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SINGLE ANCHOR NODE POSITIONING METHOD USING ANTENNA ARRAY AND MACHINE LEARNING

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Positioning is a fundamental process in wireless sensor networks (WSNs) and Internet of Things (IoT) systems to accurately track the location of nodes. This study presents a cost-effective and scalable single-anchor node positioning system integrating ZigBee technology, directional antennas, and machine learning (ML). The system utilizes a custom-designed directional antenna array and machine learning algorithms to process Received Signal Strength Indicator (RSSI) data, achieving precise localization with minimal hardware requirements. Experimental results confirm the superiority of the antenna array, demonstrating a maximum gain of 10 dBi and enhanced signal reception compared to monopole and single-patch antennas. The XGBoost model achieved high accuracy, with R^2 values of 97.76% on training and 90.95% on test data.

Keywords: Wireless Sensor Networks, ZigBee technology, node positioning, RSSI, directional antenna, machine learning.

АНТЕННА МАССИВІ МЕН МАШИНАЛЫҚ ОҚЫТУДЫ ҚОЛДАНУ АРҚЫЛЫ БІР ЯКОРЛЫ ТҮЙІНГЕ НЕГІЗДЕЛГЕН ПОЗИЦИЯЛАУ ӘДІСІ

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Позициялау - сымсыз сенсорлық желілердегі (WSN) және IoT жүйелеріндегі түйіндердің орналасуын дәл бақылау үшін негізгі процесс болып табылады. Зерттеу барысында ZigBee технологиясын, бағытталған антенналарды және машиналық оқытуды (ML) біріктіретін бір якорлық түйінді пайдаланып үнемді және масштабталатын позициялау әдісін ұсынылды. Жүйе ең аз жабдық талаптары үшін дәл орналасуды қамтамасыз ете отырып, арнайы әзірленген антенналық торды және машиналық оқыту алгоритмдерін қабылдайтын сигнал деңгейінің индикаторы (RSSI) деректерін өңдеу үшін пайдаланады. Эксперименттік нәтижелер монопольді және бір патч антенналарымен салыстырғанда, 10 дБи максималды күшейтуді және сигнал қабылдауды жақсартатын антенналық тордың артықшылықтарын растайды. XGBoost моделі оқыту деректерінде 97,76% және тестілеу деректерінде 90,95% R^2 детерминант коэффициенттерімен жоғары дәлдікке қол жеткізді.

Түйін сөздер: сымсыз сенсорлық желілер, ZigBee технологиясы, түйінді позициялау, RSSI, антенналық тор, машиналық оқыту.

МЕТОД ПОЗИЦИОНИРОВАНИЯ НА ОСНОВЕ ОДНОГО ЯКОРНОГО УЗЛА С ИСПОЛЬЗОВАНИЕМ АНТЕННОЙ РЕШЕТКИ И МАШИННОГО ОБУЧЕНИЯ

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Позиционирование является основным процессом в беспроводных сенсорных сетях (WSN) и системах Интернета вещей (IoT) для точного отслеживания местоположения узлов. В данном исследовании представлен экономичный и масштабируемый метод позиционирования с использованием

одного якорного узла, который объединяет технологию ZigBee, направленные антенны и машинное обучение (ML). Система использует специально разработанную антенную решетку и алгоритмы машинного обучения для обработки данных индикатора уровня принимаемого сигнала (RSSI), обеспечивая точное позиционирование при минимальных требованиях к оборудованию. Экспериментальные результаты подтверждают преимущества антенной решетки, демонстрируя максимальный коэффициент усиления 10 дБи и улучшенный прием сигнала по сравнению с монопольными и одиночными патч-антеннами. Модель XGBoost достигла высокой точности с коэффициентами детерминации R^2 97,76% на обучающих данных и 90,95% на тестовых данных.

Ключевые слова: беспроводные сенсорные сети, технология ZigBee, позиционирование узлов, RSSI, антенная решетка, машинное обучение.

Introduction. Wireless Sensor Networks are an integral part of modern applications, including environmental monitoring, disaster management, and the IoT. Accurate node localization is crucial for these applications as it directly affects the relevance and usability of the collected data [1].

In open environments and small-scale deployments, where issues like interference and noise are minimized, traditional methods such as GPS and multi-anchor node systems are widely used [2].

GPS-based localization offers high accuracy and global coverage but is often unsuitable for small-scale deployments due to its cost and energy consumption requirements [3-4]. Continuous operation of the GPS module significantly drains the battery of sensor nodes, which is a critical limitation in WSNs with constrained resources. Additionally, integrating GPS increases the size and complexity of sensor nodes, making it an impractical choice for compact or lightweight designs.

The study [5] investigates 3D indoor positioning in multi-story buildings using Ultra-Wideband (UWB) technology, focusing on the impact of multiple anchors on positioning accuracy and performance improvement. The study [6] examines the impact of multiple anchors in 3D indoor positioning using UWB technology, highlighting the effectiveness of Particle Swarm Optimization (PSO) in reducing Non-Line-of-Sight (NLOS) errors from 33 cm to 10 cm and significantly enhancing system accuracy under NLOS conditions. Multi-anchor node systems, while effective in many cases, present their own challenges. The need for multiple stationary reference nodes increases the cost of equipment and deployment, even for small-scale networks. Moreover, the complexity of communication and data exchange between anchor nodes reduces scalability and performance over time. These systems may also require meticulous maintenance and calibration, which can be challenging in remote or open environments.

An alternative approach involves single-anchor node systems equipped with directional antennas and ML methods. Positioning systems that use single-anchor nodes and directional antennas have been actively studied to reduce hardware costs and simplify deployment compared to traditional multi-anchor systems. Directional antennas are advantageous as they provide angular information critical for position estimation. For instance, Yong Fu et al. proposed a real-time algorithm for WSN using an antenna array to estimate the direction of arrival (DoA) combined with RSSI values [7]. While achieving sub-meter accuracy in controlled environments, the method showed significant sensitivity to multipath interference. Other approaches, like those by Wang et al., employed mechanically rotating directional antennas for angular position calculation. However, these systems introduced latency due to mechanical movements and required precise synchronization, limiting their usability in real-time applications [8]. ML methods have also been employed to improve localization accuracy by identifying complex patterns in signal data. Groth et al. introduced a calibration-free system that used a random forest model with RSSI data to map spatial coordinates [9]. While the system was effective without extensive environmental calibration, it

faced challenges with dynamic RSSI variations. Hybrid systems that combine directional antennas with advanced statistical or ML models aim to address these limitations. For instance, Schmidt et al. developed the SALOS system, which utilizes UWB signals and statistical propagation models to achieve high accuracy even under multipath propagation conditions [10]. However, its reliance on expensive UWB equipment has limited its broader adoption.

Numerous studies have been conducted using ZigBee technology for indoor localization tasks. The paper [11] examines a localization algorithm for a mobile robot in complex indoor environments using a ZigBee wireless network. An improved algorithm based on RSSI and the least squares method reduced the positioning error from 1.59 m to 0.66 m. The paper [12] focuses on the development of an indoor localization system using ZigBee modules and a 3D trilateration algorithm to determine the positions and distances between unknown nodes. To enhance accuracy, a Kalman filter and signal propagation parameter optimization are applied, reducing the average localization error from 0.6389 m to 0.16 m with optimal reader placement at a height of 2.5 m. The paper [13] introduces the MuCHLoc system, which leverages radio frequency fingerprints and multi-channel RSS measurements to improve localization accuracy. The method compensates for RSS instability by utilizing differences in signals across ZigBee channels, improving accuracy by 15% and effectively operating in dynamic environments.

This study introduces a novel single-anchor node localization system that leverages ZigBee technology, directional antennas, and machine learning to address the limitations of traditional multi-anchor setups. By integrating a directional antenna array with machine learning algorithms, the system demonstrates significant improvements in signal reception and localization accuracy. The proposed approach minimizes hardware costs, simplifies deployment, and provides a scalable, energy-efficient alternative for WSN, particularly in resource-constrained environments.

The novelty of the system lies not in the individual use of ZigBee, directional antennas, or machine learning - each of which has been previously investigated - but in the specific combination and implementation of these components in a single-anchor setup. To the best of our knowledge, this is the first study to use a custom-designed four-element patch antenna array with ZigBee modules combined with machine learning to improve localization performance using only a single anchor node. Previous approaches have relied either on multiple anchors, mechanically rotating antennas, or expensive technologies. In contrast, our system offers a practical, low-cost solution that maintains high localization accuracy without the drawbacks of mechanical movement, calibration complexity, or high hardware cost, making it particularly suitable for scalable deployment in industrial, agricultural, or remote settings.

Materials and methods.

2.1 Experimental setup

The experiment was conducted in an open field without any obstacles to minimize the impact of radio wave interference, which occurs due to the superposition of multiple waves. Figure 1 shows the experimental area, demonstrating a flat, unobstructed area free from unwanted factors.



Fig.1- Experimental area.1 - Transmitter module with patch antenna; 2 - Receiver module

To measure RSSI values, the XCTU software was used in conjunction with XBee modules (Figure 1). One module, equipped with a monopole antenna, was connected to a laptop and served as the receiver. The other module, fitted with a directional antenna array, acted as the transmitter. After connecting the two devices via the XCTU interface, signal transmission was configured, and RSSI values received by the antenna array were recorded. The primary goal of the experiment was to measure RSSI at various distances and angular positions relative to the antenna, with the collected data intended for machine learning tasks.

Measurements were taken at distances of 2 m, 5 m, 10 m, 15 m, and 20 m. The angle range varied from −10° to 190° in 10° increments, resulting in a total of 200 angular positions. To ensure the accuracy of the experiment, each angle and distance was fixed with maximum antenna stability.

2.2. Experimental devices. For the experiment, Digi XBee wireless modules were utilized to ensure reliable connectivity and data transmission. XBee modules support various wireless communication standards, including Zigbee, 802.15.4, Wi-Fi, and cellular technologies such as 3G/4G/LTE, making them a versatile solution for a wide range of applications.

These modules are widely used in IoT systems, industrial automation, smart agriculture, home automation, and telemetry. The XBee radio module used in this experiment is depicted in Figure 1, and its key technical specifications are outlined below in table 1.

Table 1 - Technical specifications

Parameter	Specification
Data Rate	250 Kbps for radio signals; up to 1 Mbps for analog signals
Range	Up to 60 m in indoor/urban environments; up to 1200 m in open areas
Transmission Power	+8 dB
Receiver Sensitivity	−103 dB (1% error rate)
Supply Voltage	2.1–3.6 V
Current Consumption	135 mA during transmission (19 dBm); 17 mA during reception

A directional antenna array, consisting of four patch antennas, was chosen for this experiment. The use of such an array was essential because the experiment could not be performed effectively with a monopole antenna, like the one used in the transceiver. Monopole antennas provide omnidirectional radiation, which results in RSSI values that depend solely on the distance between the transmitter and receiver. This characteristic makes it impossible to determine the directional orientation of the transmitter relative to the directional antenna.

To address this limitation, microstrip patch antennas with an air gap were designed, simulated, and subsequently fabricated for use in the array. These antennas were selected for their compact size and compatibility with modern wireless communication systems, including Wi-Fi, mobile networks, and satellite communication.

2.3. Designing a patch antenna using MATLAB antenna toolbox. The shape of a patch antenna can vary widely, taking forms such as square, circular, or rectangular, depending on the design goals and application requirements. For this experiment, the geometric parameters of the patch antenna were determined using the MATLAB Antenna Toolbox.

This tool enables precise optimization of antenna dimensions to achieve the desired performance characteristics. Specifically, the parameters were chosen to minimize the S_{11} parameter, which represents the reflection coefficient and indicates efficient power transfer. Alternatively, formulas (1-5), can also be used to design patch antennas

for specific operational frequencies. The geometric dimensions of the designed patch antenna are presented in Figure 2. The antenna was constructed from three primary components:

- *Conductive Patch:* The patch serves as the radiating element and is typically made of copper due to its high conductivity, although other metals may be used. The geometry of the patch directly affects the operating frequency, enabling customization for specific applications.

- *Dielectric Substrate:* The substrate is located beneath the conductive patch and isolates it from the ground plane. For this design, an *FR-4* fiberglass epoxy laminate with a dielectric constant ε = 4,4 was chosen. This material influences signal propagation speed and impedance.

- *Ground Plane:* The ground plane is positioned on the opposite side of the substrate. It directs the radiated signal, ensuring it propagates in a specific direction. A coaxial feed line is used to provide power to the patch via the ground plane. To ensure compatibility with the XBee module operating under the ZigBee protocol, which spans a wide frequency range with 16 channels spaced 5 MHz apart, the antenna includes an air gap to enhance performance. This design ensures optimal impedance matching and effective radiation across the required frequency bands.

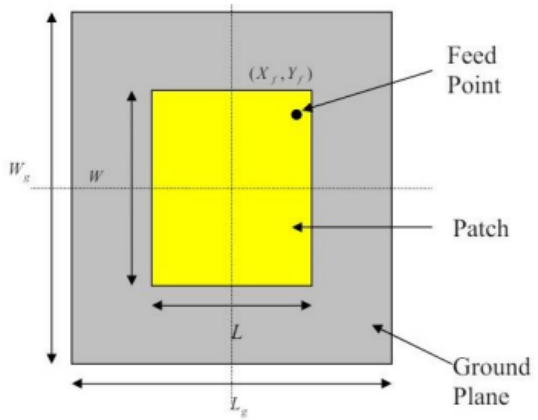


Fig.2 - Geometrical parameters of the patch antenna

The width of the microstrip patch antenna is calculated using Equation (1):

$$W = \frac{c}{2f_0\sqrt{\frac{\varepsilon_r+1}{2}}} \quad (1)$$

where:

- W: Width of the patch;
- c: Speed of light;
- f_0: Operating frequency;
- ε_r: Dielectric constant of the substrate.

To calculate the length, the following intermediate parameters are required:

1. *Effective dielectric constant* (ε_{reff}) is calculated using Equation (2):

$$\varepsilon_{reff} = \frac{\varepsilon_r + 1}{2} + \frac{\varepsilon_r - 1}{2}\left[1 + \frac{12h}{W}\right]^{-\frac{1}{2}} \quad (2)$$

where: h - thickness of the dielectric substrate.

2. *Effective length* (L_{eff}) is determined by Equation (3):

$$L_{eff} = \frac{c}{2f_0\sqrt{\epsilon_{reff}}} \quad (3)$$

3. *Extension in length* (ΔL) is obtained from Equation (4):

$$\Delta L = 0.412h\frac{(\varepsilon_{reff} + 0.3)(\frac{W}{h} + 0.264)}{(\varepsilon_{reff} - 0.258)(\frac{W}{h} + 0.8)} \quad (4)$$

4. *The actual length* (L) of the patch is computed as:

$$L = L_{eff} - 2\Delta L \quad (5)$$

2.4. Machine learning techniques. After collecting the data, it was processed and analyzed using machine learning techniques like XGBoost, Random Forest, SVM and KNN.

XGBoost is a powerful tool for addressing tasks involving regularized gradient boosting, an effective ensemble learning method designed to improve prediction accuracy [14]. Ensemble methods, such as gradient boosting, combine the outputs of multiple models to produce stable and accurate predictions.

Random Forest is an ensemble machine learning method based on using multiple decision trees for classification or regression. It has high robustness to outliers and overfitting due to the random selection of features and data when constructing trees.

Support Vector Machine is a method that uses a hyperplane to separate classes with the maximum margin between them. SVM is particularly effective for tasks with small datasets and works well with both linearly and non-linearly separable data using kernel functions.

k-Nearest Neighbors (k-NN) is a method that classifies objects based on their proximity to the k nearest neighbors in the feature space. The algorithm is simple to implement but is sensitive to the sample size and the choice of distance metric.

The performance of the model was evaluated using four key metrics: Mean Squared Error, Root Mean Squared Error, Coefficient of Determination and Mean Absolute Error.

Mean Squared Error (MSE): This loss function is used to measure the average squared difference between actual and predicted values, as shown in Equation (6):

$$L\left(y,\hat{y}\right)=\frac{1}{2}\sum_{i=1}^{n}\left(y_i-\hat{y}_i\right)^2 \tag{6}$$

where:

- y_i: Actual value.
- $\hat{y}_i$: Predicted value.
- n: Number of data points.

Root Mean Squared Error (RMSE): This loss function is used to measure the square root of the average squared difference between actual and predicted values, as shown in Equation (7)

$$RMSE=\sqrt{\frac{1}{n}\sum_{i=0}^{n-1}\left(y_i-\hat{y}_i\right)^2} \tag{7}$$

where:

- y_i: Actual value.
- $\hat{y}_i$: Predicted value.
- n: Number of data points.

Coefficient of Determination (R^2): This metric evaluates how well the model explains the variance in the target variable. It is expressed as:

$$R^2=1-\frac{SS_{res}}{SS_{tot}} \tag{8}$$

where:

- SS_{res} is the residual sum of squares.
- SS_{tot} is the total sum of squares.

Mean Absolute Error (MAE): This loss function measures the average absolute difference between actual and predicted values, as shown in Equation (9):

$$MAE=\frac{1}{n}\sum_{i=0}^{n-1}\left(|y_i-\hat{y}_i|\right) \tag{9}$$

where:

- y_i: Actual value.
- $\hat{y}_i$: Predicted value.
- n: Number of data points.

Results and Discussion. To improve the gain of a single patch antenna, an antenna array consisting of four patch antennas was assembled, as shown in Figure 3.

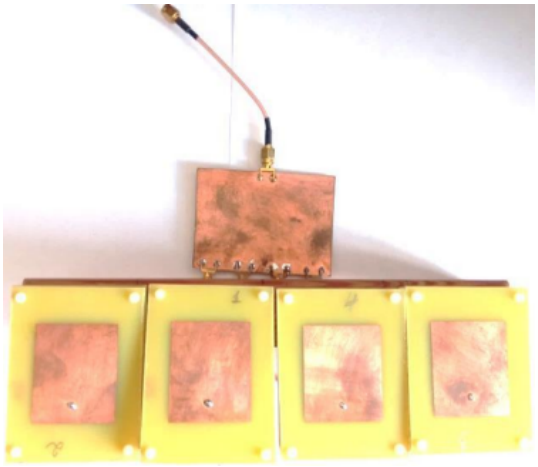


Fig.3 - The appearance of the patch antenna

During initial experiments, it was determined that the gain of a single patch antenna was insufficient, leading to packet loss during transmission and reception between isotropic and directional

antennas. By configuring all antennas in the array to operate in phase, the signals emitted by each antenna constructively interfere in the desired direction, resulting in increased gain. Simultaneously, signals in other directions destructively interfere, reducing unwanted radiation. Achieving proper phase alignment within the array was critical to maximize the gain in the desired direction while minimizing signal strength in other directions. This was accomplished through precise placement and phase delay adjustments for each antenna in the array.

The reflection coefficient (S_{22}) of the antenna array was studied in the frequency range from 2.2 to 2.7 GHz. The Figure 4 shows that the minimum value of the reflection coefficient, equal to approximately -40 dB, is achieved at a frequency of 2.56 GHz, which indicates the best matching of the antenna at this point. At the same time, the reflection coefficient values remain quite low throughout the analyzed frequency range, which makes the antenna suitable.

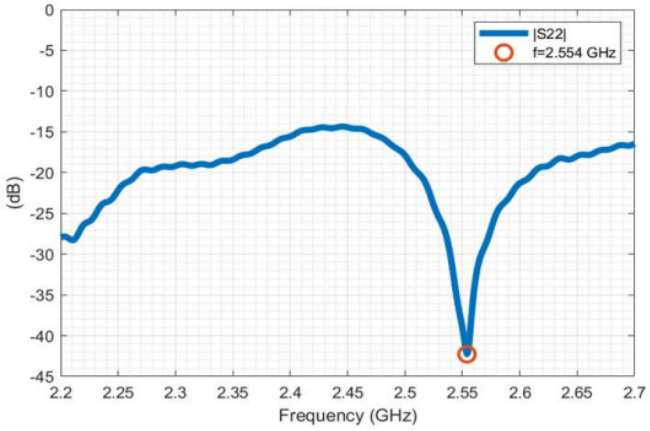


Fig.4 - The reflection coefficient of the antenna array

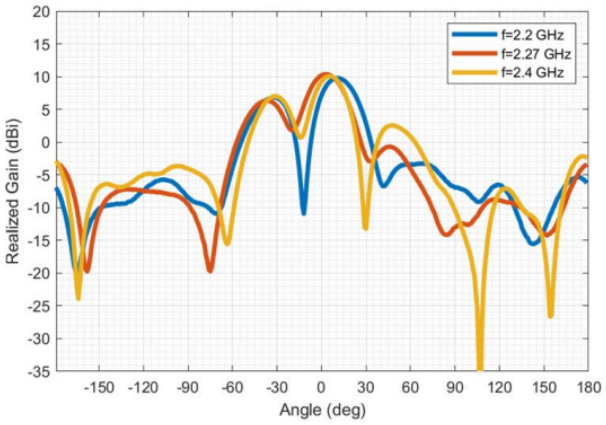


Fig.5 - The radiation patterns of the antenna

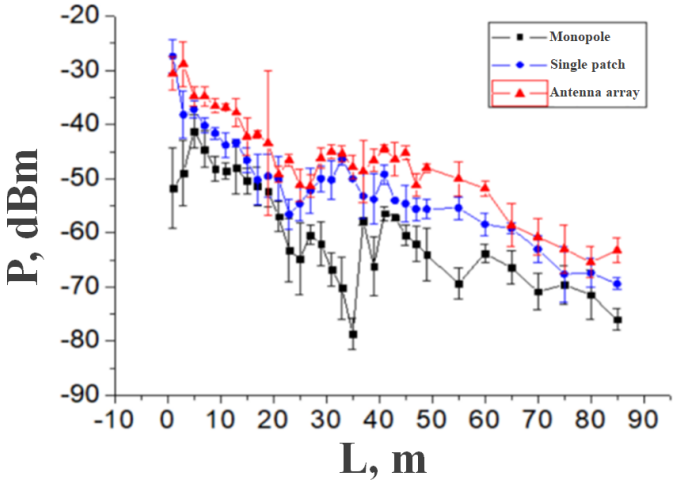


Fig.6 - The dependence of received signal power on distance for three different antennas: monopole antenna, patch antenna, and antenna array, with the same transmission power level of 18 dBm at a frequency of 2.4 GHz

The radiation patterns of the antenna were plotted for three frequencies: 2.2 GHz, 2.27 GHz, and 2.4 GHz. The maximum gain reaches 10 dBi, confirming the good directionality of the antenna. Moreover, the radiation patterns exhibit notable similarity across the different frequencies, indicating the stability of the antenna's directional characteristics within the analyzed range.

The Figure 6 illustrates the variation in received

signal strength (RSSI) as a function of the distance between the transmitter and receiver for three types of antennas: a monopole antenna (black line), a single patch antenna (blue line), and a patch antenna array with four elements (red line). The measurements were conducted with a consistent transmission power level of 18 dBm at a frequency of 2.4 GHz. The antenna array shows the best signal reception levels at all distances, confirming its superiority over the other antenna types. It is also observed that RSSI decreases with increasing distance for all antennas, which aligns with the expected theoretical behavior.

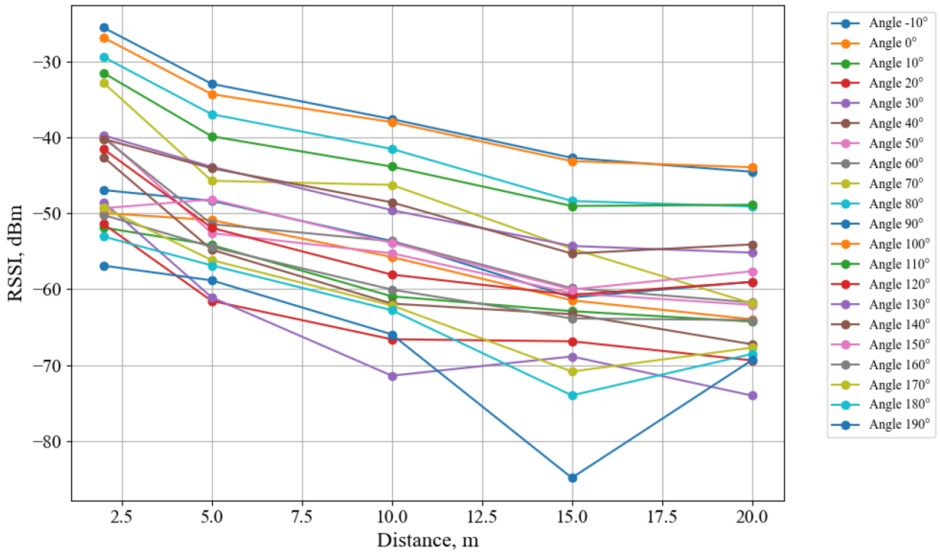


Fig.7 - RSSI dependence on distance for different measurement angles

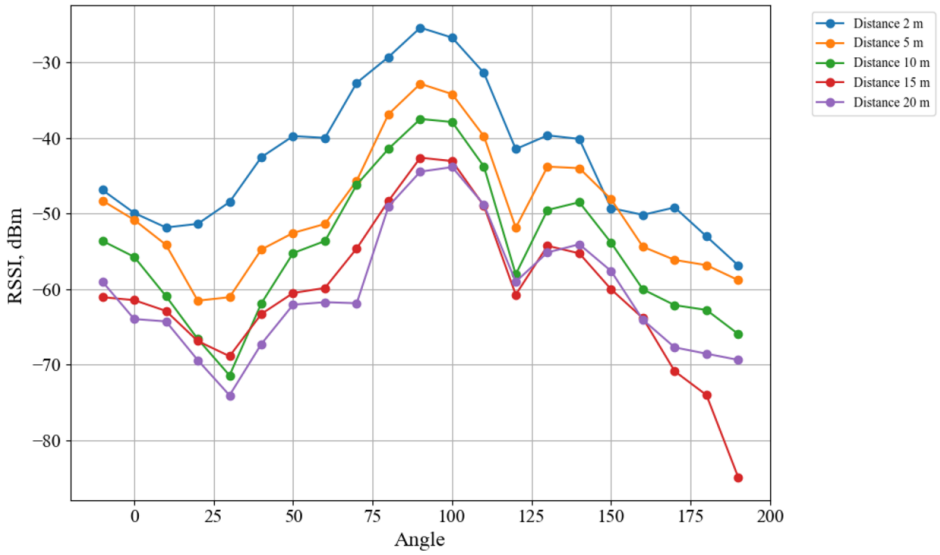


Fig.8 - RSSI dependence on the measurement angle for different distances

Figure 7 and 8 illustrates the variation in RSSI values as a function of both distance and angular position. The graph provides a clear visualization of how the RSSI by the antenna array changes under different experimental conditions.

Distance Effect: As the distance between the

transmitter and the antenna array increases, the RSSI value decreases consistently. This behavior aligns with the fundamental principles of signal attenuation over distance, where the signal strength weakens due to free-space path loss.

Angle Effect: The variation in RSSI across angular positions reflects the directional sensitivity of the antenna array. Constructive interference in the desired direction produces higher RSSI values, while destructive interference in other directions reduces the signal strength.

To enhance the understanding of how the Zigbee node' s position can be accurately determined, machine learning techniques were applied to process and analyze the collected RSSI and distance data. During the experiments, data on RSSI values were collected at various distances and angular positions relative to the antenna array. Normalization of RSSI and distance values was performed to improve the stability of model training and prevent bias due to features with large scales. Then, a comparison of four machine learning algorithms—XGBoost, Random Forest, Support Vector Machine, and K-Nearest Neighbors - was conducted. The dataset was split into training and testing sets. The models' performance was evaluated using the following metrics: MAE, MSE, RMSE, and R^2 Score. The results of model training and testing are presented in Tables 2 and 3, respectively.

Table 2 - Training results

Machine learning algorithms	MAE	MSE	RMSE	R^2 Score
XGBoost	1,0778	2,8780	1,4091	0,9776
Random Forest	1,4786	3,901165	1,9751	0,9656
Support Vector Machine	7,2566	82,3409	9,0741	0,2748
K-Nearest Neighbors	2,7802	15,3381	3,9163	0,8649

Table 3 - Testing results

Machine learning algorithms	MAE	MSE	RMSE	R^2 Score
XGBoost	2,3568	3,9470	2,9994	0,9095
Random Forest	3,1287	14,2804	3,7789	0,9002
Support Vector Machine	9,0774	115,2343	10,734	0,2754
K-Nearest Neighbors	3,2321	17,5434	4,1884	0,8896

An analysis of the results showed that the XGBoost algorithm demonstrated the best performance. It achieved the lowest error values (MAE, MSE, RMSE) and the highest R^2 Score compared to the other models. This indicates its strong generalization ability and high prediction accuracy for this task. Other models, such as Random Forest, SVM, and KNN, also showed competitive results, but their accuracy was lower, especially SVM, which had the worst R^2 Score. Thus, XGBoost is the most preferable choice for predicting RSSI values in this scenario.

The graphs in Figures 9 and 10 show a comparison of the actual and predicted RSSI values for the training and test datasets, confirming the high accuracy of the model in forecasting.

The decrease in RSSI values with increasing distance is a predictable phenomenon, described by the free-space path loss model. However, angular variation introduces additional complexity due to the directional sensitivity of the antenna array, which creates nonlinear dependencies.

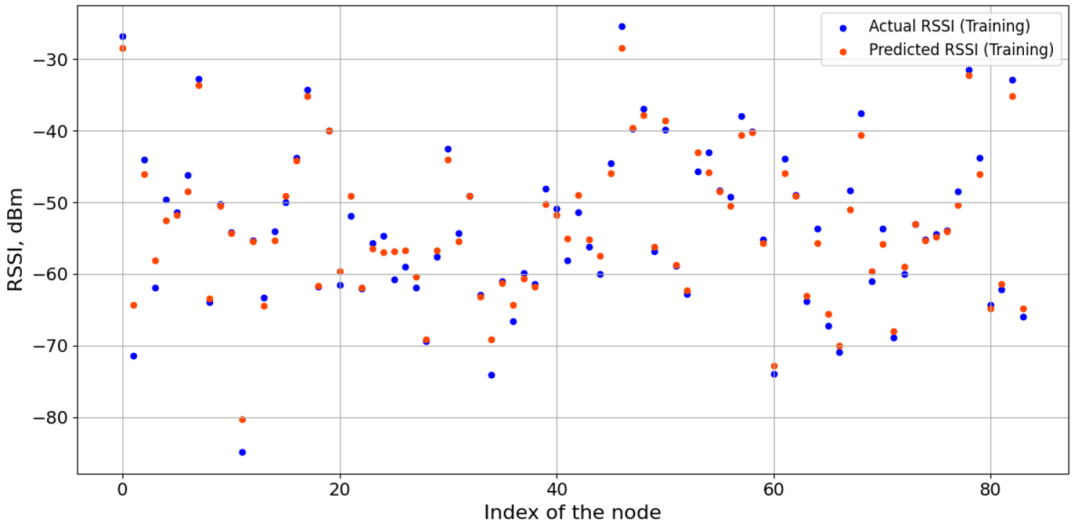


Fig.9 - Comparison of actual and predicted RSSI values on training data

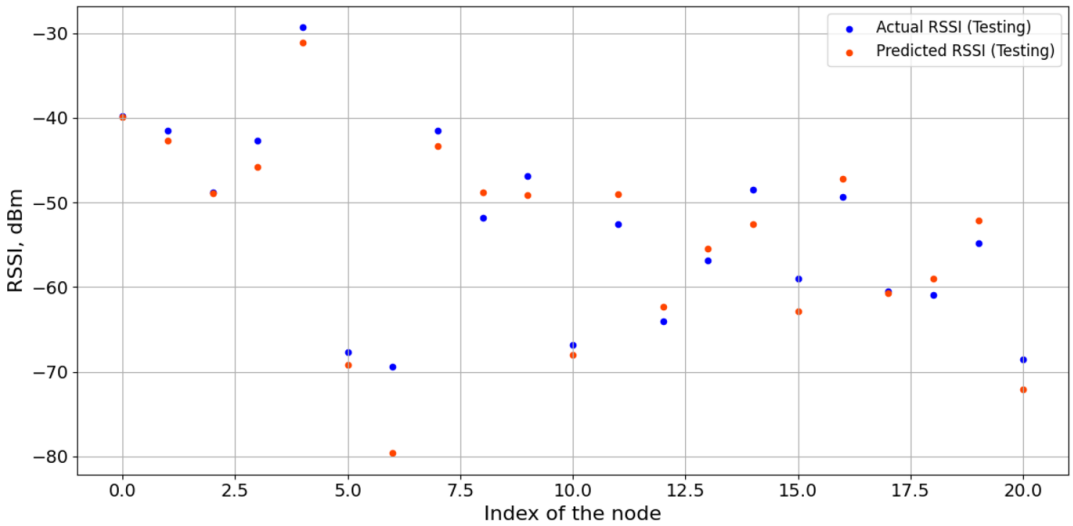


Fig.10- Comparison of actual and predicted RSSI values on testing data

Conclusion. This article presents a single-anchor node localization method that combines ZigBee technology, directional antennas, and machine learning to provide a cost-effective, scalable, and accurate solution for wireless sensor networks (WSNs). Experimental results demonstrate that the use of a directional antenna array significantly enhances signal reception, achieving a maximum gain of 10 dBi and reducing packet loss compared to monopole and single-band antennas. The system effectively captures the relationship between RSSI, distance, and angular positions, as evidenced by the consistent decrease in RSSI values with increasing distance and their variation depending on angular positions.

The XGBoost model trained on the experimental data outperformed other machine learning algorithms, achieving a training R^2 of 97.76% and a testing R^2 of 90.95%, with a training MSE of 2.878 and a testing MSE of 3.947. While the model performs well in controlled environments, variability in testing highlights the need for further optimization. The results demonstrate the potential of ZigBee-based single-anchor localization systems as a viable alternative to traditional multi-anchor setups, offering a reliable, energy-efficient, and cost-effective solution for IoT and WSN applications

requiring accurate and scalable localization systems.

A single-anchor node localization system can be applied in industrial facilities, smart buildings, medical institutions, and transportation hubs to improve the accuracy of tracking objects and personnel.

In future research, we plan to conduct experiments in urban environments and indoor spaces to study the impact of various interferences, such as Wi-Fi and multipath signal propagation, on localization accuracy.

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