Management Strategies and Engineering Sciences 2026; 8(4):1-13

RSFLoc: Robust Smart Fingerprint Localization-Based Hybrid PSO– ANN Approach in Complex Environment

Rawaa Akram Mohammad Ali [1], Negar Majma [1*] Aseel Hameed Al-Nakkash [2] Mohammadreza Soltanaghaei [1]

[1] Department of Computer Engineering, Isf.C., Islamic Azad University, Isfahan, Iran
[2] Department of Computer Engineering, Electrical Engineering, Technical College, Middle Technical University, Iraq

*** Corresponding author email address**: Negar.majma@iau.ir

Received: 2025-07-07 **Revised:** 2025-11-22 **Accepted:** 2025-11-29 **Initial Publish:** 2025-12-09 **Final Publish:** 2026-12-01

Abstract

The rapid proliferation of Internet of Things (IoT)-enabled wireless localization systems has gained prominence in electrical engineering applications, particularly in domains such as healthcare, where precise indoor positioning is essential for tracking personnel and assets. This paper introduces the Robust Smart Fingerprint Localization (RSFLoc) model, leveraging Received Signal Strength Indicator (RSSI) fingerprinting in wireless communication networks. The model enhances localization accuracy through the optimization of an Artificial Neural Network (ANN) using Particle Swarm Optimization (PSO), addressing key signal processing challenges like multipath propagation, shadowing, and environmental dynamics in indoor environments. In the offline phase, RSSI data from multiple Access Points (APs) across diverse zones are rigorously analyzed to evaluate signal robustness and model path loss (PL) characteristics. The online phase deploys the PSO-optimized ANN on a simulated ESP32 microcontroller interfaced with MATLAB/Simulink for real-time x-y coordinate estimation. Localization results are transmitted via IoT protocols to the ThingSpeak cloud platform, enabling visualization and remote monitoring through a mobile application. Experimental results demonstrate high fidelity between measured and estimated PL curves, with a low Mean Square Error (MSE) of 1.001 dB for RSSI-driven PL modeling (ranging from 3.2723×10^{-4} to 1.001 dB). The ANN model's validation MSE achieves 2.0956 m, outperforming training (MSE: 0.0557 m post-optimization) and testing phases due to improved hyperparameter tuning via PSO, which enhances convergence stability. Regression analysis reveals strong linearity ($R^2 > 0.95$) between predicted and actual locations, while error histograms indicate an 85% reduction in localization error compared to baseline methods, underscoring the model's efficacy in practical wireless communication systems.

Keywords: *PL, RSSI, ANN, PSO, fingerprint localization. MSE*

How to cite this article:

Mohammad Ali, R. A., Majma, N., Al-Nakkash, A. H., & Soltanaghaei, M. R. (2026). RSFLoc: Robust Smart Fingerprint Localization-Based Hybrid PSO– ANN Approach in Complex Environment. Management Strategies and Engineering Sciences, 8(4), 1-13.

1. Introduction

The Internet of Things (IoT) is a rapidly growing technology that is focused on linking every appliance to the Internet for communication purposes. It is anticipated to significantly alter a number of industries, including manufacturing, business, public transit, healthcare, education, and home automation [1]. The localization of objects is a crucial component of the smart world transformation process. The global positioning system (GPS) effectively meets the extensive demands of outdoors; nevertheless, its efficiency is weak and its usefulness is severely restricted in internal environments[2]. Many technologies are used in Indoor localization like WiFi [3], Bluetooth[4] , Ultra Wide Band (UWB) [5] , ZigBee [6] , computer vision [7] , and Radio Frequency Identification (RFID) [8]. WiFi, ZigBee, and Bluetooth are wireless sensor network (WSN) technologies derived from IEEE 802 standards, characterized by low power consumption and affordability. The basic idea of RFID localization is to improve wireless communication propagation by utilizing the characteristics of Radio Frequency (RF) [9]. Received Signal Strength Indicator (RSSI) values are utilized to determine the position of an item based on the theory of trilateration. With a low transmission rate and a short transmission distance, Zigbee-based localization calculates the distance between the unknown and reference places beforehand. WiFi fingerprint-based localization is widely used in the domain of indoor localization [10]. Yet, it is constrained by the fluctuating nature of WiFi signals, rendering offline data inadequately dependable and getting unstable, and low accuracy localization. Low Signal to Noise Ratio (SNR), non-Line-of-Sight (NLOS) propagation, and shadowing are additional challenges. Additionally, because of its requirements for computation, storage, and latency, the use of Machine Learning (ML) adds even more complexity, especially during the online stage of the fingerprinting process. Many ML techniques have been proposed forth to create models that can accurately predict indoor locations in real time. These techniques aim to improve the precision of fingerprinting and support the updating of radio maps when working with big datasets. In indoor localization applications, the use of Artificial Nural Network (ANN) has demonstrated promise in overcoming these obstacles and reaching better precision [11]. Optimization techniques have emerged to further improve localization performance, especially in complex indoor environments [12]. This study aims to suggest a hybrid Particle swarm optimization (PSO)-ANN approach as an innovative way to enhance indoor localization accuracy known as RSFLoc. RSFLoc successfully handles the complexity of indoor localization by utilizing the advantages of both PSO and ANN. At the offline stage, a reliable dataset is built then used to train an optimized ANN. For online stage, IoT device is simulated using MATLAB to send location information to IoT platform and displayed to at this platform. Also, a mobile application is linked to the IoT platform to display location information remotely.

2. Literature survey

This paper begins with a critical review of existing literature on fingerprint localization approaches. The hybrid deep learning-based PRLoc fingerprint indoor localization method has been introduced by [13]. The presented approach used RSSI and Round-Trip Time (RTT) measurements in lab and corridor environments to train models with varying numbers of layers in deep version of canonical correlation analysis (DCCA). The proposed approach includes creating RSSI and RTT datasets from WiFi signal at multiple RPs to determine a user's location in real time and combines these with the fingerprint dataset. The experiment results demonstrate that RRLoc can achieve accuracies 0.51m and 0.59m for office and lab environments, respectively. The researchers in [14] developed a low-cost indoor fingerprint localization system based on the nearest neighbor algorithm. The approach estimates the user's location in the room utilizing BLE beacons and a wearable device that works as a Bluetooth scanner. The system employs the Neural Neighbor algorithm with a moving average filter for enhanced performance. The system achieves a localization accuracy of 92.106% in five rooms and 85.09% in three rooms. Also, the authors in [15] designed a hybrid positioning system based on WiFi by combining WiFi, fingerprint, and acoustic ranging, along with sensors such as a gyroscope, accelerometer, and magnetometer .They used the weight K-Nearest Neighbors (WKNN) algorithm for position estimating achieving a localization accuracy of 2.01 m. The FegHIL, embedded system has been proposed in [16] using a neural network based federated learning algorithm for indoor localization. The authors used WiFi for localization issues in a complex environment. The average error of the proposed method was 3.24m. The authors in [17] used Bluetooth Low Energy (BLE) to present a fingerprint localization system. They measured RSSI at each BLE beacon and tested it using KNN and WKNN in three scenarios a laboratory, a meeting room, and a corridor. They deployed the beacons as a gradient each scenario. They found that the WKNN achieved higher accuracy than KNN in all scenarios. The authors in [18] proposed a device for indoor localization using RSSI fluctuations and SNR ratio collected from LORAWAN gateways and linked it to the IoT network. The system utilizes neural networks to predict the device's location. By measuring a beacon device's signal strength, the suggested method achieves 98.8% accuracy. With a distance of m between LoRaWAN gateways, the average error was 2.7 m. By merging predictions from several ML algorithms, the Smartlog framework [19] improves localization accuracy in a complex indoor environment. Two stages form the structure: an online stage for user location prediction and an offline stage for MLA training. A Space of Candidate Labels (SCL), produced from algorithm predictions, serves as the foundation for location estimation. A pre-collected database is used to train ML algorithms ,offline, and probability alignment is used to balance the confidence levels. The authors in [20] proposed iF_Ensemble, combining isolation forest (iForest), Support Vector Machines (SVM), Random forest (RF), and KNN to evaluate WiFi RSS data for indoor localization. The proposed method outperformed existing outlier detection techniques was evaluated against classification-based outlier detection techniques in wireless sensor networks and demonstrated superior classification-based outlier detection techniques in wireless sensor networks and demonstrated superior performance in term of precision, recall, F1-score, and accuracy. The evaluation indicated 97.8% accuracy and a 97.62% F-score when using the proposed suggested outlier. Outlier removal improved localization accuracy 2% in indoor environments. During the online phase, labels with probabilities above a threshold are extracted from each ML algorithm using RSS samples to build the SCL.

3. Materials and Methods

This section details the experimental design of the proposed framework. The investigation was conducted on the sixth floor of a hospital building, which included brick walls, concrete floors, and metal-framed glass windows and doors. The experimental environment consists of four zones (Zone 1, Zone 2, Zone 3, and Zone 4) with dimensions listed in Table 1. RSSI values from four IEEE 802.11 WiFi Access Points (AP) and installed at a height of 2 meters within the zones, were collected to build the fingerprint dataset. Each AP has LOS to one zone and NLOS to the others. Numerous Receiver Points (RPs) were placed in each zone to gather RSSI data from all APs: 26 RPs in Zone 1; 20RPs in Zone 2; 22 RPs in Zone 3; and 20 RPs in Zone 4, as shown in Fig. 1. Additional experimental settings are summarized in Table 1.

Table 1. experimental set up specifications

Parameter	Configuration
Zone1	1.5 x26m
Zone2	2.5x21m
Zone3	2.2x23m
Zone4	2.6x21m
Communication protocol	802.11n
No. channels	6
Channel Bandwidth	20MHz
Frequency	2.4GHz
Transmitter power	20dBm
Transmitter height	1.5m
RP height	1m
AP and RP antenna	Omni-direction
Transmitter gain	5dBi
Receiver gain	3dBi

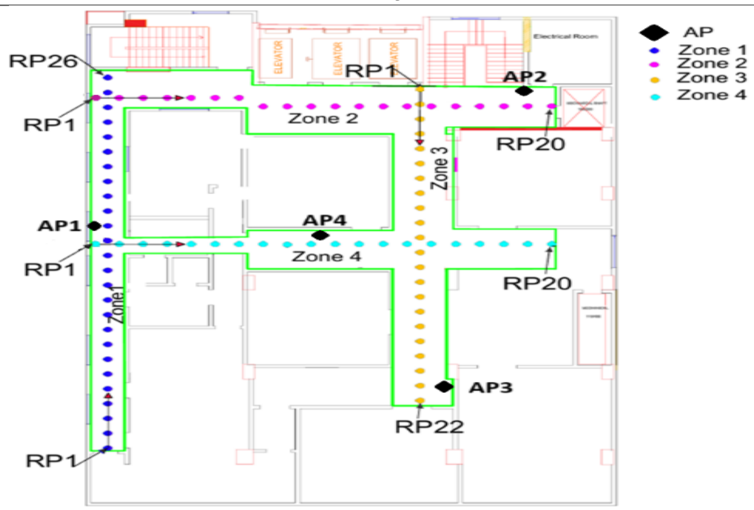


Figure 1. Distributed APs and RPs in the indoor environment.

3.1. RSSI and PL evaluation

The evaluated RSSI data were used to build a reliable dataset for fingerprint localization process. To assess the accuracy of the collected RSSI values, the Euclidean distance between the i-th RP and j-AP is calculated using Equation (1)

$$d_i = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (1)$$

Where (x_i, y_i) are the coordinates of the i-th RP, and (x_j, y_j) are the coordinates of the j-th AP. The Euclidean distance is input to the Log-normal Path Loss (PL) model, which is commonly used to model indoor radio signal propagation, as shown in Equation (2) [21].

$$PL(d)dB = PL(d_0) + 10n\log(\tfrac{d}{d_0}) + \sigma \qquad (2)$$

Where $PL(d_0)$ is average PL at the separation distance d_0, n is PL exponent, which equals 1.8 for LOS and 3.416452 for NLOS scenarios. σ is standard deviation of PL, equal to 3.626205 for LOS and 7.430673 for NLOS in this study. Considering the characteristics of multipath propagation, the received power (P_r), which represents the reduction in signal power during transmission between the transmitter and the receiver, is another important parameter. P_r can be computed using the following formula at d, as shown in Equation (3) [22]:

$$\Pr(d) = P_t - PL(d) \qquad (3)$$

Where P_t denotes the transmission power. The Mean Square Error (MSE) was calculated for each zone and all APs using Equation (4):

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(PL_{emp} - PL_{est}\right)^2 \qquad (4)$$

Where PL_{emp} is the empirical PL, that is measured at each RP, PL_{est} is the estimated PL over distance, and N is number of RP in each zone. the steps involved in this stage are illustrated in Fig. 2.

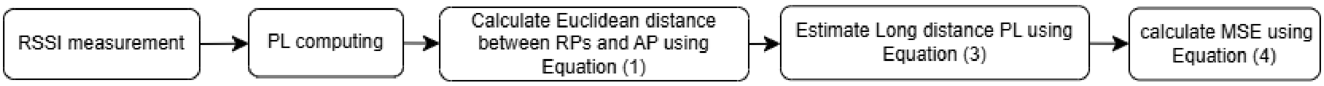


Figure 2. RSSI and PL evaluation stage.

3.2. Fingerprint localization model

After evaluation the RSSI measurement data, it can be used as a dataset for fingerprint localization model, as mentioned earlier. The fingerprint localization model consists of two stages: an offline stage (training and optimization), and an online stage (running and testing). These stages are illustrated in details in Fig. 3.

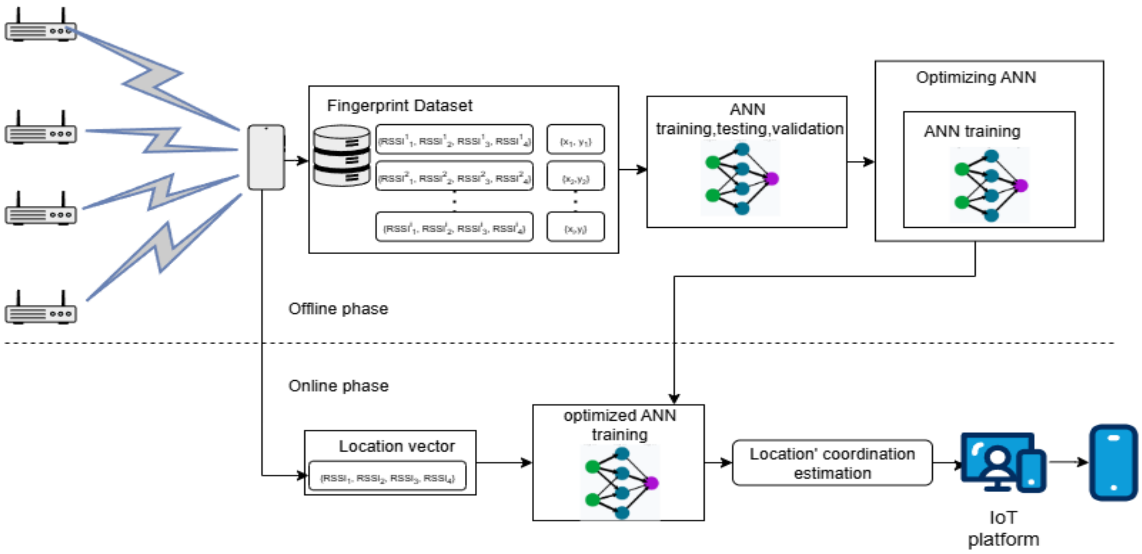


Figure 3. Proposed WiFi fingerprint localization.

In the offline stage, the proposed system utilizes a Multilayer Perceptron (MLP) ANN trained using Levenberg-Marquardt (LM) algorithm, with further optimization using PSO. The RSSI measurements dataset at the i-th RPs from four APs is structures as in (5):

$$V_i = \{RSSI_1^i, RSSI_2^i, RSSI_3^i, RSSI_m^i\} \tag{5}$$

$$p_i = \{x_i, y_i\} \tag{6}$$

Where V_i is the RSSI vector at the ith RP, p_i is ith RP' position, m is the number of AP = 1, 2,3,4. This dataset is partitioned into 75% for training, 15% for testing, and 15% for validation to ensure robust evaluation of model's generalization capability. The architecture of ANN includes: input layer with 4 neurons corresponding to is the RSSI in V_i, two hidden layers N1 and N2, each containing 10 neurons, an output layer with 2 neurons representing the x and y coordinates (location position), and LR is set to 0.5. The Forword propagation in ANN is described as in (7), and (8):

$$y_i = f\left(\sum_{i=1}^{n} w_i x_i + b_i\right)$$

$$f(x_i) = \frac{1}{1+e^{-x_i}}$$

Where w_i and b_i are the weights and biases of ith layer, respectively. f is the sigmoid activation function of the ith layer. the network is training to minimize MSE:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Y_t - Y_o)^2$$

Where N is number of RPs and Y_t and Y_o are measurement and the estimated location, respectively. To enhance localization accuracy and present a reliable localization system, PSO is applied to optimize ANN, including the LR, and the number of neurons in hidden layer 1 and2. PSO updates the particle' velocity and position using:

(7)

$$x_i^{t+1} = (x_i^t * w) + (c1 * u1 * P_{best}^t - P_i^t) + (c2 * u2 * P_{gest}^t - P_i^t) \tag{10}$$

$$P_i^{t+1} = P_i^t + x_i^{t+1} \tag{11}$$

where x_i^{t+1} is the velocity of next iteration, and x_i^t is the velocity of *ith* iteration, w is the initial weight that controls the influence of the current velocity on the velocity of the next iteration, P_{pbest}^t is the best position found by the *ith* particle ,and P_{gbest}^t is the global best position found by the swarm. The coefficient c1 and c2 control the influence of the cognitive and social components, respectively, and P_{pbest}^t and P_{gbest}^t, and u1 and u2 are random numbers distributed between 0 and 1. The cost function in PSO is MSE. Through iterative refinement, PSO identifies the optimal ANN architecture that significantly reduce the localization error. During the online phase, the optimized ANN is used for real time location estimation. The RP collects a location vector that includes the RSSI value from four APs, which are used as inputs to the optimized ANN. The ANN processes the input and estimates the coordinate location (x, y).

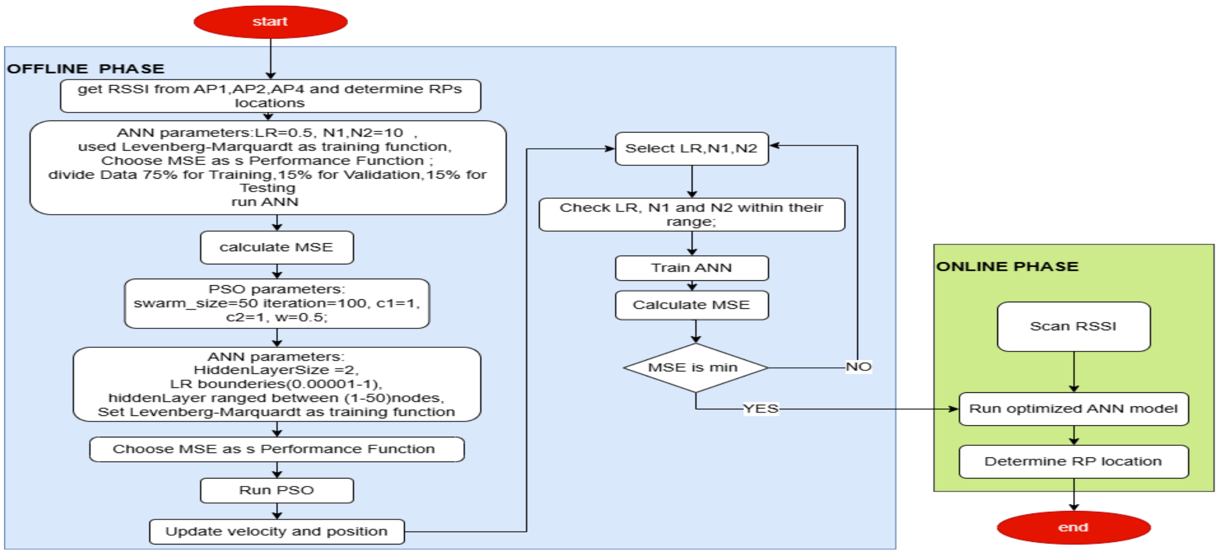


Figure 4. Flowchart of fingerprint localization processes.

During online stage, IoT device is simulated the real time operation of proposed system with Matlab 2023a, as explained in Fig. 5, to validate ANN model to estimate indoor location coordinators. The output is aggregated and transmitted to Thingspeak IoT platform for real time visualization and monitoring via ESP32 Arduino and displayed them at mobile application. Hybrid PSO-ANN fingerprint localization method, presented in the study, significantly outperforms conventional methods in term of localization precision.

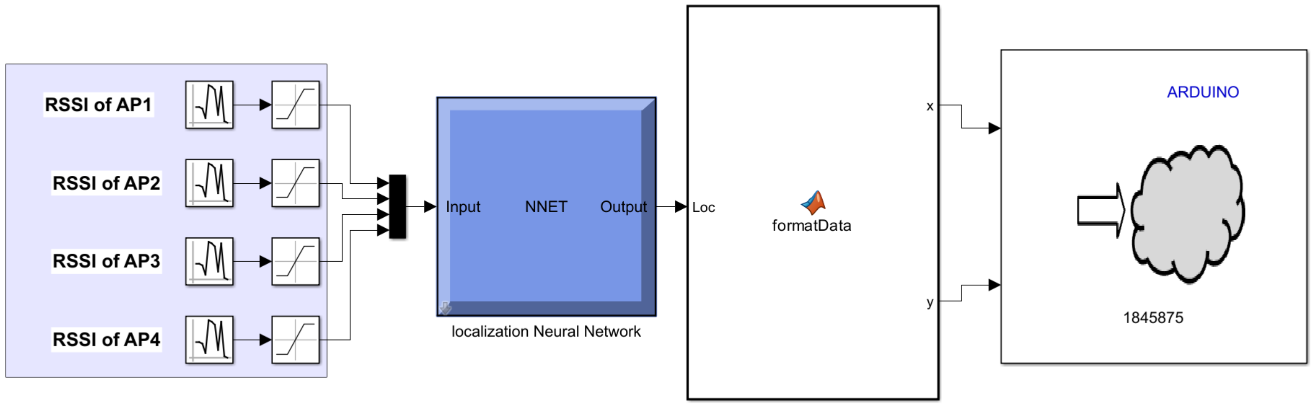
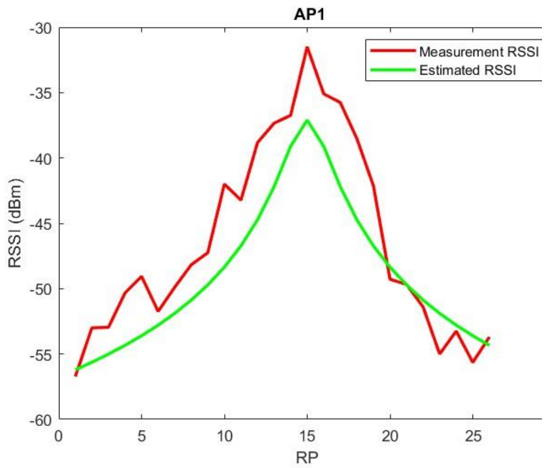


Figure 5. Simulation of IoT device

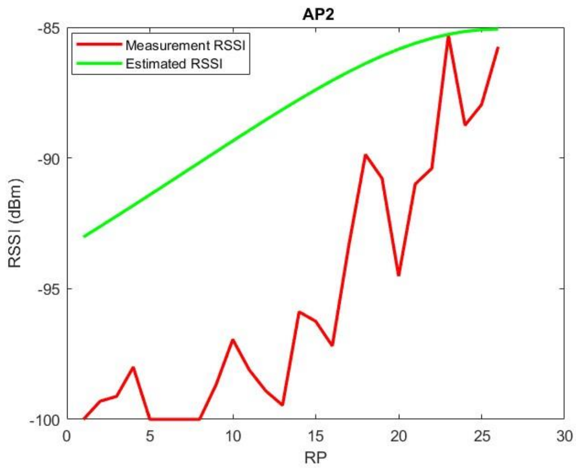
4. Results

4.1. *Offline Stage*

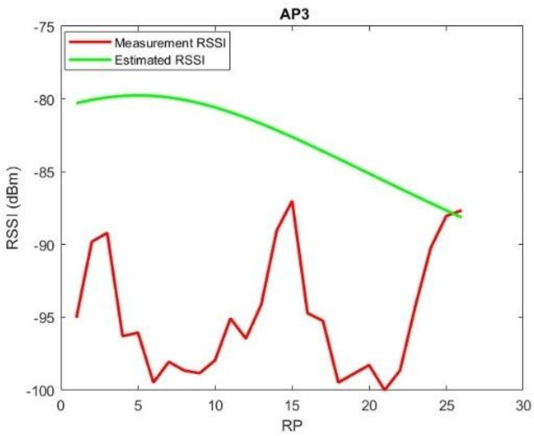
This section highlights the RSSI accuracy analysis of the dataset used in the fingerprint localization system, and discusses the optimization of the ANN model for location estimation. Fig. 6. demonstrates that AP1 has the most coverage in Zone 1 because it has a LOS with RPs, which gives it the strongest signal of all the APs. AP2 and AP3 have big fluctuations that might cause problems with connectivity in Zone 1. In contrast to AP2 and AP3, AP4 has a modest but more stable signal quality.



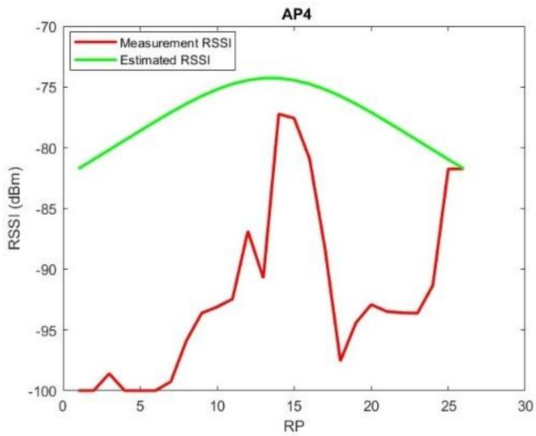
(a)



(b)



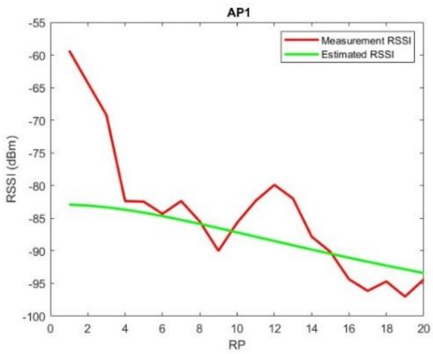
(c)



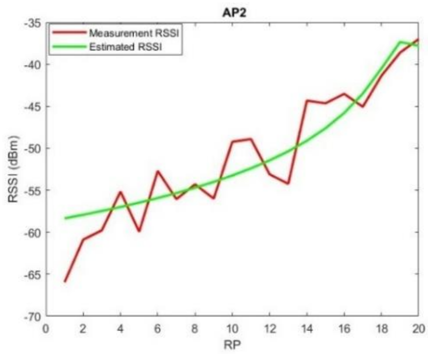
(d)

Figure 6. Measured and estimated RSSI at zone1 from: (a) AP1 , (b) AP2, (c) AP3, and (d) AP4.

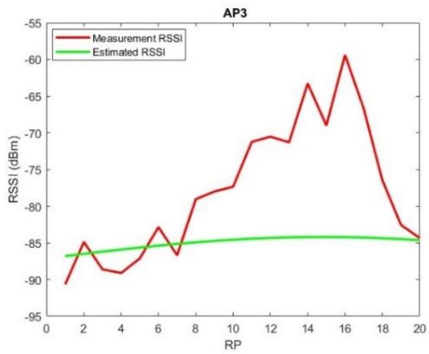
Fig. 7 compares measurement and estimated RSSI values for RPs in Zone 2 across all APs. AP2 delivered the strongest signal in it is LOS zone (Zone 2) with RSSI values decreasing gradually with distance. The tight alignment between measurement and estimated RSSI confirms accurate signal modelling for this LOS path. The NLOS APs, on the other hand, are ineffective as well since the signal is blocked. AP1 demonstrates some signal loss with distance, since small differences between the measured and estimated RSSI values indication that the model is not precise. AP3 is the worst of all the APs. It has a lot of signal instability and large estimate error, which means that there is a lot of blockage in its NLOS path. With lower signal strength, AP4 has good NOLS performance, which shows that the modeling is accurate.



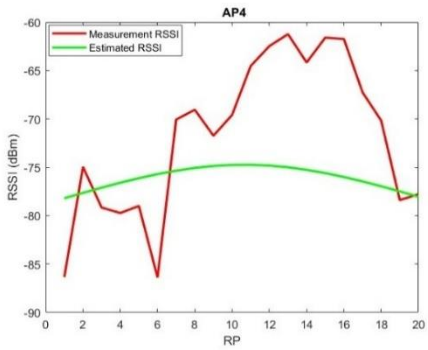
(a)



(b)



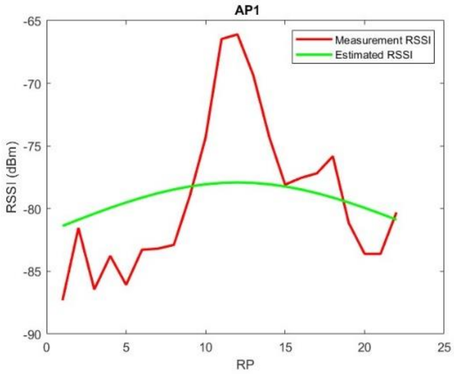
(c)



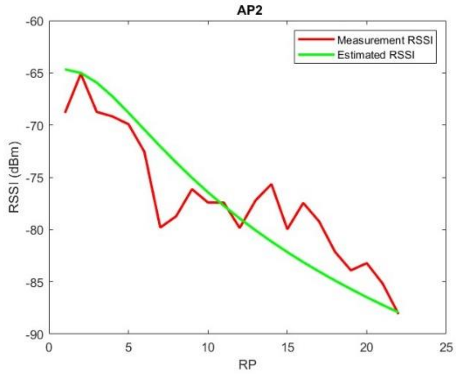
(d)

Figure 7. Measured and estimated RSSI at Zone2 from: (a) AP1 , (b) AP2, (c) AP3 , and (d) AP4.

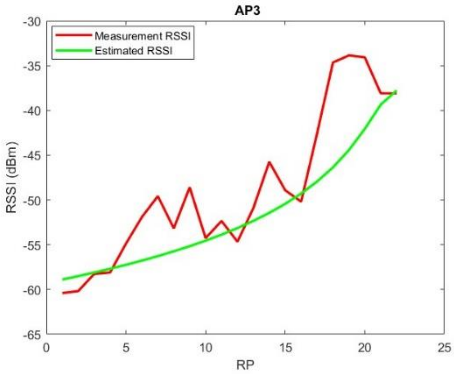
Fig. 8 presents comparisons in Zone3, where AP3 provides primary coverage. Fig. 7a demonstrates moderate attenuation (-65 dBm to -86 dBm), with minor deviations at RPs (10-15) due to their LOS connection with AP1. AP2 show a sharper mid-range drop -65 dBm to 90 dBm with increasing distance. AP3 delivers the strongest and most reliable signal in Zone 3, demonstrating effective LOS propagation. AP4 maintains signal strength between-50 to-70 dBm.



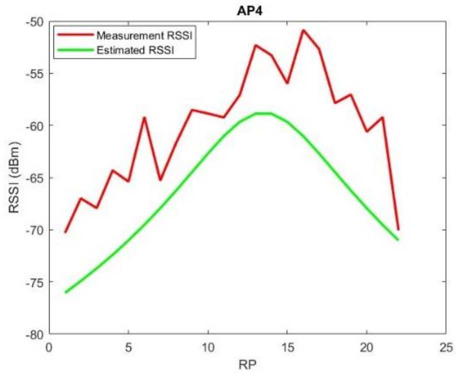
(a)



(b)



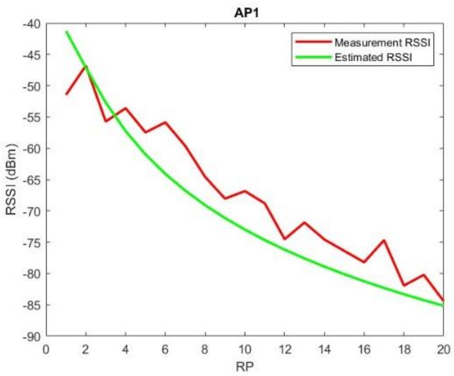
(c)



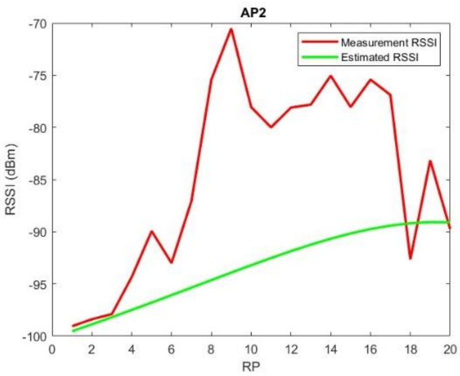
(d)

Figure 8. Measured and estimated RSSI at zone3 from: (a) AP1 , (b) AP2, (c) AP3, and (d) AP4.

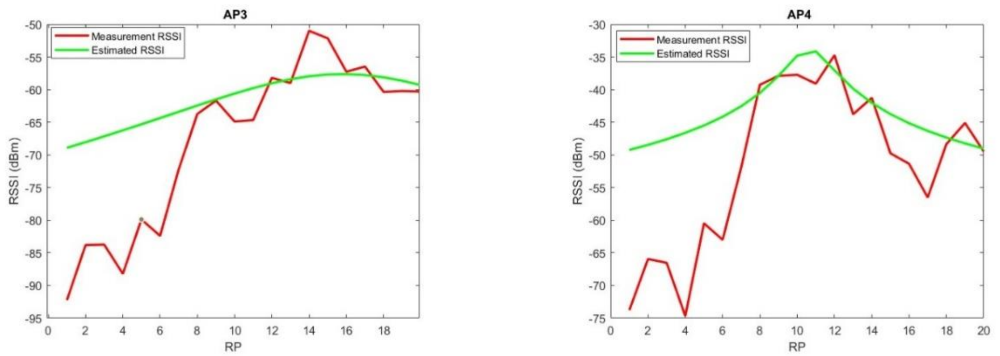
Zone 4 benefits from high coverage area by AP4 due to LoS conditions, as shown in in Fig. 9. AP1 is near Zone4 making the RPs get strong signal ranges between -45 dBm to -85 dBm decreasing with the distance, with minimal deviation between measurement and estimated RSSI Fig. 8b illustrates AP2' performance that is ranges between -70 dBm to -100dBm. AP3's RSSI variations reflect NLOS propagation, while AP4 demonstrate reliable LOS propagation with the strongest signal.



(a)



(b)



(c) (d)

Figure 9. Measured and estimated RSSI at zone4 from: (a) AP1 , (b) AP2, (c) AP3, and (d) AP4.

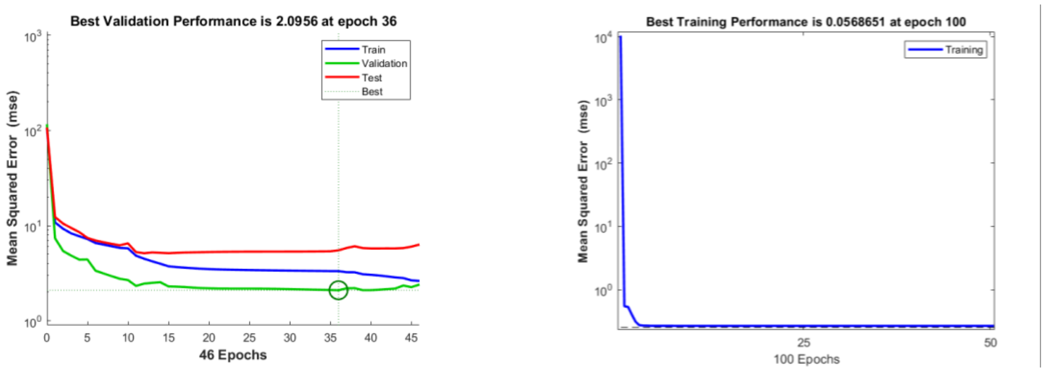
The results show that RSSI readings at various distances and in various zones varied significantly. Additionally, it is shown that the measurement and estimated values are very close because the predicted RSSI curve closely resembles the pattern of the measurement RSSI. In contrast, the measurement RSSI shows rapid changes between several RPs and a great deal of alteration. Multipath propagation, shadowing, and environmental interference are the causes of this.

The MSE values for each of the four zones' APs are displayed in Table (2). These values are a comparison between the actual RSSI-derived PL and the estimated PL from Equation (2). Remarkably low MSE values (ranging from 3.2723*10-04 to 1.001 dB) confirm the high quality of the fingerprint dataset. Minimal MSE values are primarily occur in zone intersection areas where RPs clarifies as NLOS in the estimated model maintain LOS connections with other APs in the measured model.

Table 2. MSE between estimated and measured PL.

Zone	AP1	AP2	AP3	AP4
Zone1	0.4092	0.4599	0.2394	$3.2723*10^{-04}$
Zone2	1.001	0.6244	0.0903	0.710
Zone3	0.338	0.0292	0.1081	0.945
Zone4	0.5522	0.4073	0.9877	0.1828

The proposed fingerprint localization model uses an optimized ANN, with optimal parameters the Learning Rate (LR), and the number of neurons in the two hidden layers are selected by PSO. Fig. 10 compares the of the conventional ANN and PSO optimized ANN performance. The validation curve demonstrates successful ANN training, achieving a minimum validation MSE of 2.0956 MSE at epoch 36. After optimization, the PSO-ANN exhibits major enhancements. It has a significantly decrease in training MSE of 0.05568651 m and a better training slope, which means it learns better.



(a) (b)

Figure 10. Performance of (a)ANN, (b)PSO-ANN.

Regression analysis (Fig. 11) shows high R values across training, testing, and validation phase, indicating strong linear correlation and effective learning.

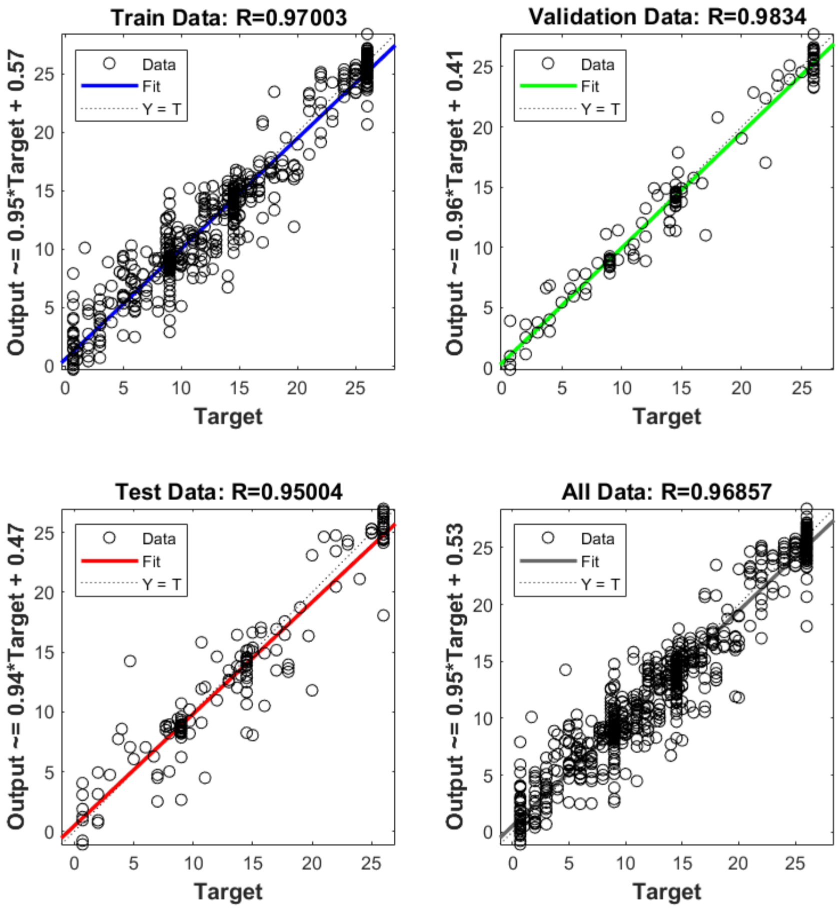


Figure 11. Regression of ANN across all partitions.

A slight R reduction occurs due to outlier . the PSO-ANN model achieves near perfect linear fit on training data (Fig. 12) , demonstrating exceptional adaption.

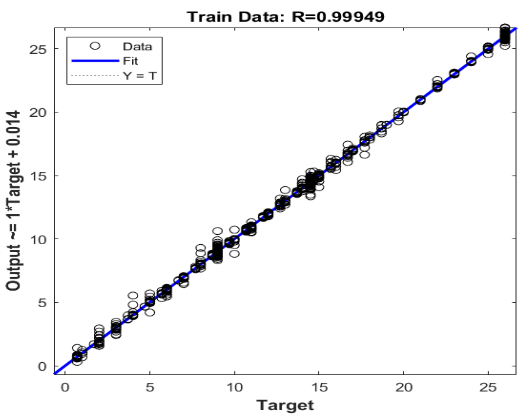
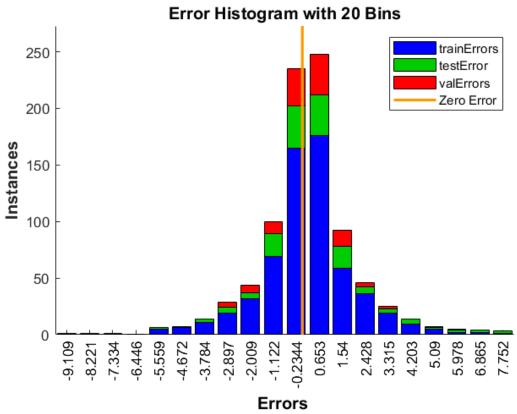
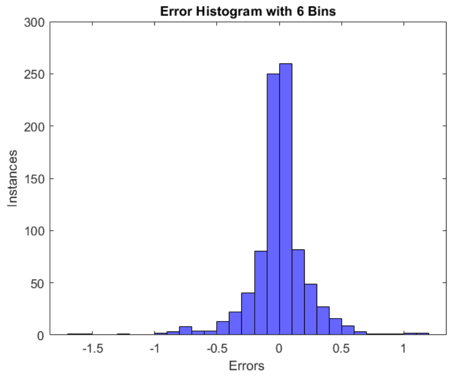


Figure 12. Regression of PSO-ANN.

In Fig. 13a, the error histogram generated by ANN illustrated the distribution of localization errors across samples, divided into 20 bins. The majority of predictions varies significantly from the ground truth, as seen by a narrow range of errors between -1.122 m and 1.54 m. The bin with the most samples has 250 samples with an inaccuracy of around -2.344 m. The error histogram of PSO-ANN in Fig. 13b , on the other hand, varies from -1.5m to 1m and has 6 bins. Two distinct peaks are observed, includes 250 sample with the error range error range of -0.1 m to 0 m, and the other includes 260 samples in the range of 0 m to 0.1 m. These results reflect a significant enhancement in precision, as 95% of localization errors fall within the narrow of -0.1 m to 0.1 m.



(a)

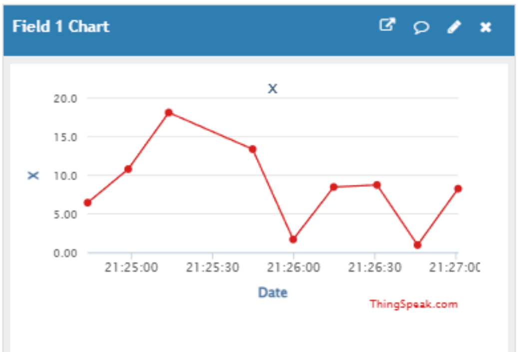


(b)

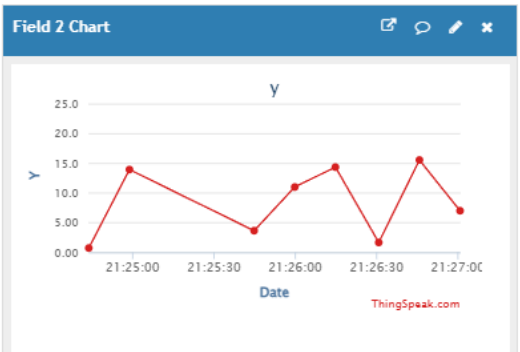
Figure 13. Histogram of localization errors of (a) ANN, (b) PSO-ANN.

4.2. Online stage

On Thingspeak platform via ESP32 Arduino, the fingerprint model provides data visualization framework for real-time localisation. Thingspeak IoT platform requires registration, channel creation, field selection, and simulation linkage. The location visualization in time series charts changes every 15 seconds. Thingspeak web API links the IoT platform to a mobile app to reflect its capabilities. The mobile app receives parameters in real time. Figure 14 shows IoT platform widgets for each parameter in real time.



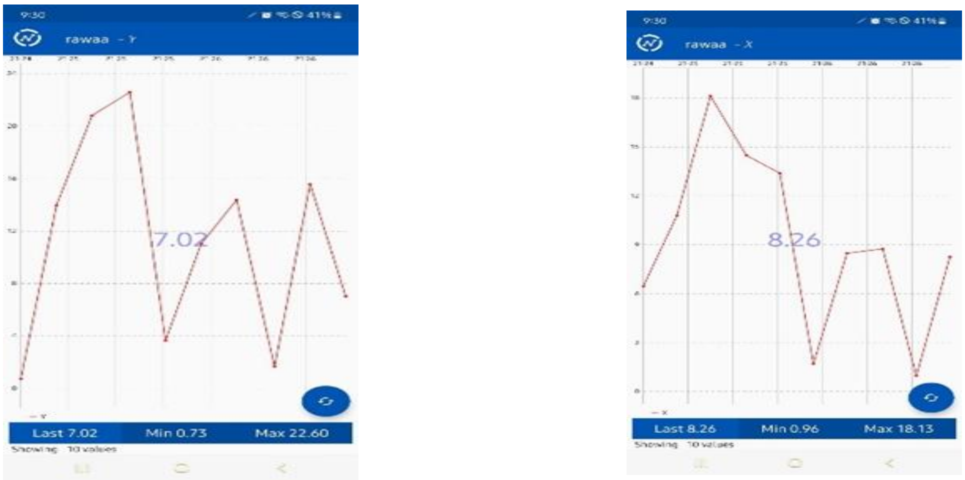
(a)



(b)

Figure 14. Location data at IoT Platform: (a)x- coordinator, (b)y-coordinator.

The presented framework integrated to a smartphone application to display data in real time, enabling remote monitoring of location changing in the environment as shown in Fig. 15.



(a) (b)

Figure 15. The transmitted location at the smartphone application.

5. Conclusion

In this study, a comprehensive evaluation of RSSI robustness and fingerprint localization modelling was conducted through the integration of ANN and PSO. Alterations in RSSI values between different zones and APs show that signal strength is sensitive to space in indoor setting. Despite inherent RSSI fluctuations caused by multipath propagation, shadowing, and environmental interference, the estimated RSSI trends closely followed the measurement data, indicating strong predictive alignment. The MSE between the measured and estimated PL models was consistently below 1.0005dB across all APs in the zones, reflecting high consistency between the models. The minimal MSE observed in transitional zones in attributed to discrepancies between LoS and NLoS condition in the measurement and estimated models. The results obtained from the PSO-ANN model confirm the effectiveness of the proposed approach for indoor fingerprint localization. The integration of RSSI-based fingerprint with PSO for ANN parameter optimization provides a robust and high accurate solution for indoor localization. Also, the presented system transmits real-time location coordinates to IoT platform enabling remote access and visualization via an Android application for remote monitoring.

Authors' Contributions

Authors equally contributed to this article.

Acknowledgments

Authors thank all participants who participate in this study.

Declaration of Interest

The authors report no conflict of interest.

Funding

According to the authors, this article has no financial support.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

References

[1] V. Choudhary, P. Guha, G. Pau, S. J. E. Mishra, and S. Indicators, "An overview of smart agriculture using internet of things (IoT) and web services," p. 100607, 2025.

[2] S. J. I. i. I. P. S. Pešić, "Modern Challenges in Indoor Positioning Systems: AI to the Rescue," p. 65, 2024.

[3] S. C. Narasimman and A. J. I. S. J. Alphones, "DumbLoc: Dumb indoor localization framework using Wi-Fi fingerprinting," vol. 24, no. 9, pp. 14623-14630, 2024.

[4] Z. Luo, W. Li, Y. Wu, H. Dong, L. Bian, and W. J. I. I. o. T. J. Wang, "Accurate indoor localization for bluetooth low energy backscatter," 2024.

[5] W. Zhao, A. Goudar, M. Tang, and A. P. J. a. p. a. Schoellig, "Ultra-wideband time difference of arrival indoor localization: from sensor placement to system evaluation," 2024.

[6] J. Li, S. Yu, Z. Wei, and Z. J. S. Zhou, "An Enhanced ZigBee-Based Indoor Localization Method Using Multi-Stage RSSI Filtering and LQI-Aware MLE," vol. 25, no. 9, p. 2947, 2025.

[7] K. Choutri, M. Lagha, S. Meshoul, H. Shaiba, A. Chegrani, and M. J. S. Yahiaoui, "Vision-based UAV detection and localization to indoor positioning system," vol. 24, no. 13, p. 4121, 2024.

[8] A. Girgensohn, M. Patel, J. T. J. P. Biehl, and U. Computing, "Radio-frequency-based indoor-localization techniques for enhancing Internet-of-Things applications," vol. 28, no. 1, pp. 385-401, 2024.

[9] Y. Bai, "Development of a WiFi and RFID based indoor location and mobility tracking system," RMIT University, 2024.

[10] S. Huang, K. Zhao, Z. Zheng, W. Ji, T. Li, and X. Liao, "An optimized fingerprinting-based indoor positioning with Kalman filter and universal kriging for 5G internet of things," *Wireless Communications and Mobile Computing,* vol. 2021, pp. 1-10, 2021.

[11] S. L. Ayinla, A. Abd Aziz, M. Drieberg, M. Susanto, and M. J. I. O. J. o. t. C. S. Yahya, "An Enhanced Deep Neural Network Approach for WiFi Fingerprinting-Based Multi-Floor Indoor Localization," 2024.

[12] B. Naresh, C. Ravikumar, P. L. Prasanna, B. S. Madhuri, S. Nimmala, and P. Srinivas, "Hybrid Deep Learning-Based Localization for Energy-Efficient Wireless Sensor Networks in Indoor IoT Environments," in *2024 8th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, 2024: IEEE, pp. 407-412.

[13] H. Rizk, A. Elmogy, and H. J. S. Yamaguchi, "A robust and accurate indoor localization using learning-based fusion of Wi-Fi RTT and RSSI," vol. 22, no. 7, p. 2700, 2022.

[14] L. Bouse, S. A. King, and T. Chu, "Simplified Indoor Localization Using Bluetooth Beacons and Received Signal Strength Fingerprinting with Smartwatch," *Sensors,* vol. 24, no. 7, p. 2088, 2024.

[15] Z. Zhang, Y. Yu, L. Chen, and R. Chen, "Hybrid Indoor Positioning System Based on Acoustic Ranging and Wi-Fi Fingerprinting under NLOS Environments," *Remote Sensing,* vol. 15, no. 14, p. 3520, 2023.

[16] D. Gufran and S. Pasricha, "FedHIL: Heterogeneity resilient federated learning for robust indoor localization with mobile devices," *ACM Transactions on Embedded Computing Systems,* vol. 22, no. 5s, pp. 1-24, 2023.

[17] R. Safwat, E. Shaaban, S. M. Al-Tabbakh, and K. Emara, "Fingerprint-based indoor positioning system using BLE: real deployment study," *Bulletin of Electrical Engineering and Informatics,* vol. 12, no. 1, pp. 240-249, 2023.

[18] T. Perković, L. Dujić Rodić, J. Šabić, and P. Šolić, "Machine learning approach towards lorawan indoor localization," *Electronics,* vol. 12, no. 2, p. 457, 2023.

[19] L. Li, X. Guo, and N. Ansari, "SmartLoc: Smart wireless indoor localization empowered by machine learning," *IEEE Transactions on Industrial Electronics,* vol. 67, no. 8, pp. 6883-6893, 2019.

[20] M. A. Bhatti, R. Riaz, S. S. Rizvi, S. Shokat, F. Riaz, and S. J. Kwon, "Outlier detection in indoor localization and Internet of Things (IoT) using machine learning," *Journal of Communications and Networks,* vol. 22, no. 3, pp. 236-243, 2020.

[21] S. Kurt and B. Tavli, "Path-Loss Modeling for Wireless Sensor Networks: A review of models and comparative evaluations," *IEEE Antennas and Propagation Magazine,* vol. 59, no. 1, pp. 18-37, 2017.

[22] R. Gulia, *Path loss model for 2.4 GHz indoor wireless networks with application to drones*. Rochester Institute of Technology, 2020.