Metaheuristic algorithms for 3D localization show positioning accuracy, scalability, and computational efficiency improvements.	Complex search spaces, large-scale deployments, ensuring accurate 3D localization.	3D localization in SA to optimize sensor network placement and enhance resource allocation.
ML-Driven Localization for SA (Singh et al., 2024)	Integrating ML algorithms for precise Localization in agriculture.	Explored ML techniques and fusion technologies to enhance localization accuracy for real-time monitoring challenges.	Localization accuracy, energy efficiency, scalability, robustness in dynamic agricultural conditions.	Applications in SA, including precision farming, livestock management, and crop monitoring.
Hybrid Metaheuristics for SA (Sharma & Tripathi, 2022)	Combining metaheuristics (e.g., PSO, Genetic Algorithms) with ML techniques to create hybrid frameworks for robust 3D localization in agriculture.	Proposed a hybrid approach using PSO and Genetic Algorithms with ML for localization, ensuring accuracy and energy efficiency in agricultural environments.	Dynamic environments, large-scale deployments, energy efficiency, and noise handling.	Hybrid approaches in IoT-based SA to handle complex, dynamic environments and ensure efficient operations.
Real time agriculture application (Obaideen et al., 2022)	simulated a real-time agriculture application for an automated irrigation scenario.	Demonstrated an intelligent irrigation system that automates water delivery based on real-time soil and environmental data.	Resource optimization, real-time monitoring, automated control in agriculture.	Case study showcasing automated irrigation; relevant for validating smart agriculture localization frameworks.
Weighted Correction-Based Localization(Chang et al., 2024)	Simulated a real-time smart agriculture system for automated irrigation using IoT and sensor data analytics.	Demonstrated an intelligent irrigation system that automates water delivery based on real-time soil and environmental data.	Resource optimization, real-time monitoring, automated control in agriculture.	Case study showcasing automated irrigation; relevant for validating smart agriculture localization frameworks.

2.5 Identified Research Gaps

Although many advancements have been made in localization techniques and their application in WIoT for monitoring agriculture, few gaps remain in this field. Existing methods cannot deliver accurate results in dynamic, heterogeneous environments that fail to resolve real-time variations and interference. ML is used for data analysis and error detection, but when ML is combined with the localization method, it gives more benefits that remain unutilized. Hybrid approaches, such as integrating Conventional with ML and other advanced techniques that could improve accuracy and adaptability, remain undiscovered and require vertical drop.

Data transmission and processing require a large amount of energy consumption in the localization method, so parameter energy efficiency is always a crucial challenge in WIoT. Moreover, many algorithms suffer from real-time processing capabilities, limiting their applicability in large-scale or dense sensor networks and scalability. Specially designed localization methods for tracking activities such as pest detection, asset tracking, and crop monitoring remain underdeveloped, even after they have their unique requirements. Prior scholarly work has done much research in solving issues like localization accuracy, often overlooking other critical factors like robustness to noise, computational time, and energy consumption. Moreover, studies mainly depend upon simulations, which do not meet the requirement of real-world complexities like dynamic obstacles and network obstructions. Recent studies have also shown that no deep attention has been paid to the energy-efficient parameter, which is essential even after integrating with agricultural technologies like pest control and automated irrigation. To fulfil the modern demands for WIoT, agricultural activities must first resolve the prevailing issues and then design a robust technology fit for scalability, sustainability, efficiency, and accuracy.

Despite recent progress in WIoT localization techniques, several research gaps persist. Existing methods lack robustness against environmental noise, dynamic obstacles, and terrain variation—conditions commonly encountered in real-world agricultural deployments. Many models fail to simultaneously optimize for localization accuracy, energy consumption, and computational complexity. Furthermore, while ML has shown promise for anomaly detection, its integration with optimization-based localization techniques remains underutilized. Hybrid solutions involving data-driven filtering and metaheuristic optimization are still in early stages of development. There is also a lack of practical implementations that validate simulation models through field trials in diverse topographical conditions. Our proposed framework addresses these shortcomings by introducing a three-layered hybrid model tailored for SA's unique challenges.

3. Problem Statement

For innovative agriculture applications, monitoring the environment and collecting accurate real-time data are necessary. It is challenging to calculate the precise location of the node in such scenarios. The environmental noise affects the RSSI value, resulting in low accuracy. Conventional localization techniques have low performance as they have high computation costs. The traditional methods are also less suitable for large WIoT networks and are less efficient in managing energy consumption during data transmission among the nodes. Most of the time, the data collected through the WIoT nodes are erroneous. Removing or mitigating anomalies is crucial for efficient localization via position estimation. To address the challenges of anomalies, localization error, and energy consumption, we proposed a hybrid optimized 3D localization scheme in a WIoT network for SA.

4. Methodology of Proposed Work

Figure 1 shows the methodology of the proposed scheme, which proceeds in the following steps:

- **(i) Data Acquisition:** The RSSI values are acquired through sensor nodes along with timestamps and provided as the input for the following process for location estimation.
- **(ii) Localization Techniques:** The PSO and trilateration techniques are used to estimate the location of the nodes, minimize the location error, and refine the estimated position.
- **(iii) Anomaly Detection:** The RF reduces anomalies in the RSSI data. These anomalies are generated by environmental noise and hardware failures. The process of anomaly detection is essential as it enhances Localization accuracy because erroneous inputs are highly prone to increasing errors.
- **(iv) Evaluation:** The proposed scheme is evaluated using parameters viz localization error, energy consumption, scalability and convergence time in three scenarios of SA: crop monitoring, pest detection, and asset tracking.

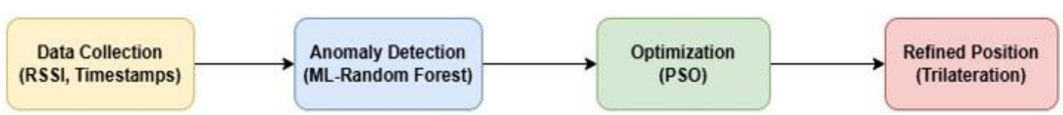

Figure 1. Proposed methodology.

In the PSO optimization process, the initial positions of unknown sensor nodes are assigned using a uniform random distribution within the defined 3D space. This approach ensures that the particles are systematically spread across the search space as the optimization begins. It also enhances the likelihood of converging toward the global optimum. To prevent particles from moving outside the valid region, boundary constraints are applied during iterations. To balance exploration and algorithmic simplicity, we didn't use heuristic-based initialization, as uniform random seeding can balance it.

We selected the RF algorithm for anomaly detection as it is robust and efficient in handling noisy, non-linear, and high-dimensional RSSI data. Unlike other classifiers like Support Vector Machines (SVM), K-Nearest Neighbors (KNN), or decision trees, RF minimizes overfitting through ensemble averaging, requires minimal hyperparameter tuning, and provides high classification accuracy for noisy input data. Due to the feature of fast inference, the RF algorithm is also suitable for real-time IoT applications in SA. Its feature importance capability further helps in understanding environmental factors contributing to anomalies.

This study operates under several practical assumptions, including the static position of sensor nodes after deployment and prior knowledge of the path-loss exponent for each terrain type. The RSSI values are modelled using Gaussian noise to simulate environmental interference. In real-world deployments, factors such as terrain heterogeneity, multi-path propagation, node hardware variation, and synchronization delays may introduce additional uncertainties. These aspects will be explored in future field implementations to further validate the model's performance.

5. Mathematical Model for Hybrid Optimized 3D Localization Scheme

The mathematical model for the proposed scheme has three key components—data acquisition and anomaly detection, optimization, and refinement. The data is gathered from the WIoT nodes deployed in the network. These nodes include the unknown and anchor nodes (whose location is known). The data includes the anchor nodes' location, RSSI value, transmission power, and environmental parameters. PSO is applied to estimate the unknown node's position, which minimizes the error between calculated and estimated distances. Applying the ability of local exploitation and global exploration, PSO refines potential solutions effectively. This quality makes it more suitable for implementing agricultural scenarios with many sensor nodes.

Anomaly detection is incorporated using a RF classifier to improve dependability. It identifies and eliminates the anomalous RSSI values caused by environmental factors like noise, sensor interference, and malfunctioning. The preprocessing step of anomaly detection provides only legitimate data as input to the localization algorithms. A closed-form geometric technique, i.e., trilateration, is used to refine the estimated positions after removing the anomalous data. This refinement is done by calculating the distance of nodes and the position of the anchor nodes. The proposed approach provides high accuracy because PSO is used for broad optimization and trilateration for fine-tuning.

The input parameters are the position of the anchor nodes and the distance to the anchor nodes. (x_i, y_i, z_i), is the anchor nodes' position, where $i = 1,2, \dots, m$, where, m is the number of anchor nodes. Equation (1) calculates the distance to Anchor Nodes (d_i):

$$d_i = 10^{\frac{p_t - p_r}{10 - n}} \tag{1}$$

where, p_t is Transmission power (dBm), p_r is the RSSI value from anchor node i, and n is the Path-loss exponent (environment-dependent).

Equation (2) calculates the objective function. The objective is to minimize the error between the measured distances (d_i) and the estimated distances ($\hat{d}_i$):

$$E(\hat{x},\hat{y},\hat{z}) = \sum_{i=1}^{m}(\sqrt{(\hat{x}-x_i)^2+(\hat{y}-y_i)^2+(\hat{z}-z_i)^2}-d_i)^2 \quad (2)$$

where, $(\hat{x},\hat{y},\hat{z})$ is the estimated position of the unknown node.

PSO is applied as an optimization technique whose goal is to minimize the objective function value, i.e., $E(\hat{x},\hat{y},\hat{z})$.

Equation (3) calculates the value of velocity update:

$$v_p^{t+1} = \omega . v_p^t + c_1 . r_i . \left(P_{best}^p - x_p^t\right) + c_2 . r_2 . (G_{best} - x_p^t) \quad (3)$$

The position update is calculated from Equation (4)

$$x_p^{t+1} = x_p^t + v_p^{t+1} \quad (4)$$

where, ω is inertia weight, c_1 and c_2 are cognitive and social coefficients, r_1 and r_2 are random values in [0,1], and P_{best} G_{best} are the Best-known positions for the particle and globally.

After PSO optimization, the solution is refined using closed-form trilateration as Equation (5):

$$X = (A^T A)^{-1} A^T b \quad (5)$$

A is a matrix derived from anchor node coordinates, b is a vector of distances d_i , and $X = (\hat{x},\hat{y},\hat{z})^T$ is the refined position.

Before optimization, anomalous RSSI values are filtered using a RF classifier as in Equation (6):

$$y = f(X;\theta) \quad (6)$$

where, X is the feature vector from RSSI data, θ is the parameters of the trained RF model, $y \in \{0,1\}$ is the indicator of valid (1) or anomalous (0) data. Anomalous RSSI values are excluded, ensuring robust optimization.

The localization accuracy is the estimated position is calculated as Equation (7):

$$Error = \frac{1}{n}\sum_{j=1}^{n}\sqrt{(\hat{x}_j-x_j)^2+(\hat{y}_j-y_j)^2+(\hat{z}_j-z_j)^2} \quad (7)$$

where, n is the number of test nodes.

Total energy consumption is measured as Equation (8):

$$E_{consumed} = \sum_{i=1}^{n} P_i , T_i \quad (8)$$

P_i is the power consumed, and T_i is the time for computation. Computational cost is measured as the total number of iterations and time required for PSO convergence.

Algorithm 1: Data Processing and Optimization Using PSO

Input:
  N: Total number of sensor nodes
  m: Total number of anchor nodes
  (x_i, y_i, z_i): Anchor node position for $i = 1, \dots, m$

p_r: Received Signal Indicator (RSSI) values
p_t: Transmission power of node
η: Path-loss exponent
PSO parameters: ω, c_1, c_2

Begin

Step A: Data Acquisition

A1. **Initialize_Sensor_Node_Locations** (*N, Width, Height, Depth*):
Randomly initialize the position of N unknown nodes:
$\{(x_i, y_i, z_i)\}_{j=1}^{N}$

A2. **Compute_Distance** (d_i):
For each anchor node $i = 1, \dots, m$
$d_i = 10^{\frac{p_t - p_r[i]}{10=\eta}}$
End For

Step B: Anomaly Detection

B1. **Filter_Anomalous_RSSI_data** (P_r):
Use a Random Forest Classifier
Extract features from RSSI data:
$X = [P_r, variamce, mean, RSSI\ trend]$
Classify anomalies using the model:
$y = f(X; \theta)$
For $i = 1, \dots, m$
If $y = 0$
Mark $P_r[i]$ as anomalous and exclude it
End if
End for

Step C: Particles Swarm Optimization (PSO)

C1**. Initialize_Particles**
Initialize k particles with random position (x_p, y_p, z_p)
Assign random velocities (v_x, v_y, v_z)

C2. **Compute_Initial_Fitness** (E):
For each particle $p = 1, \dots, k$:
$E_p = \sum_{i=1}^{m}(\sqrt{(x_p - x_i)^2 + (y_p - y_i)^2 + (z_p - z_i)^2} - d_i)^2$
End For

C3. I**terative_Optimization** (A, *B, Y, n, λ*):
While stopping criteria not met (maximum iteration/threshold)
For each particle $p = 1, \dots, k$:
Update Velocity:
$v_p^{t+1} = \omega . v_p^t + c_1 . r_1 . (P_{best}^p - x_p^t) + c_2 . r_2 . (G_{best} - x_p^t)$
Update Position:
$x_p^{t+1} = x_p^t + v_p^{t+1}$
End For
Re-evaluate fitness E_p for each particle
Update P_{best} and G_{best}

End

Output: Optimized position of unknown nodes via PSO

Algorithm 2: Trilateration Refinement and Evaluation

Input:
  Optimized position form Algorithm 1
  Anchor position (x_i, y_i, z_i)
  Distances d_i

Begin
Step A: Trilateration Refinement
A1. **Linearize Distance Equations**:
  For each anchor node $i = 1, \ldots, m$
   $(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2 = d_i^2$
  End For
A2. **Matrix Representation**
  Define:

$$A = \begin{bmatrix} 2(x_2 - x_1) & 2(y_2 - y_1) & 2(z_2 - z_1) \\ \vdots & \vdots & \vdots \\ 2(x_m - x_1) & 2(y_m - y_1) & 2(z_m - z_1) \end{bmatrix}$$

$$b = \begin{bmatrix} d_1^2 - d_2^2 - x_1^2 + x_2^2 - y_1^2 + y_2^2 - z_1^2 + z_2^2 \\ \vdots \\ d_1^2 - d_m^2 - x_1^2 + x_m^2 - y_1^2 + y_m^2 - z_1^2 + z_m^2 \end{bmatrix}$$

A3. **Refine Position Using Trilateration**
  Compute:
   $X = (A^T A)^{-1} A^T b$
  Where $X = (\hat{x}, \hat{y}, \hat{z})^r$
Step B: Evaluation
B1. **Compute Localization Error**:
  Compute the average localization error:

$$Error = \frac{1}{N} \sum_{j=1}^{N} \sqrt{(\hat{x}_j - x_j)^2 + (\hat{y}_j - y_j)^2 + (\hat{z}_j - z_j)^2}$$

B2. **Compute Energy Consumption**:
  Evaluate energy consumed by the system:
   $E_{consumed} = \sum_{i=1}^{N} P_i . T_i$
B3. **Record Computational Performance:**
  Log the total iterations, convergence time, and computational cost.

End
Output: Final refined positions, localization error, and system energy consumption.

Algorithm 1 outlines the process to address the issues raised by environmental noise and computational efficiency by incorporating data preprocessing and optimization techniques. The RF technique is applied for anomaly detection. It ensures the reliability of RSSI data by filtering out noise and erroneous values to improve the quality of input data for the localization process. Afterwards, the PSO technique estimates the positions of unknown sensor nodes by reducing the error between calculated and estimated distances. The iterative nature of the PSO technique balances exploration and exploitation, which makes it well-suited for large-scale WIoT networks.

Algorithm 2 refines the estimated positions after the localization of unknown nodes from PSO using trilateration and closed-form geometric computations to improve accuracy. The linearized distance equations amend any deviations introduced in the optimization phase. Evaluating localization error and energy consumption shows the precision and feasibility of the proposed approach for WIoT networks for agricultural scenarios. Maintaining energy efficiency, this refinement phase ensures robust performance in noisy or complex environments. Combining deterministic refinement with heuristic optimization, the proposed hybrid algorithm ensures scalability and precision.

The computational complexity of the proposed hybrid model depends on three components: PSO-based position estimation, RF-based anomaly detection, and trilateration refinement.

- The time complexity of PSO algorithm is $O(P \times I)$, where P is the number of particles and I is the number of iterations required for convergence.
- RF-based anomaly detection is performed once during preprocessing and is parallelizable. The complexity of RF anomaly detection model is $O(T \cdot F \cdot \log F)$, where T is the number of trees and F is the number of features.
- The trilateration refinement has a complexity of $O(n^3)$, where n is the number of anchor nodes. IS involves a system of linear equations using matrix operation.

The combined approach remains efficient and scalable for medium- to large-scale deployments, mainly due to PSO's global convergence behaviour and the one-time RF preprocessing.

6. Simulation Framework and Parameters

The simulation environment was developed using a combination of software tools. The RF classifier for anomaly detection was implemented using Python's Scikit-learn library. The PSO algorithm and trilateration refinement were simulated using MATLAB for matrix-based optimization. Visualization and performance graphs were generated using Seaborn and Matplotlib in Python. The input RSSI data were synthetically generated, simulating varying terrain and noise conditions. While no real-world dataset was used, the complete simulation code and synthetic data generation scripts are available upon request for academic use.

Three primary simulation scenarios are considered: crop monitoring, pest detection, and asset tracking. These tools enable the implementation of algorithms for data processing and anomaly detection to simulate WIoT and visualize sensor data in agricultural environments. Sensor nodes observe the soil moisture level, temperature, and humidity across a large field to monitor the crop. The purpose is to achieve high localization accuracy to deploy an automated irrigation system. For pest detection, the sensor nodes track the pattern of pest movement in greenhouses to provide real-time location data for effective measurement of direct pest control. Asset tracking is done by implanting IoT devices on agricultural machinery to optimize resource usage through precise positional tracking.

The simulation incorporates parameters like sensor nodes, anchor nodes, deployment area dimensions, RSSI value, and path-loss exponent. The number of unknown sensor nodes (N) ranges from 100 to 500, while anchor nodes (m) vary between 10 and 50. We considered a 3D space with dimensions 100 × 100 × 50 arbitrary units as the deployment area. The RSSI value (p_r) has a range from 2.0 to 4.0. The value depends on signal attenuation and gets impacted by the path-loss exponent (η). The inertia weight (ω) is taken within the range of 0.5 to 1.0 for PSO parameters. Each of the acceleration coefficients (k_1, k_2) is set to 1.5. The stopping criteria or PSO algorithm is defined as a maximum of 200 iterations or an error threshold. Here, the number of particles (k) have range between 50 to 100.

The inertia weight and acceleration coefficients are crucial for balancing exploration and exploitation in the PSO algorithm. The inertia weight is set between 0.5 and 1.0 because this range allows the particles to explore the solution space broadly during the initial iterations. The task focuses on exploitation as the algorithm converges by broadly exploring the search space. It also improves convergence stability and solution quality. The acceleration coefficients are chosen based on standard practices to balance the cognitive and social components equally. The cognitive components are individual experiences, while the social cognitive are the swarm experience components. The choice of moderate values saves from premature convergence by ensuring that particles are influenced adequately by both personal and global best solutions.

In the simulation, Additive White Gaussian Noise (AWGN) is introduced into the RSSI values to simulate signal degradation. Environmental interference, sensor hardware variation, and multipath fading are some reasons for the signal degradation. The noise acquires a zero-mean Gaussian distribution with varying standard deviations to represent different noise levels, i.e. 5%, 10%, 15%, and 20%. This modelling closely approximates real-world RSSI fluctuations and allows performance evaluation of the localization algorithm under controlled noisy conditions.

The simulation assumes perfect time synchronization between sensor and anchor nodes. This assumption simplifies modeling and allows the evaluation of localization performance without introducing timing-induced biases. While synchronization discrepancies can affect real-world RSSI-based methods, our framework focuses on handling signal strength variability. Future implementations will consider synchronization errors and propose timing-resilient enhancements

The simulation framework employs two main algorithms, i.e., "Data Processing and Optimization Using PSO" and “Trilateration Refinement and Evaluation”. Algorithm 1 begins with data acquisition by initializing sensor node locations and computing distances among nodes using RSSI values. Anomalous RSSI data is filtered out by using a RF Classifier. Afterwards, the PSO technique is applied to optimize the positions of unknown sensor nodes. Through iterative updates of particle velocities and positions, the position of unknown nodes is optimized by evaluating fitness at each step till meeting the stopping criteria. To refine the positions of the nodes estimated by Algorithm 1, Algorithm 2 takes place. Algorithm 2 linearizes the distance equations to represent them as a matrix to calculate refined positions. The evaluation phase calculates localization error using root mean square error (RMSE) and consumed energy and logs computational performance metrics.

Evaluation metrics, including localization error, energy consumption, and computational performance, are used to test the scheme's performance. Localization accuracy is measured by calculating the RMSE between actual and estimated positions. Energy consumption evaluates the efficiency of the system, and computational performance metrics provide the count of total iterations, convergence time, and computational cost. **Table 2** summarizes the key parameters and their respective values/ranges for simulating the hybrid localization framework described in the algorithms. **Table 3** provides an overview of the effect of various terrains on simulation parameters and evaluation metrics. The table compares node density, noise levels, and topography, i.e., flat, hilly, and mixed terrains), the application of RF (for anomaly detection), PSO, and trilateration technique for localization by evaluating localization accuracy, energy consumption, and computational cost across three distinct simulation scenarios. It concludes that flat terrains achieve the highest localization accuracy and lowest computational cost, while hilly and mixed terrains are found more challenging due to their complexity.

Table 2. Simulation parameters.

Parameter	Description	Values/Range
N (Sensor Nodes)	Total number of unknown sensor nodes randomly deployed in the 3D area	100–500
m (Anchor Nodes)	Total number of anchor nodes.	10-50
Deployment Area Dimensions	Width, height, and depth of the 3D deployment area	100 × 100 × 50 (arbitrary units)
p_r (RSSI)	Received Signal Strength Indicator values	Varies based on signal attenuation
η (Path-Loss Exponent)	Path-loss exponent affecting signal attenuation	2.0–4.0
PSO Parameters		
ω	Inertia weight for velocity control	0.5–1.0
c_1, c_2	Acceleration coefficients for cognitive and social components	$c_1 = 1.5$, $c_2 = 1.5$
Number of Particles (k)	Total number of particles initialized in the PSO	50–100
Stopping Criteria	Criteria for stopping PSO iterations	Max 200 iterations or error threshold
Algorithm 2 Inputs	Optimized positions from PSO and corresponding anchor positions	From Algorithm 1
Evaluation Metrics		
Localization Error Metric	Root Mean Square Error (RMSE) between actual and estimated positions	Computed during evaluation
Energy Consumption (E)	Energy consumed by the system during Localization	Computed for sensor nodes
Computational Performance	Total iterations, convergence time, and computational cost	Recorded during simulations

Table 3. Comparison of simulation parameters and evaluation metrics across terrain types.

Parameter	Flat terrain	Hilly terrain	Mixed terrain
Node Density	High / Medium / Low (Adjustable)	High / Medium / Low (Adjustable)	High / Medium / Low (Adjustable)
Noise Levels	Low / Medium / High	Medium / High	Variable (depends on sub-terrain)
Topography	Uniform and level	Varying elevation with obstructions	Combination of flat and uneven surfaces
RSSI Signal Reliability	High	Low	Medium
Localization Accuracy	High (1.2 – 1.8 m)	Low (2.5 – 3.9 m)	Moderate (1.9 – 2.8 m)
Energy Consumption (J)	8 – 10	10.5 – 13	9.5 – 12
Computation Time (s)	0.25 – 0.35	0.45 – 0.7	0.35 – 0.5
Impact on Performance	Highly stable, suitable for real-time precision	Increased error and delay due to terrain effects	Adaptive performance, depends on terrain layout

6.1 Impact of Terrain Conditions on Localization Metrics

The localization performance of WIoT networks is significantly affected by terrain conditions. In flat terrains, the signal propagation remains relatively uniform with minimal interference, resulting in high localization accuracy and reduced computation time. In contrast, hilly terrains introduce physical obstructions and variable elevation, which cause signal shadowing, multi-path fading, and increased RSSI fluctuations—leading to higher localization error, energy usage, and longer convergence time. It performs moderately in the mixed terrain scenario. The results are based on node placement, density, and heterogeneity. The proposed scheme follows the approaches of anomaly detection and multiple refinement-based trilateration techniques by consistently adapting to terrain-induced variability. **Table 3** compares simulation parameters and evaluation metrics across terrain types to maintain stable accuracy across diverse agriculture scenarios.

7. Results and Discussions

The performance of the proposed scheme is evaluated by comparing it with DV-Hop (Distance Vector-Hop) and AMPLI (Anchor-Based Multipath Localization Improvement) methods in three agricultural scenarios, i.e. crop monitoring, pest detection and asset tracking. The work is implemented by applying the algorithms to synthetic data generated under different noise conditions. The trade-offs were explored to identify the most appropriate solution for each scenario. The performance is evaluated based on the varying noise levels on the specified parameters, i.e., localization accuracy, energy efficiency, and computation time, as shown in **Table 4**.

Table 4. Summary of the key metrics used.

Method	Localization accuracy (Mean error)	Energy efficiency (Power consumption)	Computation time	Resilience to noise
Hybrid Method with ML	Lowest error (1.2-3.0 meters)	Higher	Higher computation time	Most resilient
DV-Hop	Higher error (2.0-4.2 meters)	Low	Low computation time	Sensitive to noise
AMPLI	Moderate error (1.8-3.9 meters)	Low	Low computation time	Moderate noise sensitivity

Table 5 shows that at varying noise levels of 5%, 10%, 15%, and 20%, the proposed hybrid method with ML continuously showed the lowest mean localization error (MLE), with the resulting values of 1.2m, 1.7m, and 2.3m, respectively. Meanwhile, the DV-Hop approach has high localization errors with MLE values of 2.0 m, 2.8 m, 3.6 m, and 4.2 m at different noise levels. The AMPLI approach has moderate localization error, i.e., 1.8 m at 5% noise to 3.9 m at 20% noise. State-of-the-art techniques are found to be less energy-efficient than the proposed energy efficiency parameter scheme. The proposed hybrid method with ML is faster in computing time compared to state-of-the-art approaches.

To validate the consistency of the proposed approach, statistical analysis was conducted over 30 independent runs for each application scenario. As shown in **Table 5**, the low standard deviations and narrow 95% confidence intervals across all cases confirm the reliability and robustness of the hybrid with ML model under varying agricultural conditions.

Table 5. Evaluation of performance metrics across various scenarios.

Scenario	Method	Localization error (m)	Standard deviation (m)	95% Confidence interval (m)	Energy (J)	Computation time (s)
Crop Monitoring	Hybrid with ML	1.20	0.10	[1.16, 1.24]	9	0.34
	DV-Hop	2.00	N/A	N/A	11	0.50
	AMPLI	1.81	N/A	N/A	10.5	0.45
Pest Detection	Hybrid with ML	1.70	0.13	[1.64, 1.76]	10	0.50
	DV-Hop	2.80	N/A	N/A	13	0.70
	AMPLI	2.40	N/A	N/A	12	0.65
Asset Tracking	Hybrid with ML	1.80	0.11	[1.76, 1.84]	8	0.25
	DV-Hop	3.00	N/A	N/A	10.5	0.40
	AMPLI	2.60	N/A	N/A	9.8	0.35

The simulations have been performed on three agriculture scenarios: asset tracking, pest detection, and crop monitoring. Compared to state-of-the-art localization approaches, the proposed scheme outperforms all three scenarios.

These results highlight the trade-off between accuracy, energy consumption, and computation time. The Hybrid scheme with ML offers the best localization accuracy. Still, it comes with the cost of higher energy consumption and longer computation time, making it ideal for scenarios where precision is critical. Meanwhile, state-of-the-art equipment is more suitable for applications where energy efficiency and speed are prioritized over accuracy, especially in environments with minimal noise. The choice of method ultimately depends on the application's specific requirements, including the desired balance between accuracy, energy consumption, and real-time performance, as shown in **Figure 2**.

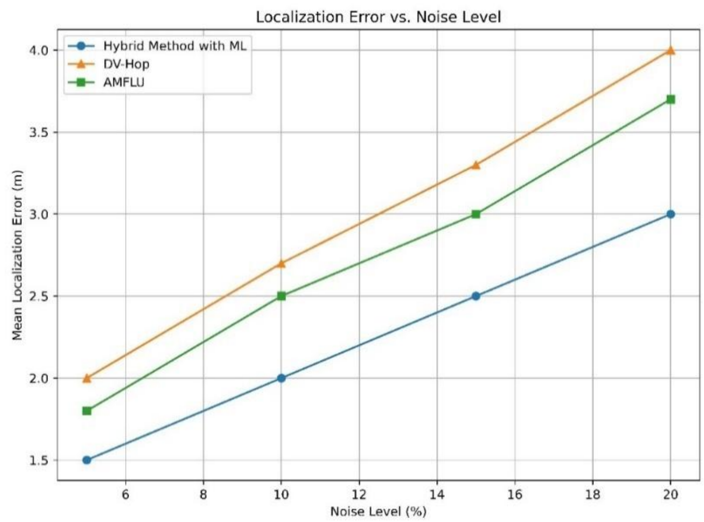

Figure 2. Accuracy vs. noise level.

The simulations have been performed on three different agriculture scenarios: asset tracking, pest detection, and crop monitoring. Compared to state-of-the-art localization approaches, the proposed scheme outperforms all three scenarios.

For the automated irrigation feature of SA, it is crucial to deploy the sensor nodes precisely to implement compelling crop monitoring scenarios. **Figure 3** demonstrates that the proposed scheme results in the lowest computation time (0.34s), localization error (1.2 m), and energy consumption (9 J). AMPLI approach has moderate performance with a computation time of 0.45 s, localization error of 1.81 m, energy consumption of 10.5 J. DV-Hop has highest computation time of 0.5 s, localization error (2.0 m), and energy consumption of 11 J.

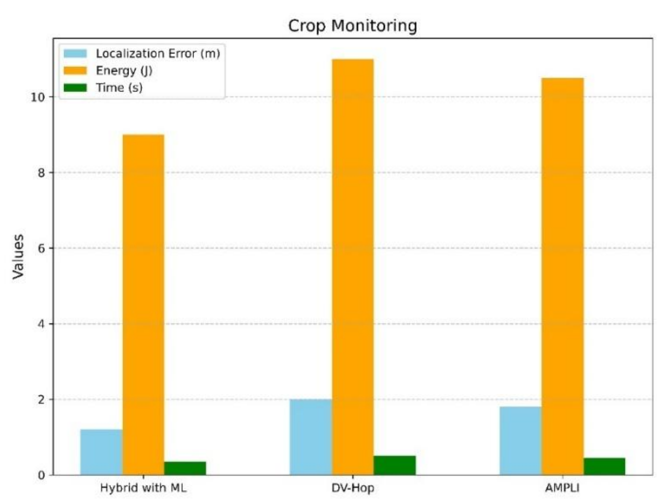

Figure 3. Performance evaluation across crop monitoring.

The hybrid with ML scheme outperforms the other methods for the pest detection scenario (where real-time tracking and anomaly detection are critical). **Figure 4** demonstrates that the proposed scheme also outperforms this scenario with low energy consumption (10 J), localization error (1.7 m), and computation time (0.5 s). At the same time, DV-Hop has the most significant localization error (2.8 m), energy consumption (13 J), and computation time (0.7). The AMPLI trails the proposed scheme, having a moderate localization error (2.4 m), energy consumption (12 J), and computation time (0.65).

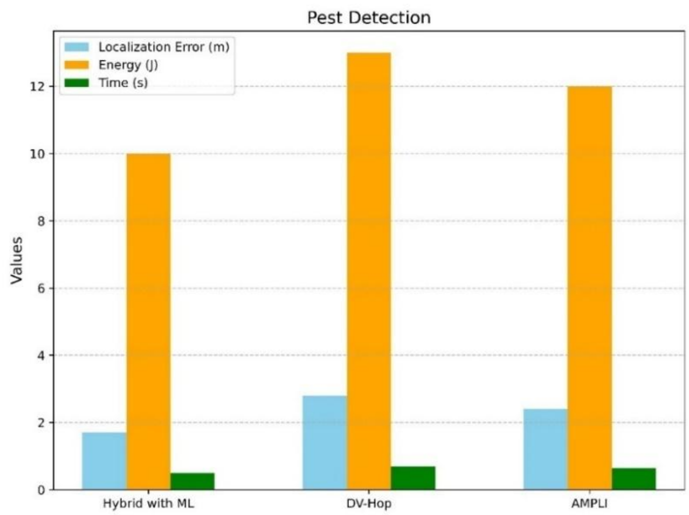

Figure 4. Performance evaluation across pest detection.

Figure 5 shows that the proposed scheme outperforms the asset tracking scenario, achieving the lowest values for energy consumption (8 J), computation time (0.25 s), and localization error (1.8 m). Both AMPLI and DV-Hop are less effective compared to the proposed scheme. AMPLI has moderate performance with a localization error (2.6 m), energy consumption (9.8 J), and computation time (0.35 s). In comparison, DV-Hop has the highest localization error (3.0 m), energy consumption (10.5 J), and computation time (0.5 s).

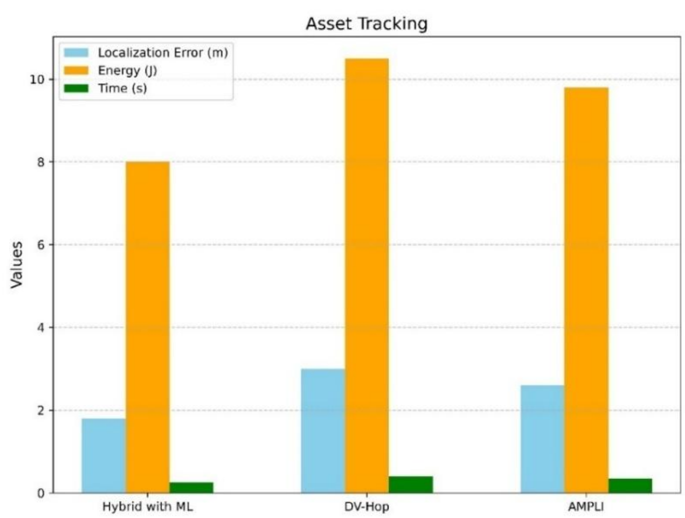

Figure 5. Performance evaluation across asset tracking.

Figure 6 visualizes the distribution of the unknown and anchor nodes in the 3D WIoT Node network. Unknown sensor nodes and anchor nodes are deployed randomly in a 3D terrain. The anchor nodes are represented by green stars (*), and unknown sensor nodes are represented by red circles (o). **Figure 7** demonstrates the outcome of the localization process after implementing the proposed scheme. In this figure, the blue triangles (Δ) show the nodes after the position is estimated.

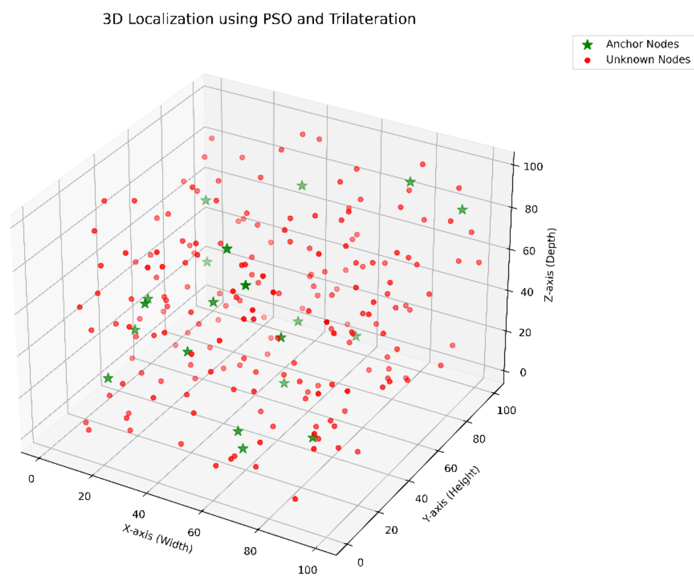

Figure 6. 3D WIoT node distribution.

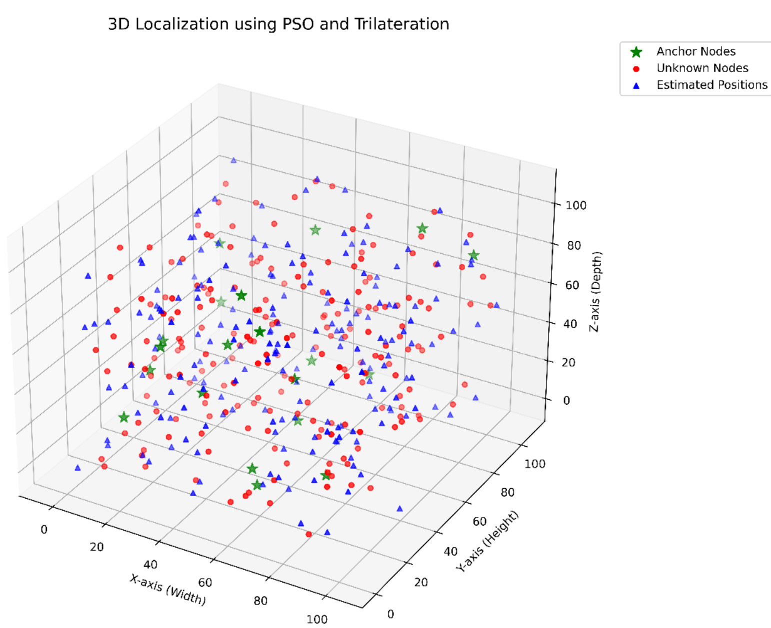

Figure 7. Location estimation through proposed algorithm.

The proposed hybrid localization scheme demonstrates strong scalability for high-density WSN deployments. In simulations, we performed an evaluation that involved up to 500 unknown sensor nodes. The proposed system maintained stable localization accuracy with only a moderate increase in computation time. Using parallelizable modules, such as PSO for position estimation and RF for anomaly detection, the framework can efficiently adapt to larger networks, making the model suitable for large-scale SA scenarios that demand accurate, energy-efficient localization over extended areas.

8. Insight and Implications

The proposed hybrid optimized method for 3D localization in the WIoT network for SA provides intelligent support to the farming system and enables modern farming. The hybrid scheme improves localization accuracy by dealing with adverse environmental conditions and noises. The RF method refines the erroneous data from the RSSI values. Another important factor is to create a sufficient balance between energy efficiency and computational cost. The PSO method is compelling because it reduces energy and computational costs. This makes the infrastructure suitable for real-time applications because these applications, like automated irrigation systems or precision farming tools, require low energy and fast processing for data. This approach can accommodate terrain variations, demonstrating its adaptability, but it can impact signal propagation and localization accuracy in outdoor agriculture settings.

This work is significant for precision agriculture, where locating the nodes exactly is critical because exact location plays a key role in applications like pest control, automated irrigation, and soil monitoring. By enhancing the accuracy, the approach can target the task quickly and efficiently; ultimately resources can be optimized and waste can be reduced. Additionally, improved efficiency makes the real-time applications work better, like tracking pests rapidly and making the system more autonomous. The solution can be cost-effective because it works well on large-scale agricultural land and improves energy efficiency and computational cost, simultaneously reducing cost and increasing the lifespan of the IoT infrastructure.

The proposed scheme offers considerable economic and commercial benefits. Improved localization enables more accurate deployment of sensors for tasks like irrigation, equipment monitoring, and pest control, which directly translates to optimized resource utilization and reduced operational costs. From a commercial standpoint, this model can be integrated into smart farming systems, offering scalable and cost-effective solutions for agritech startups and agricultural automation companies. The reduced energy footprint and higher accuracy also extend the lifespan of deployed networks, making the solution viable for commercial deployments in large-scale agriculture.

9. Conclusion and Future Scope

This paper presents a three-stage Hybrid Optimized 3D Localization scheme, including PSO, RF and trilateration techniques in WIoT networks for SA to address the issues of energy consumption, computational costs, and inaccurate localization error. The combination of PSO and RF provides high accuracy compared to state-of-the-art techniques. The RF-based is used for anomaly detection and can filter inaccurate sensor data by handling the environment's noisy data and dynamic behaviour. The PSO algorithm estimates the initial node location. Afterwards, the trilateration technique is used to refine the estimated positions.

Unlike existing localization methods that typically rely on standalone approaches—either optimization, geometric, or ML techniques—our proposed work integrates all three into a unified hybrid model. This tri-layered framework is distinctly designed to handle dynamic environmental noise, resource constraints, and the demand for real-time data accuracy. This sets our work apart by offering a comprehensive and scalable solution tailored for SA, a domain where no single method has previously been sufficient to meet all operational requirements. The results validate that our hybrid scheme outperforms DV-Hop and AMPLI methods, achieving localization errors as low as 1.2 meters, energy consumption of 8–10 J, and computation times under 0.5 seconds across three practical agricultural scenarios.

The current implementation is simulation-based and tested on synthetic datasets. Future work will focus on real-world field deployments and extension to extreme terrains. Moreover, integrating communication protocols such as LPWAN or 5G and exploring reinforcement learning for adaptive optimization could further enhance performance. The methodology can also be extended to smart city infrastructure, livestock tracking, and environmental disaster monitoring.

Conflict of Interest

The authors' names listed in the manuscript certify that they have no affiliations with or involvement in any organization or entity with any financial or non-financial interest in the subject matter or materials discussed in this manuscript. This paper falls under the PhD research work of the first author under the supervision of the second author.

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AI Disclosure

During the preparation of this work the author(s) used generative AI in order to improve the language of the article. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

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