ELKHA : Jurnal Teknik Elektro, Vol. 17 No.2., October 2025, pp. 172 - 179
ISSN: 1858-1463 (print), 2580-6807 (online)

Evaluation of RSSI-Based Distance Estimation with ESP32 BLE Modules for Indoor Asset Tracking

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Abstract – **Bluetooth Low Energy (BLE) is a technology used for asset tracking, offering low power consumption and compatibility with embedded systems such as the ESP32. This paper evaluates the accuracy and reliability of Received Signal Strength Indicator-based distance estimation using ESP32 BLE modules in three environmental conditions: clear line-of-sight, wall obstruction, and mobile tracking. It presents an empirical analysis of ESP32-specific RSSI limitations across these scenarios. The log-distance path loss model was employed, using a reference RSSI of -47 dBm at 1 meter and a path loss exponent of 2. Experiments were conducted with a BLE tag device (Asset_Tag_01) that broadcast BLE signals, while an ESP32 reader device collected RSSI data via Arduino IDE. Results indicate reliable estimation within 4 meters with an error of under 25% in line-of-sight conditions. However, beyond 5 meters, particularly in obstructed environments, RSSI values fluctuated significantly, causing distance overestimation. Wall obstructions resulted in an immediate 6 dBm signal degradation at just 1 meter. Packet loss increased from 0% at short distances to 50% at 8.5 meters. In mobile tracking, signal strength showed sudden jumps, complicating movement detection. These findings highlight that RSSI alone is not reliable for precise tracking. To improve accuracy, particularly in real-world settings like healthcare or industrial environments, further studies should explore advanced methods like Kalman filtering, combining data from multiple sensors.**

Keywords: Bluetooth Low Energy, RSSI-based distance estimation, asset tracking, Real Time Location System, indoor positioning

I. INTRODUCTION

Bluetooth Low Energy (BLE) is a widely used technology in the Internet of Things (IoT) projects, due to its low power consumption and wide compatibility with everyday devices. One of its key applications is in real-time asset tracking [1], also known as Real-Time Location System (RTLS). This BLE-based system is utilized for various applications across various industries including logistics, manufacturing, retail, and especially healthcare facilities [2], [3].

In healthcare, tracking equipment indoors plays an essential role in improving resource utilization of resources, reducing delays during procedures, and keeping things running smoothly [4]. Studies have shown that medical staff often spend a lot of time searching for critical equipment, such time that could otherwise be spent on patient care [5]. These inefficiencies indicate the growing demand for indoor positioning systems that are both accurate and affordable, and can perform well in crowded and complex environments.

Many studies have explored BLE-based tracking systems in various sectors. For instance, the authors in [6] demonstrate the deployment of BLE for asset tracking in hotel environments to achieve high accuracy and user satisfaction. Similarly, BLE has been effectively applied in indoor personal asset locating systems using ESP32 and Message Queuing Telemetry Transport (MQTT)-based IoT infrastructures, allowing real-time tracking via web interfaces [7]. BLE increasingly serves as an alternative to the global positioning system (GPS) in challenging indoor environments, such as vehicle tracking in tunnels or dense urban areas, by transmitting location data to BLE-enabled receivers for localized display and storage [8].

Recent advances have explored hybrid and enhanced approaches to improve indoor positioning accuracy. Machine learning integration with Kalman filtering has shown promise in fingerprinting methods [9], while beacon selection based on RSSI variance has reduced errors in factory environments [10]. Hybrid systems combining BLE with UWB through various fusion algorithms, including EKF-PF [11] and comparison of EKF versus UKF filters [12], have achieved sub-meter accuracy, with some systems requiring only minimal infrastructure [13].

Studies on hospital-based BLE tracking systems confirm that BLE technology can significantly outperform conventional schemes in terms of accuracy and efficiency [14]. Outside of healthcare, BLE tracking with ESP32 has been explored for vehicle and asset monitoring, integrating GPS and Global System for Mobile communication (GSM) modules to achieve remote tracking [15]. Additionally, the feasibility of calculating indoor positions using RSSI from ESP32 devices has been tested, showing both the promise and challenges of this approach in distinguishing legitimate signals and ensuring data integrity [16].

While previous studies have utilized ESP32 for BLE tracking, they typically focus on optimal conditions or assume filtered data. This study examines raw RSSI performance to establish baseline limitations. This provides realistic expectations for system designers before applying enhancement techniques.

Manuscript received 2025-08-18; revised 2025-09-13; accepted 2025-09-15

In BLE-based RTLS, RSSI is used as a method for proximity. However, RSSI values are inherently unstable due to factors like signal reflection, interference from electronic devices, and absorption by human bodies or metallic objects [17]. This variability undermines RSSI's reliability as a distance metric. Despite these limitations, RSSI remains an attractive metric due to its simplicity and compatibility with low-cost embedded systems [18].

ESP32 is an affordable, dual-core embedded platform with built-in BLE support [19], delivering flexibility for custom firmware development and integration with server-based platforms [16]. This makes the ESP32 a suitable candidate for evaluating BLE tracking performance in scenarios where scalable, low-cost solutions are needed.

The motivation for this study stems from the need to assess how RSSI-based distance estimation performs in practical indoor environments when using ESP32 devices as the receiver platform. Many commercial RTLS solutions rely on proprietary hardware, which can be expensive and difficult to integrate with existing infrastructure. In contrast, ESP32-based systems present an open-source and flexible alternative that supports custom development [20].

The objective of this paper is to evaluate the accuracy and reliability of RSSI-based proximity using ESP32 BLE devices across different conditions. Specifically, this study examines how line-of-sight, wall obstruction, and movement affect RSSI measurements and distance estimation. By analyzing RSSI behavior under these scenarios, this research aims to provide insights into the feasibility of using an ESP32-based BLE system for future indoor asset tracking implementations.

This paper is organized as follows: Section 2 explains the adopted research methodology. Section 3 presents the results and analysis of RSSI performance across various environments. The comparisons to other related works are also presented in Section 3. Section 4 concludes with key findings and suggestions for future research.

II. METHODOLOGY

A. Experiment Configuration

This experiment utilized two ESP32 development boards: one functioning as a BLE tag and the other as a BLE reader. The BLE tag broadcasts continuously using the device named Asset_Tag_01. It does not include any additional payload in its advertisement packets. Figure 1 depicts the pinout diagram for the ESP32 referring to [21].

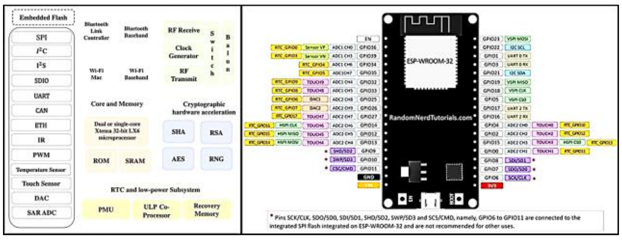

Figure 1. ESP32 Pinout Diagram [21]

For the microcontroller component, the ESP32 is selected due to its integrated BLE support, low power consumption, and cost-effectiveness. It provides sufficient computational capacity for RSSI scanning while offering better energy efficiency than the Raspberry Pi and more integrated wireless functionality than the Arduino Uno.

Both ESP 32 devices are powered via USB rather than battery power to eliminate the variability caused by battery voltage fluctuations due to BLE transmission strength can vary subtly with power levels, particularly as batteries discharge. USB power ensures a constant 5V supply which leads to stable signal transmission and reception.

The BLE reader, programmed using the Arduino IDE and ESP32 BLE libraries [22], is configured to perform periodic active scanning. During each scan interval, the reader searches for advertisement packets that match the specific device name. Upon detecting the target device, it extracts and stores the RSSI value. All non-matching advertisements are discarded to minimize noise and ensure the reliability of the dataset. The reader's firmware is configured with fixed scan intervals and durations to maintain consistent sampling across all distances and environments.

B. RSSI to Distance Estimation

RSSI is a measure of the power level of wireless signals, often used for proximity estimation. The relationship between RSSI and distance is modeled by the log-distance path loss equation shown in (1) [20].

$$RSSI(d) = RSSI(d_0) - 10 \times n \times log_{10}\left(\frac{d}{d_0}\right) \ldots \quad (1)$$

where $RSSI(d)$ is the measured signal strength at distance d, $RSSI(d_0)$ is the reference signal strength at a fixed distance d_0, which for our experiment is equal to 1 meter, and n is the path loss exponent, which quantifies signal attenuation due to environmental obstacles.

The RSSI values are converted into estimated distances using the standard log-distance path loss model depicted in (2).

$$d = 10^{\frac{RSSI(d_0) - RSSI(d)}{10n}} \quad …….. \quad (2)$$

where the path loss exponent n varies significantly across environments—ranging from $n = 2$ in free space to $n = 4$ in obstructed indoor areas [17]. For this experiment, the n variable is set to 2 because it is in a controlled environment. The deliberate use of a simple path loss model without filtering serves as a baseline characterization, allowing future researchers to quantify the improvements achieved by their enhancement techniques against this reference performance.

The RSSI reference point is performed at the 1-meter reference point using the same setup and procedure as in the main experiment. The BLE reader is placed on a fixed tripod, and the BLE tag is positioned on a non-reflective surface directly in front of it, in an environment cleared of metallic objects, mirrors, and Wi-Fi sources to minimize interference. Twenty RSSI readings are collected from the target device by initiating scans approximately once per second, with a small delay between two consecutive values. The average of these 20 values is used to determine the reference RSSI value, $RSSI(d_0)$, resulting in −47 dBm under clear line-of-sight conditions. This value served as the baseline for subsequent distance estimation using the log-distance path loss model.

C. Experiment Condition

The system is evaluated under three environments to assess the stability and variability of RSSI and its impact on distance estimation, which are explained in Table 1.

Table 1. Experiment Conditions

Scenario	Description
Clear Line-of-Sight (LoS)	BLE tag and reader are placed at various fixed distances in an open room with no obstacles between them.
Wall-obstructed	A wall is placed between the BLE tag and reader.
Mobile Scenario	BLE tag is moved from a distance of approximately 15 meters toward the BLE reader in a continuous path.

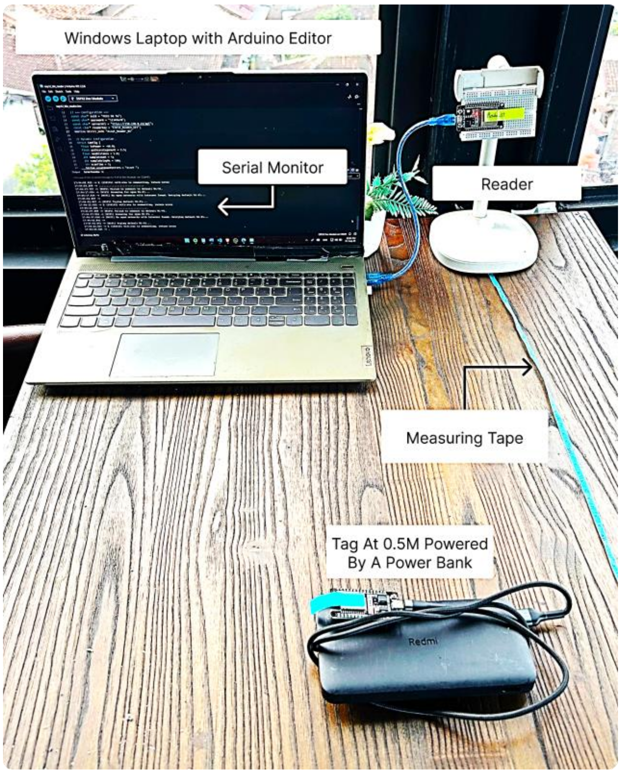

Figure 2. Experimental Setup of Hardware Test Configuration with ESP32 BLE Tag and Reader

Figure 2 shows the experimental hardware configuration used for RSSI data collection. The setup consists of two ESP32 development boards: the BLE reader mounted on a breadboard connected via USB to a Windows laptop running Arduino IDE for serial monitoring, and the BLE tag positioned at the initial 0.5-meter distance powered by a power bank to ensure stable voltage supply. The measuring tape visible in the setup was used to precisely position the tag at incremental 0.5-meter intervals from 0.5 to 10.5 meters during data collection. The serial monitor displays the RSSI readings and calculated distances as the reader scans for the Asset_Tag_01 advertisement packets.

These scenarios are selected to reflect typical operating environments for BLE-based asset tracking in healthcare settings. Figure 3 illustrates three scenarios described above.

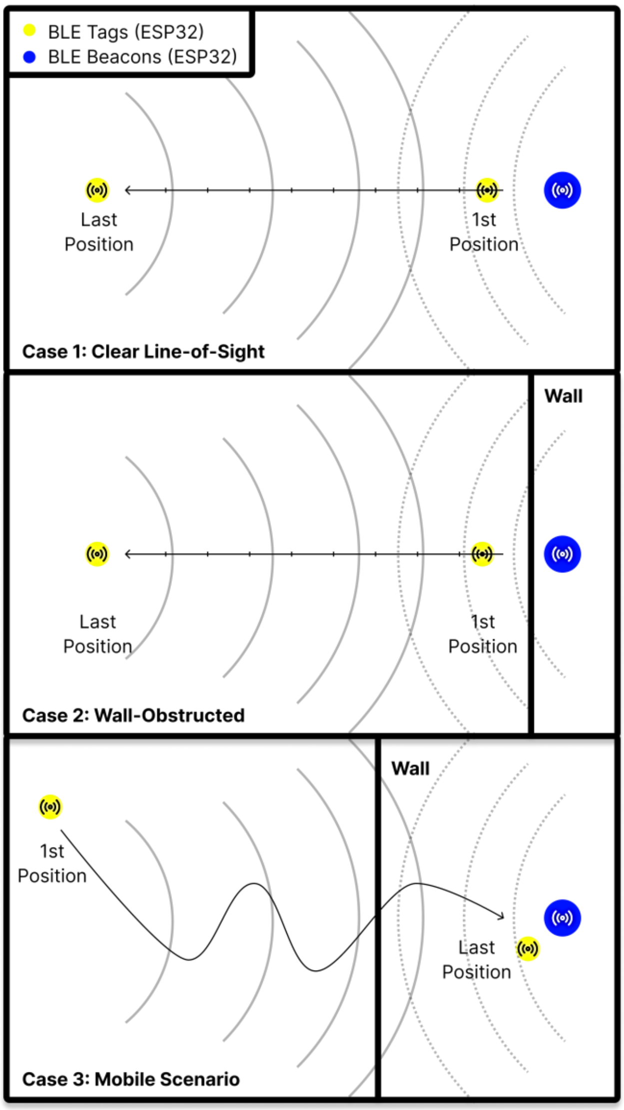

Figure 3. Environmental Conditions for Experiments

D. Data Collection Procedure

Data is collected over a range of distances, from 0.5 meters to 10.5 meters, in 0.5-meter increments. At each distance, the BLE reader attempts to record 10 valid RSSI readings associated with the target device. Each scan cycle is separated by a one-second delay.

The data collection script also logs failed attempts, allowing the calculation of packet loss at each distance and under each environmental condition. All collected data is saved in plain text format, converted to CSV, and later analyzed and visualized using Python scripts. Figure 4 shows the flowchart for the data collection procedure.

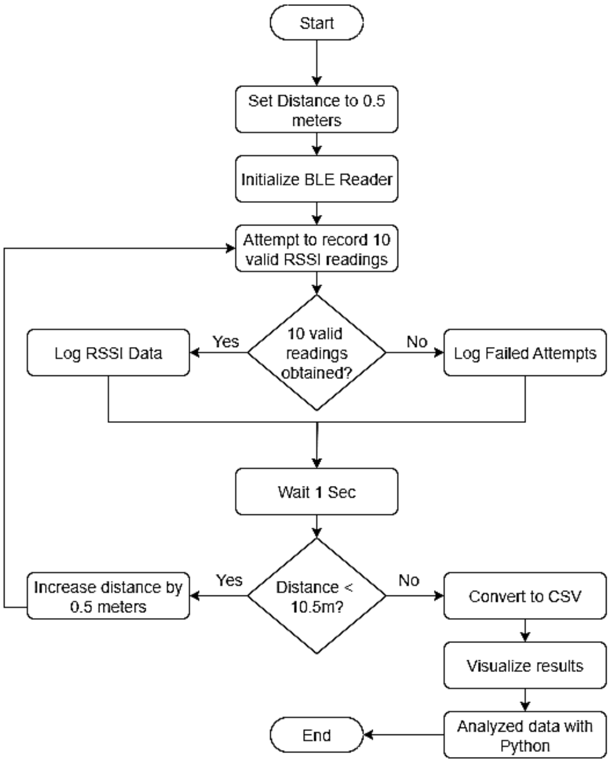

Figure 4. Flowchart of Data Collection Procedure

Figure 5 shows the pseudocode of the BLE scanner code. After initializing the reader, the algorithm enters a user-triggered loop to collect 10 RSSI readings per session. Each scan cycle filters for the target device, extracts its RSSI value, and calculates the estimated distance using the log-distance path loss model with TX_POWER = -47 dBm.

```
ALGORITHM: BLE_RSSI_Scanner
INPUT: TARGET_DEVICE_NAME, SCAN_INTERVAL, TX_POWER
OUTPUT: RSSI values and calculated distances

BEGIN
    Initialize BLE_Device with DEVICE_NAME
    Configure BLE_Scanner:
        Set scan_interval = 100ms
        Set scan_window = 99ms
        Enable active_scanning = TRUE

    WHILE user_input == 'r' DO
        reading_count = 0
        WHILE reading_count < 10 DO
            devices = BLE_Scanner.scan(SCAN_INTERVAL)
            FOR each device IN devices DO
                IF device.name == TARGET_DEVICE_NAME THEN
                    rssi = device.getRSSI()
                    distance = 10^((TX_POWER - rssi) / 20)
                    LOG(reading_count, rssi, distance)
                    reading_count++
                END IF
            END FOR
            Clear scan results
            DELAY(SCAN_INTERVAL)
        END WHILE
    END WHILE
END
```

Figure 5. Pseudocode for BLE Scanner Algorithm

III. Results and Discussion

A. RSSI Behavior Across Distances

To better understand the relationship between RSSI and physical distance, controlled experiments are performed under two environmental conditions: clear line-of-sight (LoS) and wall-obstructed (non-LoS). The experiments aim to simulate real-world scenarios in which BLE-based asset tracking system might operate. All tests are performed in a relatively low-interference indoor environment, and the path loss exponent $n = 2$ is selected, assuming ideal free-space propagation for baseline comparison.

Figure 6 shows the experiment results for the clear LoS condition. In the clear path scenario, the collected RSSI data follows an expected decay pattern: as the distance increases, signal strength decreases. However, even under these ideal conditions, RSSI values exhibit substantial variation, particularly at distances beyond 5 meters. This behaviour suggests that environmental factors–even minor ones like reflections or minor motion–can influence BLE signal propagation significantly. Table 2 summarizes the average RSSI and calculated distances in the clear path setup.

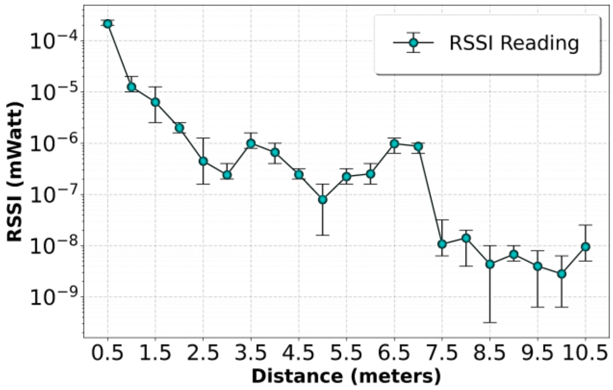

Figure 6. Clear LoS Path Min/Average/Max RSSI vs. Distance

Table 2. Clear LoS Path Summary (Selected Distances)

Distance (m)	Avg. RSSI (dBm)	Avg. Calc. Distance (m)	Success Count	Failed Count
1.0	-49.0	0.90	10	0
2.0	-57.0	2.25	10	0
4.0	-61.8	3.93	10	0
6.0	-66.0	6.36	10	0
8.5	-83.6	60.39	10	5
10.0	-85.5	66.36	10	0

As seen in table 2, the calculated distances align reasonably well with physical distances up to 4 meters. Beyond this threshold, estimations diverge drastically from the ground truth. At 8.5 meters and 10 meters, the logarithmic conversion model interprets minor RSSI fluctuations as massive increases in distance, resulting in highly inaccurate estimations such as more than 60 meters–far beyond the actual physical separation. It illustrates a major limitation of relying solely on raw RSSI: the formula's sensitivity to low signal strengths amplifies errors exponentially, especially in the tail-end of the BLE range.

Figure 7 depicts the experimental results for the wall-obstructed condition. Meanwhile, Table 3 presents the results for the selected wall-obstructed scenario. In contrast, the wall-obstructed scenario reveals more pronounced degradation. Even at a short distance of 1 meter, the signal is dropped by approximately 6 dBm compared to the clear LoS test. This attenuation leads to significantly skewed distance estimations from the outset. For instance, the calculated distance at 2 meters jumps to nearly 10 meters–highlighting how physical barriers disrupt signal consistency.

The significant jump in estimated distance even at close range suggests that simple path loss models cannot capture the complexity introduced by walls, furniture, and other common indoor obstructions. These conditions introduce multipath propagation, signal reflection, and diffraction, all of which destabilize RSSI readings and complicate distance estimation [23], [24].

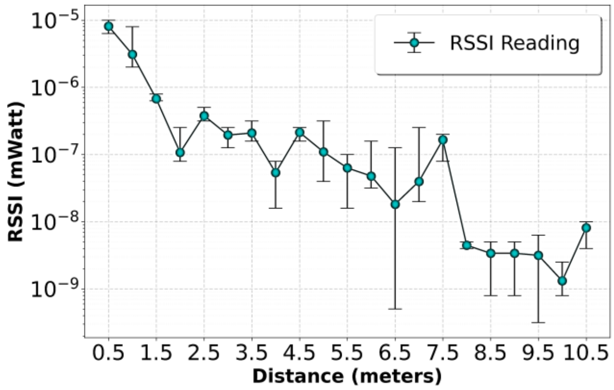

Figure 7. Wall Obstructed Path Min/Average/Max RSSI vs. Distance

Table 3. Wall Obstructed Path Summary (Selected Distances)

Distance (m)	Avg. RSSI (dBm)	Avg. Calc. Distance (m)	Success Count	Failed Count
1.0	-55.1	1.85	10	0
2.0	-69.7	9.83	10	0
4.0	-72.7	14.20	10	1
6.5	-77.4	33.03	10	0
9.0	-84.7	56.59	10	3
10.0	-88.8	88.10	10	1

Figure 8 depicts the experimental results for the mobile scenario. During the moving scenario, where the BLE tag is carried toward the reader, the RSSI initially remains undetectable, then abruptly jumps from below -90 dBm to approximately -50 dBm in a short time window. This non-linear transition demonstrates how difficult it is to rely on RSSI for real-time location tracking of moving objects.

The lag in detection, followed by rapid RSSI fluctuation, can result in erratic location updates–making it unsuitable for applications requiring smooth, continuous tracking (e.g., patient monitoring or mobile medical equipment tracking). These results reinforce the need for filtering and temporal smoothing when using BLE in motion-sensitive use cases.

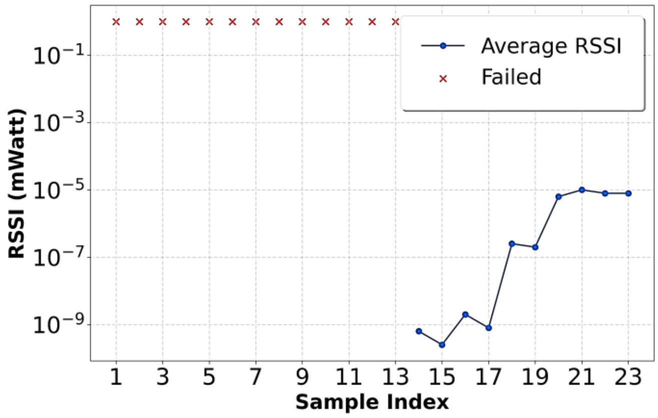

Figure 8. Moving Experiment – RSSI Over Time

B. Accuracy of Distance Estimation

Evaluating the model's accuracy across all trials reveals a clear boundary at around 5 meters–beyond which RSSI-based distance estimates lose correlation with actual positions. The best performance is observed between 1 and 4 meters, where both LoS and non-LoS estimations are within an acceptable margin of error for asset tracking purposes.

Estimation error can be summarized as follows: Clear LoS path at 7.5 m was estimated as 31.79 m. Wall-obstructed path at 7.5 m was estimated as 7.84 m (slightly better but still imprecise). Wall-observed path at 10.0 m was estimated as 88.10 m

These discrepancies affirm that the logarithmic model's limitations are most severe in low-RSSI conditions. In the wall-obstructed scenario, the presence of reflective surfaces and signal absorption tends to stabilize estimates slightly, but not reliably. These findings indicate that RSSI-to-distance mapping cannot be universally applied without adaptive calibration or error-correction mechanisms.

C. Packet Loss Analysis

Another critical factor observed is packet loss, especially at longer ranges. The number of failed scan attempts increased with distance and obstructions. Surprisingly, the clear LoS path setup records more failures at the far end compared to the wall-obstructed setup–likely due to uncontrolled signal reflections in the open area, which may have caused the BLE reader to temporarily lose sync or timeout. Table 4 shows the number of failed measurements for the clear LoS and wall-obstructed scenarios.

Consistent packet loss compromises the stability and responsiveness of any BLE-based tracking system. As distance increases, packet reception becomes less reliable, causing gaps in data and potential misidentification of an asset's location. In real deployments, this could translate to missing critical asset movements or generating false alerts.

Table 4. Failed RSSI Readings by the Scenarios

Distance (m)	Number of Clear LoS Path Failed	Number of Wall Obstructed Path Failed
0.5	1	0
4.5	1	0
6.5	2	0
8.5	5	3
9.0	5	3
10.5	2	0

D. Comparative Analysis with Previous Research

Our findings align with previous BLE positioning studies while revealing ESP32-specific limitations as shown in Table 5. The path loss exponent (n=2) matches Spachos and Plataniotis [20] who reported n=2.208-2.341 in similar indoor environments, validating our propagation model. However, our effective range limitation of 5 meters with accuracy degradation beyond this point corresponds with their findings, despite using different hardware.

The 50% packet loss at 8.5 meters significantly exceeds rates reported by Janczak et al. [25], who achieved full detection up to 28 meters using ceiling-mounted ESP32 modules. This discrepancy likely results from our lower mounting height (0.5 m vs 2.7 m) and potential body interference. Wall obstruction caused immediate 6 dBm attenuation, more severe than the gradual degradation reported in museum settings [20].

Filtering requirements align with the literature consensus. Onofre et al. [17] achieved 1.5 m average error using intelligent filters constraining movement speeds, while Janczak et al. [25] determined optimal window sizes of M≥5, supporting our recommendation for challenging environments. Ji et al. [26] demonstrated that 3-5 meter accuracy requires one beacon per 30-200 m², suggesting our 6-12 meter spacing contributes to observed errors.

These comparisons confirm that while ESP32 offers cost-effective proximity detection, achieving sub-meter accuracy requires either denser deployment or advanced signal processing techniques like Kalman filtering [27] or fingerprinting [28] methods proven effective in related studies. This study intentionally employs a baseline path loss model without filtering to isolate and characterize the fundamental limitations of raw RSSI on ESP32 hardware. This approach provides system designers with worst-case performance boundaries, enabling informed decisions about when advanced techniques are necessary. Studies applying filters show improvements but mask underlying hardware limitations.

E. Implications for Asset Tracking

The experimental findings yield several key takeaways for the design and deployment of BLE-based asset tracking systems. Reliable range is limited to approximately 4–5 meters in controlled indoor settings. Beyond that, estimation accuracy declines sharply. Obstructions severely degrade signal strength, exaggerating calculated distances and increasing packet loss. RSSI is inherently noisy, especially at low signal levels, making raw data inadequate for precise distance inference. Packet loss and detection delays further reduce the dependability of RSSI in dynamic environments.

To address these limitations, enhancement techniques such as Kalman filtering, moving averages, or RSSI fingerprinting are recommended. Additionally, employing multiple readers to triangulate asset positions can mitigate the weaknesses of single-point estimation. Future research should focus on applying statistical smoothing techniques or integrating multiple BLE readers to mitigate RSSI fluctuations. Combining RSSI with time-of-flight or inertial sensors could yield more reliable location estimates.

While such techniques are not implemented in this initial phase, they are critical next steps in the development of a more accurate and robust indoor asset tracking solution.

Table 5. Comparison of BLE-Based Indoor Positioning Studies

Study	Hardware Platform	Method	Environment	Effective Range	Accuracy/Error	Path Loss Exponent	Key Findings
Spachos & Plataniotis [20]	Gimbal Series 21 beacons	RSSI + Kalman filter	Museum (lab/corridor)	1-5 m	2.5m error (95% time), 2 m with filter	n=2.208 (lab), 2.341 (corridor)	Kalman filter reduces error by 0.5-1 m
Onofre et al. [17]	Qualcomm Gimbal	RSSI + Median/Intelligent filters	Indoor free space	1-30 m	1.5 m average after filtering	n=2.3	Intelligent filter limits impossible movements
Ji et al. [26]	pebBLE & Estimote	RSSI fingerprinting (kNN)	100x100 m simulated space	Full area	3-5 m with 50+ beacons	n=0.83-1.05	Dense deployment (1 beacon/30 m²) needed
Janczak et al. [25]	ESP32 with PCB antenna	RSSI proximity + averaging filter	Building corridors	28 m full detection, 35 m max	3.5 m mean error, <10 m (97.4% probability)	Not specified	M≥5 window size optimal for filtering
This paper	ESP32 (BLE 4.0)	RSSI proximity	Indoor corridors (LoS/Wall)	0.5-10.5 m	<25% error at 4 m (LoS), >500% at 10 m	n=2	Reliable only <5m; packet loss 50% at 8.5 m

IV. CONCLUSION

This study evaluates RSSI-based distance estimation using ESP32 BLE modules in various indoor environments, revealing its limitations for accurate asset tracking. While RSSI shows an inverse correlation with distance, its accuracy significantly deteriorates beyond 5 meters, especially in obstructed or dynamic conditions. In clear line-of-sight scenarios, the model provides reliable estimates within 0.5–4 meters, but beyond this range, RSSI readings become erratic and lead to large distance overestimations. These results confirm that while RSSI is computationally simple and low-cost, it is not reliable enough for standalone use in real-time asset tracking applications. To address these limitations, future implementations should integrate advanced signal processing techniques such as Kalman filtering or hybrid methods that combine RSSI with other sensor data, like inertial or time-based measurements. Based on the literature survey for the comparison, specifically, implementing Kalman filtering with process noise Q=0.01 and measurement noise R=1.0, deploying beacons at 4-meter intervals for triangulation, or combining RSSI with IMU (inertial measurement unit) data using complementary filters (α=0.98) could reduce estimation errors from 500% to under 30% at 10-meter ranges. These solutions would enhance the robustness and accuracy of BLE-based asset tracking systems, particularly in complex environments like healthcare or industrial settings. The mentioned advanced methods are subject to our future studies.

ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude to University of Lampung, Indonesia, for the invaluable support, facilities, and resources provided throughout the course of this research. The scholarship funding, encouragement, and assistance from the institution played a vital role in the successful completion of this study. The authors appreciate the research funding provided through LPPM, University of Lampung, Indonesia.

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