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Empirical Path Loss Characterization for Zigbee Wireless Sensor Networks in Cassava Farms Using a Dual-Slope Log-Distance Model

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Abstract

This research addresses the significant challenge of unreliable wireless communication, which hinders the performance of ZigBee-based wireless sensor networks (WSNs) in precision agriculture. A dual-slope log-distance path loss model was developed to accurately predict signal propagation complexities in dense vegetative environments for improved wireless communication. The study was conducted on a cassava farm in Ondo State, Nigeria, characterized by vegetation heights of 1.8 meters, making it an ideal site for investigation. A systematic methodology was employed, incorporating radio frequency measurements in both line-of-sight and non-line-of-sight conditions. This involved deploying two XBee S2C modules operating at 2.4 GHz, with one designated as a coordinator and the other as a router. The collection of Received Signal Strength Indicator (RSSI) and throughput data occurred at 5 meter intervals, with variations in the router's orientation. Results revealed a maximum communication range of 70 meters under non-line-of-sight conditions, compared to 140 meters in line-of-sight scenarios, where the path loss exponent was determined to be 1.78. The path loss exponents for the cassava fields were found to be 2.55 and 4.25. The developed dual-slope path loss model showed a strong fit to additional empirical data from a separate cassava farm location, achieving a Mean Absolute Percentage Error (MAPE) of 3.30 % and an R-squared value of 0.94. Hence, this model offers a comprehensive framework for characterizing radio wave propagation in agricultural environments, enhancing data transmission reliability and energy efficiency in smart farming applications.

Keywords: Path loss, ZigBee, Wireless Sensor Networks, Cassava farms, Dual-slope model, Non-line-of-sight, Signal propagation, IoT.

1. INTRODUCTION

In recent years, wireless sensor networks (WSNs) have witnessed significant advancement due to their vast applications in fields such as the Internet of Things (IoT), precision agriculture, health management, environmental monitoring, and industrial automation [1, 2]. Basically, WSNs are distributed, self-organized networks consisting of small, low-power sensor nodes that can monitor their surrounding environment to gather data, process the collected data, and wirelessly transmit the data to a central base station [3]. Long Range Radio (LoRa), ZigBee and SigFox wireless protocols are the common wireless access technologies used in WSNs. However, for short-range communication networks that prioritize coverage and scalability, ZigBee wireless technology, which adheres to the IEEE 802.15.4 standard, outperforms other technologies due to its low power consumption, low cost, and robust mesh networking capabilities [4]. According to Ahmed *et al.*, [5], the application of WSNs in precision agriculture is of paramount importance to every nation for food security and economic growth. The technology driving precision agriculture is WSNs, which allow the farmers to monitor the farm environments remotely and provide an effective way of collecting, processing, and transmitting data to designated base station. The data received at the base station are sometimes further analysed to assist the farmers in making decisions that would improve their yield with higher productivity [6, 7].

WSNs facilitate smart farming by monitoring environmental parameters like temperature, humidity, soil moisture, and rainfall, and enabling smart irrigation when necessary. In addition, WSNs enable intruder detection, and fertilizer application [8], which indeed aid farm management. Furthermore, smart farming which WSNs enables helps farmers and soil to work better by doing the right thing at the right time on farm. In addition, remote decision such pest and fertilizer management that smart farming using WSNs enables also assist farmers in reducing waste and other negative environmental consequences. Despite these advantages that WSNs offers to smart farming, performances of WSNs largely depend on network coverage, communication reliability and energy efficiency. However, signal attenuation occur between transmitter and receiver in farm environments due to absorption, reflection, and scattering, resulting in unreliable communication links [9, 10]. This signal attenuation or reduction is usually due to path loss, which is the weakening of signal strength as the radio wave travels from the transmitter to the receiver as a result of challenges pose on the signal by vegetative settings [11]. The common path loss models such as free space and two-ray have proven unsuitable for WSNs in agricultural applications [12] and even vegetative models, such as the Modified Exponential Decay (MED), ITU-R, and COST-235, often produce significant errors in farm settings [6]. In view of these limitations, poor management of the limited energy resources of the sensor nodes will degrade the network lifetime as well as the system performance. This eventually leads to huge financial losses for farmers through wrong predictions from an unreliable monitoring system [13]. Hence, there is a need to integrate an ideal model of radio wave propagation into the planning and design of the WSNs [14, 15]. This is because WSNs designed by using unrealistic path loss models will not perform well when deployed in farm environments, as the radio wave propagation is wrongly characterized.

Therefore, in this research work, cassava farm was employed as a case study for the characterization of path loss in WSNs. Cassava (*Manihot esculenta*), a food and cash crop in Nigeria, contributes greatly to the gross domestic product (GDP) and forms the backbone of much of the country's agricultural economy [16, 17]. Despite its great economic potential, cassava farming faces challenges in capturing real-time environmental data, such as soil moisture, temperature, and pest infestation, which are needed to improve the crop yields [18, 19]. Consequently, farmers recently are using WSNs to increase farm produce's productivity and sustainability [20, 21]. However, the effective deployment of WSNs on cassava farms is complicated by environmental factors that affect signal transmission. In particular, the path loss characteristics of cassava fields are affected by dense foliage and variable terrain, resulting in unpredictable signal attenuation that compromises data transmission reliability. Therefore, it is very important to develop a robust path loss model specifically designed for ZigBee-based WSNs in cassava farms to improve network reliability and data flow efficiency in such complex agricultural environments. Thus, the aim of the study presented in this paper is to develop a suitable path loss model for ZigBee-based wireless sensor networks in a cassava farm environment. The outcomes of this study will facilitate the establishment of energy-efficient WSNs designed to benefit Nigeria's agricultural sector, ultimately improving the efficiency and sustainability of cassava cultivation. The rest of the paper is organized as follows: Section 2 contains the literature review while Section 3 describes the materials and method employed. Section 4 discusses the results obtained while the paper is concluded in Section 5 with summary of the study's findings and recommendations.

2. LITERATURE REVIEW

Path loss modelling in agricultural environments has been a focal area of research due to the unique signal propagation challenges posed by dense vegetation, varied crop types, and prevalent non-line-of-sight (NLOS) conditions. Conventional models, such as free-space path loss, often fall short in these settings, where foliage density, crop height, and other environmental factors alter signal attenuation significantly [22]. As depicted in Figure 1, phenomena like diffraction, scattering, and ground reflection interact intricately with radio waves in agricultural environments, influencing signal behaviour and propagation. These interactions result in distinctive path loss characteristics across different agricultural settings, necessitating specialized approaches for accurate signal prediction and effective Wireless Sensor Network (WSN) deployment [23]. Additionally, these path loss dynamics directly influence the energy consumption of sensor nodes, as devices require higher transmission power to maintain connectivity in challenging propagation environments, thereby reducing their operational lifespan and impacting network sustainability [24].

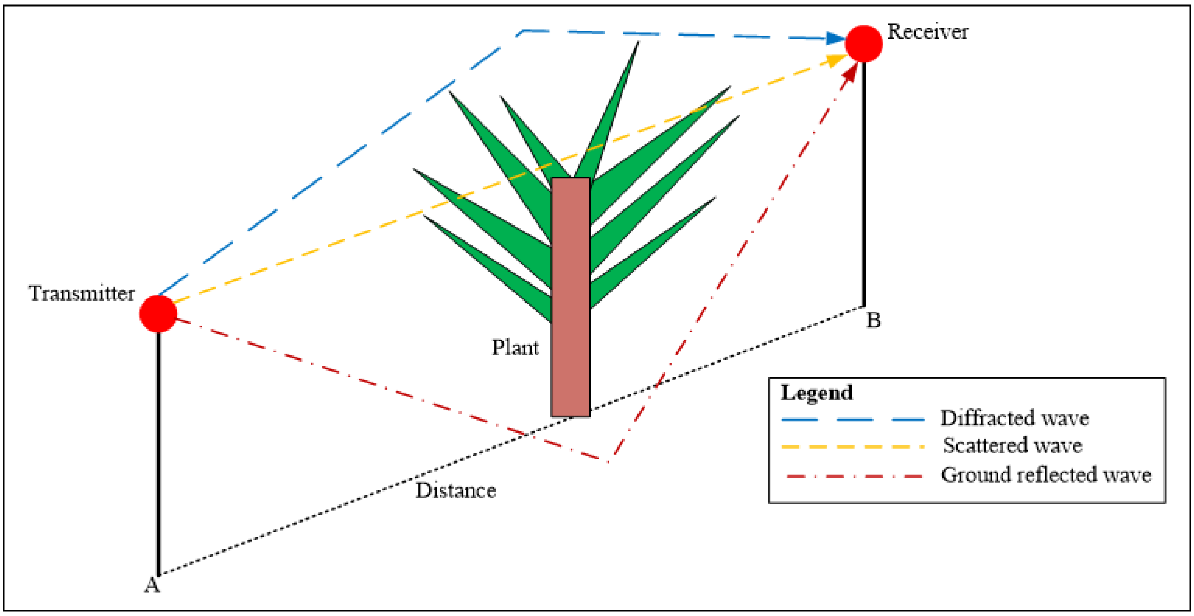

Figure 1: Radio wave propagation in agricultural environments

In response to these challenges, various studies have introduced innovative techniques to refine path loss models for agricultural applications, recognizing that energy efficiency is closely tied to accurate path loss prediction. For example, Barrios-Ulloa *et al.*, [6] utilized machine learning to model path loss in cassava fields, providing an alternative where traditional models struggle to account for dense vegetation effects. This adaptation not only improves coverage but also reduces the energy expenditure of ZigBee nodes by optimizing transmission power based on localized path loss conditions. Similarly, Jawad *et al.*, [9] employed Particle Swarm Optimization (PSO) to enhance the precision of an empirical path-loss model, addressing the need for adaptive modelling in smart agriculture where crop layouts and dense foliage significantly affect signal transmission. These studies underscore the inadequacies of generalized models in capturing the nuances of agricultural environments, especially where complex NLOS conditions prevail, impacting the energy budgets required for continuous data collection and transmission.

Crop-specific studies further reveal the influence of vegetation type on path loss, underscoring the importance of tailored models. In rice field sensor networks, Gao *et al.*, [25] reported significant path loss attributed to crop height and density, indicating that each crop type requires consideration of its unique attenuation characteristics. This crop-specific modelling not only enhances accuracy but also optimizes the energy consumption of nodes, as fewer retransmissions are required when models accurately predict signal strength. Pal *et al.*, [26] found similar effects in millet and rice fields, observing that different vegetation types can substantially affect received signal strength. Together, these findings highlight the necessity for models that account for specific agricultural factors to accurately predict path loss in diverse farming landscapes, thereby reducing the energy costs associated with signal loss and retransmissions in dense agricultural environments.

Vegetation density and type particularly impact ZigBee WSNs in agriculture, where foliage absorption and scattering play a crucial role in signal attenuation. Hakim *et al.*, [27] studied path loss in dense forests and found that foliage density significantly increased signal attenuation, emphasizing the critical need for environment-specific models in agricultural contexts to minimize energy consumption. Yoshimura *et al.*, [28] explored the effects of vegetation at both 920 MHz and 2.4 GHz and found that higher frequencies suffered greater attenuation due to foliage, necessitating higher transmission power and consequently more energy usage to maintain stable connections. These findings confirm the substantial role of vegetation density and type on ZigBee signal reliability, particularly for regions with high foliage density, such as those studied by Castellanos and Teuta [23] in the Amazon, where vegetation ratios directly correlated with path loss levels. This increased attenuation necessitates adaptive transmission strategies to ensure that sensor nodes can sustain their energy over time, supporting longer network operation and reducing the need for frequent maintenance.

The limitations of single-slope path loss models in agricultural contexts have led researchers to investigate dual-slope models to address the varying conditions caused by vegetation density and type. For instance, Oyie and Afullo [29] conducted a comparative study showing that dual-slope models significantly improve accuracy over single-slope models in dense vegetation. This approach, particularly relevant for low-power, near-ground sensor networks, is supported by studies like Olasupo *et al.*, [30], who demonstrated that terrain-specific calibration enhances model accuracy by capturing the effects of ground clutter and crop canopy variations, thereby minimizing unnecessary energy expenditure. Srisooksai *et al.*, [31] and [32] further validated dual-slope models in fruit orchards and tall grass fields, emphasizing that these models can adapt to dynamic agricultural landscapes. By adjusting transmission power requirements in both line-of-sight (LOS) and NLOS conditions, dual-slope models help conserve energy, ensuring efficient WSN performance in energy-constrained environments.

Collectively, these studies demonstrate the necessity of vegetation-aware, dual-slope, and empirical path loss models for reliable agricultural WSN performance. Dual-slope models, in particular, provide flexibility by adjusting for rapid signal attenuation in both LOS and NLOS conditions, as illustrated by Barrios-Ulloa *et al.*, [6], who advocate for machine-learning-enhanced dual-slope models in agricultural settings like cassava fields. This adaptability positions dual-slope models as particularly suitable for large-scale WSN deployment, with Miao *et al.*, [33] showing that integrating received signal strength (RSS) data in dual-slope models can improve sensor location estimation, thereby enhancing coverage and network efficiency in expansive farmlands. Consequently, this contributes to improved energy efficiency by reducing retransmissions, conserving battery life, and supporting sustainable WSN deployments in challenging agricultural landscapes.

3. MATERIALS AND METHODS

3.1 Study Area Description

This study was conducted on a cassava farm selected to analyse path loss in both line-of-sight (LOS) and non-line-of-sight (NLOS) conditions, allowing for in-depth examination of wireless signal propagation through dense vegetation. The farm is located at Lat. 7°10′47″ N, Long. 4°43′41″ E in Oke Igbo Local Government Area of Ondo State, Nigeria, and covers a flat area of 60 meters by 100 meters. The cassava plants, characterized by broad leaves, dense foliage, and robust woody stems, attain an average height of 1.80 meters, with a ridge spacing of 0.41 meters and inter-plant spacing of 0.78 meters. These characteristics produce substantial scattering effects on signals, making this environment ideal for evaluating the performance of ZigBee-based wireless sensor networks in vegetated agricultural settings.

3.2 Equipment Setup and Radio Frequency Measurements

The radio frequency (RF) measurements in this study, which included range and throughput tests, were conducted in both a cassava farm (NLOS) and an open field (LOS) to thoroughly examine path loss. Two XBee S2C ZigBee modules were deployed to develop a path loss model by measuring the Received Signal Strength Indicator (RSSI) and throughput values. One XBee module served as a coordinator node, while the other operated as a router node. The coordinator, in a fixed position, was powered by a laptop via USB, while the router was powered through the 3.3 V pin of an Arduino Uno, which was supplied by a 9V battery. Both nodes were placed at an antenna height of 1.0 m throughout the measurements. In this study, the transmit power of the two XBee-S2C modules was set to 8 dBm, with a receiver sensitivity of –102 dBm, and both the transmitter and receiver antennas had a gain of 2 dBi.

During the field measurement conducted, the router was incrementally moved away from the coordinator, with RSSI and throughput data collected every 5 meters until communication was lost. RSSI and throughput data were taken at various angles from the coordinator, specifically at 60°, 90°, and 120°, to assess directional impact on signal propagation. The coordinator was connected to a laptop, allowing RSSI and throughput data capture through X-CTU software. This experimental setup is similar to that used in Jawad *et al.*, [9], which also involved configuring ZigBee modules for RSSI-based path loss analysis in a controlled environment. The configuration of equipment used for RF measurements in the farm field is illustrated in Plate 1.

In the X-CTU configuration setup for evaluating the range and throughput of XBee S2C modules, several parameters were carefully chosen to ensure accurate performance analysis. As shown in Figure 2, the range test is configured with a packet payload of 10 bytes and a transmission interval (Tx interval) of 500 ms. A total of 100 packets are transmitted, yielding local and remote RSSI values at -45 dBm. The success rate indicator confirms that 100% of packets were successfully sent and received, ensuring reliable data on signal strength and communication quality across the specified range between the coordinator and router modules.

Similarly, in the throughput test depicted in Figure 3, the packet payload size is also set to 10 bytes, with the test running for 30 seconds as shown in the elapsed time field. Real-time transfer ratios are displayed, with an average transfer rate of 2.59 Kbps and an instantaneous transfer rate of 2.69 Kbps. This configuration facilitates consistent measurement of both throughput and signal range, offering valuable insights into the performance of XBee S2C modules in the cassava farm (NLOS) and open field (LOS) environments.

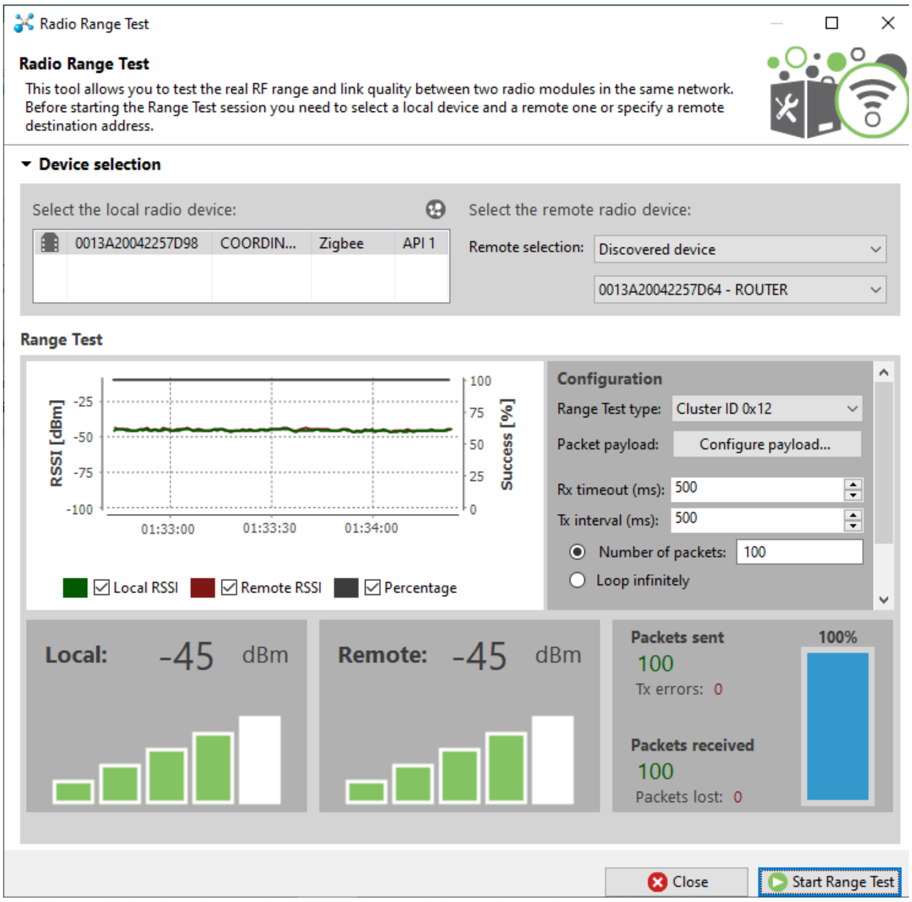

Figure 2: X-CTU configuration setup for range test

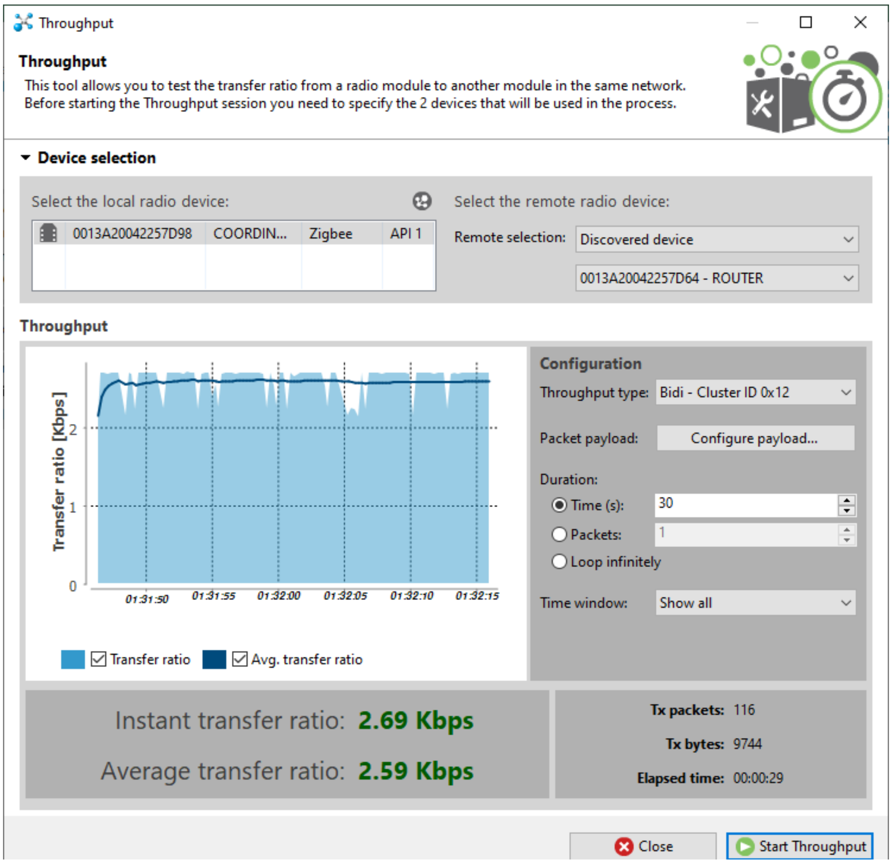

Figure 3: X-CTU configuration setup for throughput test

Plate 1: Equipment Setup for RF Measurements

3.3 Path Loss Model Formulation

In this research work, a two-slope log-distance model was employed to characterize the radio wave propagation in the cassava farm environment. This model was chosen due to its ability to capture the varying attenuation effects in environments with mixed LOS and NLOS conditions, such as cassava farms with dense vegetation. The two-slope path loss model divides the environment into two distinct regions based on the breakpoint distance (BPD); the region closer to the transmitter where LOS conditions dominate and the region farther away where NLOS effects become significant. The two-slope path loss equation was derived using the experimental RSSI measurements collected at varying distances from the transmitter. The RSSI values were processed using the least squares regression line analysis, a statistical method that minimizes the error between the measured data points and the model predictions. This approach ensured that the model parameters accurately reflected the propagation characteristics of the cassava farm.

The two-slope path loss model [34] is expressed in (1):

$$PL\,(d_i) = \begin{cases} PL\,(d_b) + 10n_1 \log\left(\frac{d_i}{d_b}\right) & d_i \le d_b \\ PL\,(d_{b+1}) + 10n_2 \log\left(\frac{d_i}{d_{b+1}}\right) & d_i > d_b \end{cases} \quad \ldots\ldots\ldots\ldots (1)$$

Where $PL(d_b)$ is the path loss at 1 meter, n_1 and n_2 are the path loss exponents. The distance d_b is known as the breakpoint distance. The breakpoint distance is the distance at which the path loss curves for NLOS and LOS intersects.

The relationship between path loss, transmit and received power is given as:

$$PL[dB] = P_t[dBm] - P_r[dBm] + G_t[dB] + G_r[dB] \quad \ldots(2)$$

Where P_t is the transmit power, P_r is the received power, G_t and G_r are the gain of the transmitter and receiver antennas respectively.

3.4 Validation of Empirical Path Loss Model

The empirical path loss model developed in this work was validated by conducting a range test in another cassava farm located in Okitipupa Local Government Area of Ondo State, Nigeria. The equipment setup is the same as the first RF measurement campaign. The measured path loss and predicted path loss was plotted against the communication range and statistical analysis was performed to determine if the empirical path loss model fits the measured path loss. In order to validate the developed path loss model, the statistical measures considered include Mean Absolute Error (MAE), Mean Square Error (MSE), Root Mean Square Error (RMSE), and Mean Absolute Percentage Error (MAPE).

4. RESULTS AND DISCUSSION

In this section, RF measurement results for XBee-S2C RF modules in a cassava farm and open field environment at Oke Igbo Local Government Area of Ondo State, Nigeria are presented and discussed in details.

4.1 RESULTS

The RSSI measurement data obtained from the open field, representing LOS conditions, and the cassava farm, representing NLOS conditions, were utilized to characterize the path loss of the XBee-S2C module using Equation (2). The measurement data is presented in Table 1, and the analysis was conducted using Microsoft Excel to ensure precision and reliability in processing the data.

The variation of average RSSI measurements of the X-Bee Module with the distances between the transmitter node and receiver node both in the open field and cassava farm environment is presented in Figure 4. Similarly, the estimated path loss values for the open field in variation with the logarithm of the distance between the transmitter node and the receiver node is shown in Figure 5. Likewise, Figure 6 shows the estimated path loss values for the cassava farm in variation with the logarithm of the distance between the transmitter node and the receiver node.

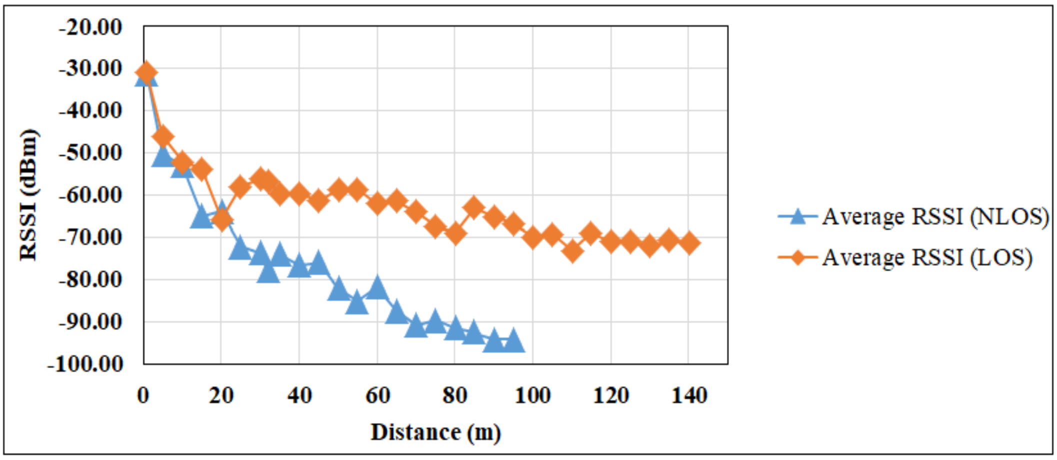

Figure 4: The RSSI Range Test Results of X-Bee Module

Table 1: RSSI and throughput measurement data for LOS and NLOS scenarios

Distance (m)	Average RSSI NLOS (dBm)	Average RSSI LOS (dBm)	Average Path Loss NLOS (dB)	Average Path Loss LOS (dB)	Throughput NLOS (kbps)	Throughput LOS (kbps)
1	-31.44	-31.00	43.44	43.00	2.62	2.66
5	-50.11	-46.00	62.11	58.00	2.61	2.59
10	-53.00	-52.00	65.00	64.00	2.58	2.65
15	-64.89	-53.67	76.89	65.67	2.58	2.6
20	-63.78	-65.67	75.78	77.67	2.59	2.66
25	-72.22	-58.00	84.22	70.00	2.6	2.65
30	-73.78	-56.33	85.78	68.33	2.57	2.64
32	-77.78	-56.67	89.78	68.67	2.57	2.62
35	-73.89	-59.67	85.89	71.67	2.6	2.64
40	-76.56	-59.67	88.56	71.67	2.58	2.64
45	-76.00	-61.33	88	73.33	2.6	2.64
50	-82.00	-58.67	94	70.67	2.65	2.63
55	-85.11	-58.67	97.11	70.67	2.19	2.59
60	-81.78	-62.00	93.78	74.00	2.64	2.61
65	-87.33	-61.33	99.33	73.33	1.56	2.61
70	-90.67	-64.00	102.67	76.00	2.59	2.62
75	-89.67	-67.33	101.67	79.33	2.19	2.61
80	-91.33	-69.00	103.33	81.00	1.31	2.62
85	-92.33	-63.00	104.33	75.00	0.83	2.65
90	-94.11	-65.00	106.11	77.00	0.16	2.62
95	-94.11	-66.67	106.11	78.67	0.92	2.6
100		-70.00		82.00		2.64
105		-69.33		81.33		2.58
110		-73.00		85.00		2.57
115		-69.00		81.00		2.57
120		-71.00		83.00		2.57
125		-71.00		83.00		2.56
130		-72.00		84.00		2.59
135		-70.67		82.67		2.56
140		-71.33		83.33		2.58

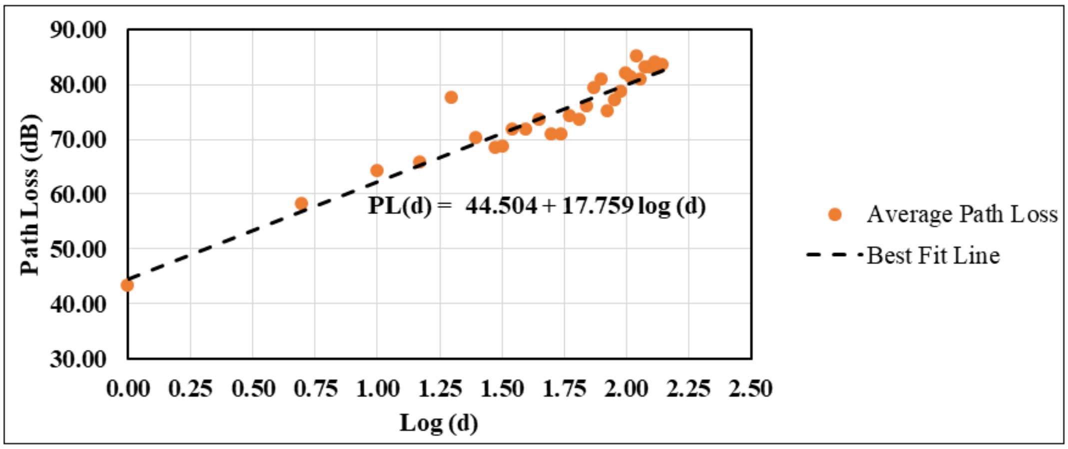

Figure 5: The Path Loss Curve of X-Bee Module in the Open Field

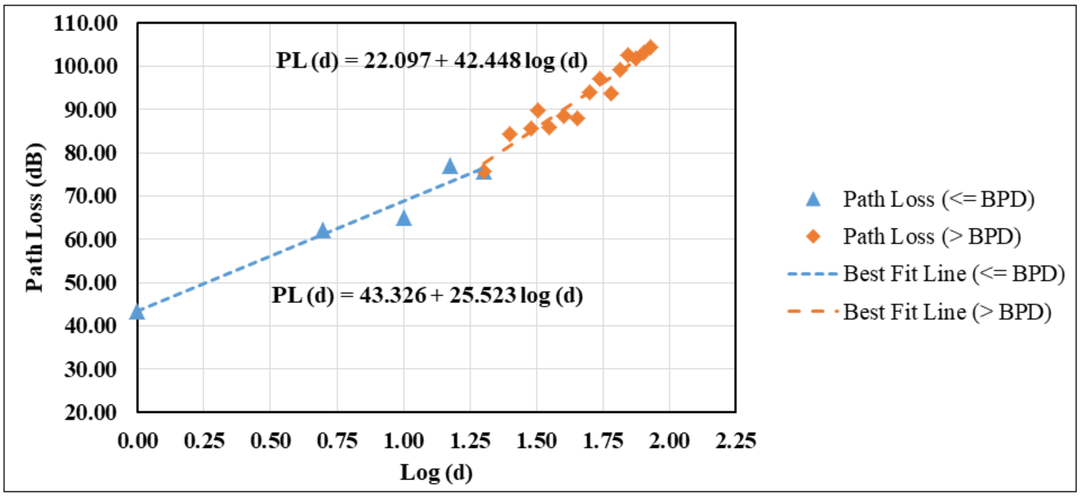

Figure 6: The Path Loss Curves X-Bee Module in the Farm Environment

The developed empirical path loss model equation is expressed in (3)

$$PL\,(d) = \begin{cases} 43.33 + 25.52\log(d) & d \leq d_b \\ 22.10 + 42.45\log(d) & d > d_b \end{cases} \quad \text{..................} \ (3)$$

The results of the throughput test performed in the open field and cassava farm plantation are presented in Figure 7.

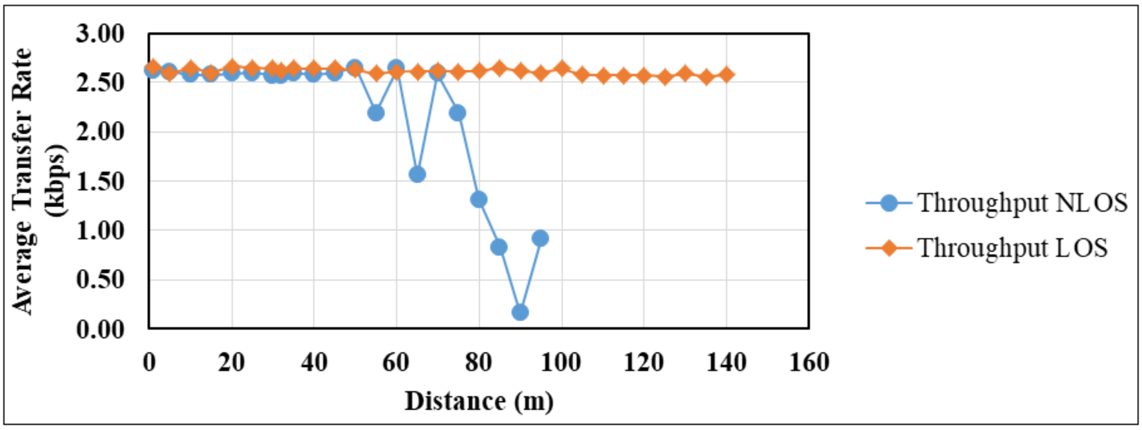

Figure 7: The Throughput Curves of X-Bee Module for LOS and NLOS scenarios

The result of the range test conducted in the cassava farm located at Okitipupa Local Government Area of Ondo State is presented in Figure 8;

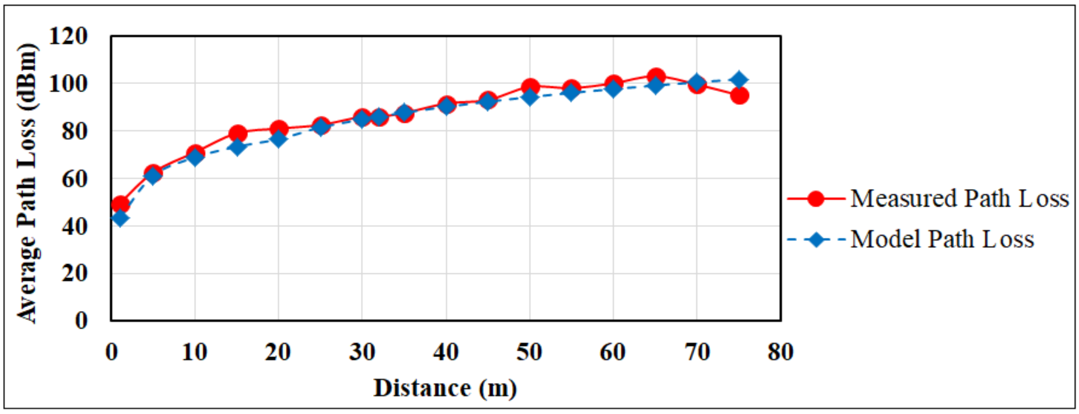

Figure 8: The validation of empirical path loss

The statistical measures of the developed empirical path loss model are presented in Table 2.

Table 2: The statistical measures of the empirical path loss model

MAE	MSE	RMSE	MAPE	R-squared
1.70882353	11.237	3.35 dB	3.30%	0.94

4.2 DISCUSSION

As shown in Figure 4, the Received Signal Strength Indicator (RSSI) values consistently decrease as the distance between the two nodes increases in both measurement environments. In the open field, the RSSI values ranged from –31 dBm to –71 dBm, whereas in the cassava plantation, the values varied from –31 dBm to –94 dBm. Notably, the two curves intersect at a specific distance, referred to as the crossover or breakpoint distance, which is approximately 20 m. Before this crossover distance, the RSSI values for the XBee module in both environments decreased at a similar rate; however, post-crossover, the farm field exhibited a more pronounced decline in RSSI values. This decrease underscores the negative impact of foliage along the radio wave propagation path. This phenomenon aligns with the findings of Olasupo *et al.*, [30], who observed a similar increase in path loss in environments with natural grass, and Aldosary and Kostanic [22], who reported increased attenuation in tree-obstructed environments. These studies emphasize the critical role of vegetation in influencing the propagation characteristics of radio waves.

In Figure 5, a consistent linear relationship between the two variables is observed, with the path loss exponent for the open field (line-of-sight scenario) calculated at 1.78. While this value closely approximates the free space path loss exponent of 2.00, which indicates that the free space path loss model tends to overestimate the path loss variations experienced by the XBee module in the open field. The estimated path loss for the cassava farm field, depicted in Figure 6, reveals path loss exponents of 2.55 and 4.25 for distances prior to and subsequent to the breakpoint distance, respectively. This increase in path loss exponent is consistent with the findings of Barrios-Ulloa *et al.*, [6], who observed that agricultural environments with dense vegetation, such as cassava fields, significantly affect radio wave propagation. Lopez-Iturri *et al.*, [35] also reported similar increases in path loss exponents in dense forest environments, where foliage severely attenuates the radio signal, further corroborating the results observed in this study.

Figure 7 shows that the average data transfer ratio for the radio module in the open field is 2.61 kbps, compared to 2.17 kbps in the cassava plantation. The open field exhibited a steady data transfer ratio, whereas in the cassava farm, a uniform transfer ratio was maintained up to a communication distance of 50 m, beyond which fluctuations were observed. This variability is attributed to reflections and fading effects prevalent in the foliage-rich environment, as noted by Aldosary and Kostanic [22].

The results from the range test depicted in Figure 5 indicate that the XBee module has a coverage radius exceeding 140 m in the open field and approximately 75 m in the cassava farm. However, the throughput test results illustrated in Figure 7 reveal that reliable data communication cannot be assured beyond a communication range of 70 m. Consequently, the maximum communication range for the XBee module is determined to be 70 m. Beyond this range, the data transfer rate becomes unreliable, which is consistent with the findings of Alsayyari and Aldosary [24], who reported similar limitations on the effective communication range of wireless sensor networks in environments with substantial obstructions.

Graphically represented in Figure 8, the path loss model demonstrates a close fit to the measured path loss data. Additionally, Table 2 indicates that the developed model for this study achieves a Mean Absolute Percentage Error (MAPE) of 3.30%, which is less than 10%, signifying an excellent fit. Another key statistical measure, the R-squared value, approaches unity, while the acceptable Root Mean Square Error (RMSE) for path loss models is established at less than 6 dB. These results are consistent with the findings of Barrios-Ulloa *et al.*, [6], who achieved similar levels of accuracy using machine learning techniques for path loss prediction in agricultural environments. The validation of the developed path loss model confirms its efficacy in accurately predicting radio wave propagation behaviour within a cassava farm environment.

5. CONCLUSION

This study has developed an empirical path loss model in ZigBee-based WSNs in cassava farm environments, effectively addressing the critical challenges posed by vegetation density on wireless signal propagation. Empirical range and throughput tests with XBee-S2C modules were conducted under NLOS conditions representing cassava farm and LOS scenarios in open field, leading to the development of a two-slope log-distance path loss model. The maximum communication range was observed to be 70 meters in the cassava farm, while it extended to 140 meters in the open field. The path loss exponents were determined to be 2.55 and 4.25 for distances before and after the breakpoint in the cassava farm, respectively, contrasting with a path loss exponent of 1.78 in the open-field scenario. These findings underscore the significant impact of dense vegetation on signal attenuation, which is crucial for the design and simulation of WSNs in precision agriculture.

The path loss model developed in this study offers a robust framework for characterizing radio wave propagation in densely vegetated agricultural environments and lays the groundwork for accurate prediction of energy consumption in ZigBee-based WSNs. This predictive capability is essential for optimizing the energy efficiency of network nodes, thus supporting prolonged operation in remote or power-constrained farming setups. The results of this study shows that the developed path loss model for this study establishes valuable insights for farmers by accurately estimating communication ranges for their unique crop settings, which can improve WSN deployment strategies for monitoring soil conditions, crop health, and environmental factors. Ultimately, this contributes to more efficient farming practices and better crop yields through the strategic use of wireless communication technology in smart agriculture.

Future research should encompass extensive field testing across diverse agricultural landscapes and seasonal variations to further enhance the developed model's robustness. Additionally, adjusting antenna heights and orientations may improve link reliability in areas with dense vegetation.

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