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MODIFIED COST-235 EMPIRICAL PATHLOSS MODEL FOR AGRICULTURAL-WSN USING PARTICLE-SWARM-OPTIMIZATION

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ABSTRACT: The increasing demand for agricultural products yearly encourages farmers to seek solutions to migrate from conventional farming to smart and precise farming by utilizing technological advances such as implementing wireless sensor networks (WSN). Unlike conventional farming, this technology is believed to provide many advantages, including low cost, high efficiency, optimized land use, and high productivity results. However, this system is highly dependent on the availability of network interconnection where the bottleneck is the instability of signal strength and path loss, especially for radio wave propagation from the transmitter (Tx) in the form of sensors to the receiver (Rx) in the form of data processors where its performance depends on the distance, agricultural, environmental conditions, and surrounding vegetation. This paper explicitly examines and analyzes radio wave propagation modeling for measuring radio frequency (RF) signal strength in local agriculture's 2.4 GHz WSN system, such as Adan rice, corn, and peanuts. The particle-swarm-optimization (PSO) method is used to modify empirical path loss models such as Weissberger, ITU-vegetation, COST-235, Egli, and FITU-R, which also involve the influence of rain attenuation. Several other factors are also considered in the evaluation and analysis, i.e., the planting period of agricultural crops (seedlings, growth, and maturity), vegetation depth, and the height of the Tx-Rx antenna from the ground. The results of the experimental evaluation show that the PL COST-235 model continues to be optimized using the PSO method because it has the lowest RMSE both in conditions without and with rain attenuation, which are 23.30 and 9.33, respectively. Meanwhile, after the selected model is optimized using the PSO method, the RMSE for both conditions becomes 2.49 and 5.29.

ABSTRAK: Permintaan yang semakin meningkat terhadap produk pertanian setiap tahun mendorong para petani untuk mencari penyelesaian bagi beralih daripada pertanian konvensional kepada pertanian pintar dan tepat dengan memanfaatkan kemajuan teknologi seperti penggunaan rangkaian sensor tanpa wayar (WSN). Berbeza dengan pertanian konvensional, teknologi ini dipercayai memberikan banyak kelebihan, termasuk kos yang rendah, kecekapan yang tinggi, pengoptimuman penggunaan tanah, dan hasil produktiviti yang tinggi. Namun begitu, sistem ini sangat bergantung kepada ketersediaan rangkaian interkoneksi di mana kelemahan utamanya adalah ketidakstabilan kekuatan isyarat dan kehilangan laluan (path loss), terutamanya bagi penyebaran gelombang radio dari pemancar (Tx) berbentuk sensor ke penerima (Rx) berbentuk pemproses data, yang prestasinya bergantung kepada jarak, keadaan persekitaran pertanian, dan tumbuh-tumbuhan di sekeliling. Kajian ini secara khusus meneliti dan menganalisis pemodelan penyebaran gelombang radio untuk mengukur kekuatan isyarat frekuensi radio (RF) dalam sistem WSN

2.4 GHz di pertanian tempatan seperti padi Adan, jagung, dan kacang tanah. Kaedah pengoptimuman kawanan zarah (particle-swarm-optimization, PSO) digunakan untuk mengubah suai model kehilangan laluan empirikal seperti Weissberger, ITU-vegetation, COST-235, Egli, dan FITU-R, yang turut melibatkan pengaruh pelemahan hujan. Beberapa faktor lain juga dipertimbangkan dalam penilaian dan analisis ini, seperti tempoh penanaman tanaman pertanian (anak benih, pertumbuhan, dan kematangan), kedalaman tumbuh-tumbuhan, dan ketinggian antena Tx-Rx dari permukaan tanah. Hasil penilaian eksperimen menunjukkan bahawa model PL COST-235 terus dioptimumkan menggunakan kaedah PSO kerana ia mempunyai nilai RMSE paling rendah dalam kedua-dua keadaan tanpa dan dengan pelemahan hujan, iaitu masing-masing 23.30 dan 9.33. Sementara itu, selepas model yang dipilih dioptimumkan menggunakan kaedah PSO, nilai RMSE bagi kedua-dua keadaan menjadi 2.49 dan 5.29.

KEYWORDS: *Agriculture-WSN, FITU-R, Pathloss, Particle-Swarm-Optimization, Root-Mean-Square-Error.*

1. INTRODUCTION

FAO stated that global supply and demand for agricultural products as food such as rice, wheat, corn, peanuts, etc., increased above 2,846 million tons per harvest season in 2024-2025 [1]. Several other factors also triggered a significant increase in agricultural output to be more effective, smart, precise, and operate efficiently, reduce farm labor costs, and support environmental sustainability [2], precise control over plant placement, soil conditions, to the use of chemicals, and minimize waste and costs [3], including the ability to monitor plant growth and development precisely in the presence of diseases or pests, nutrient provision, yield estimation, and production levels [4, 5]. One of these smart and precise agricultural technologies can be a combination of the implementation of a wireless sensor network (WSN) with the Internet of Things (IoT) architecture as a general monitoring system [6] and a smart agricultural management system such as that applied in Bangladesh agriculture [7], agricultural irrigation in greenhouses [8], and the application of certain network protocols [9].

One of the focuses of the study on the WSN system, especially related to radio wave propagation, is the measurement of radio frequency (RF) in the form of signal strength from sensors that carry information such as temperature, humidity, soil nutrient content, etc. to the node so that this paper is made to describe it. The availability of interconnection dictates the connection from sensors to nodes in the WSN system. One of the main obstacles in the WSN is the path loss (PL), namely the loss of the radio wave propagation path from the transmitter (Tx) to the receiver (Rx), which depends on the distance, the condition of the type of agricultural environment including weather, and the surrounding vegetation so that it can reduce the quality of the connection. The path passed through the farmland by the radio wave propagation signal reduces the signal strength due to attenuation, absorption, reflection, refraction, and scattering by trees, leaves, vegetation, and other environmental conditions. Several studies have examined PL in the agricultural sector, such as a study by [10] for agricultural products in the form of corn, rice, and peanuts, a study by [11] for corn growth variations, and a study by [12] for fruit farming. PL methods investigated in studies [10]-[12] include: in [10] using models such as ITU-vegetation, Weissberger, and COST-235 with a WSN system frequency of 2.4GHz, in [11] using the Log-normal distribution method for the 2.4GHz WSN system, and in a study by [12] where the PL calculation involves the effect of rain attenuation with a wireless system with a frequency of 433MHz and 2.4GHz. From this description, it is apparent that it is necessary to study in more depth how radio wave propagation from the WSN system, especially PL, can be applied to several agricultural products at once, which may have different environmental and vegetation characteristics so that it is hoped that a general formulation of radio wave propagation modeling can be found that can represent all agricultural products.

This paper evaluates and analyzes the propagation of radio waves from RF measurements in the form of signal strength using a 2.4 GHz WSN system. The particle-swarm-optimization (PSO) method is still rarely applied to PL modeling, especially in agriculture, as reported in [13]. This method is used to obtain an accurate PL model that fits the surrounding environmental conditions. In the study [13], the PSO method was applied to grass farming, such as the alfalfa plant, to model exponential and polynomial PL. There is also a PSO method to determine PL, but it is applied to cellular networks, such as studies by [14] and [15]. PSO in this paper is used to modify empirical PL models such as Weissberger (W), ITU-vegetation (ITU), COST-235, Egli, and FITU-R by involving the influence of rain attenuation, which is then compared with PL results from RF measurements on local agricultural yields and lands such as Adan rice, peanuts, and corn. Adan rice, especially, needs little water in its growing land. It is a rice variant that grows in the highlands of the interior of North Kalimantan, Indonesia, i.e., the Krayan Area, Nunukan [16]. Therefore, this rice is known as highland rice, a major commodity in areas bordering neighboring countries, such as Malaysia. For these various reasons, the PL study of local Adan rice vegetation is worthy of study.

Evaluation of PL was conducted by considering several factors such as distance, Tx-Rx height, planting period of agricultural crops, and especially the influence of environmental characteristics as reported by [17]. What makes this paper more valuable is the additional contribution to the study of PL related to vegetation that influences it when compared to several previous related studies, including the study by [18] where the measurement location was in a tropical area which is known to have very high rainfall or wetlands as reported by [19], and the type of rice planted was not common because it could grow in land with less water or dry land. Thus, this research can increase technical knowledge in wireless radio wave propagation and its planning, which is influenced by relatively extreme environmental conditions.

This paper is organized as follows: Section 2 explains the methods used, such as research stages, including research materials, reviews of empirical models of PL, and the PSO method. Section 3 presents all study results and is followed by a discussion, including signal strength measurements, PL calculations, and performance modifications of PL. The paper ends with Section 4, which contains the conclusions of this study.

2. METHOD

This section describes how to collect measurement data, including the area, descriptions of empirical PL models, and the PSO method for determining modified PL.

2.1. Measurement Area and Data Collection

In this study, the strength of the RF signal was measured in the form of a received signal strength indicator (RSSI, P_r) on three types of local agricultural crops, such as Adan rice, corn, and peanuts, at their respective planting locations as shown in Fig. 1. This RF measurement considers three growth conditions of the three types of plants, i.e., the seedling period, growth period, and maturity period. According to a study [20], Adan rice in Krayan, Nunukan, Indonesia, has a maximum height of up to 1.5 m with an average planting period of 6.5 months. According to a study by [21], local corn in the same area has a maximum height of around 1.8m with a planting period of 3 months. Meanwhile, according to a study by [22], peanuts has an average height of 0.45m with a planting period of up to 2 months.

Measurements were carried out at the planting location of the three types of plants to obtain RSSI values. RF signal strength measurements were taken when each plant had the three conditions mentioned previously, i.e., seedling, growth, and maturity periods, where the time and height of the three plants adjusted to the height and planting period based on studies [20]-[21] for Adan rice, corn, and peanuts. For Adan rice, the height of the plant during the seedling, growth, and maturity periods was 0.2m, 1.2m, and 1.4m, respectively. In corn plants, measurement data was taken with the height of the three planting periods, respectively around 0.2m, 1.4m, and 1.8m. In peanut plants, data was taken when the height in the three planting periods was around 0.1m, 0.2m, and 0.4m. The size of the three plants determines the height of the Tx and Rx installation. Fig. 2 shows the location of Tx and Rx during the measurement where there are wet and dry rice fields of Adan rice in Krayan, Nunukan, Indonesia. The location of Tx is conditioned to be fixed while the location of Rx is varied moving forward and up 20m along the size of the rice field, which is 40m × 500m. In contrast, corn and peanut plants have areas measuring 30m × 250m and 25m × 150m, respectively.

(a) Adan rice (b) Corn (c) Peanuts

Figure 1. Measurement environment for the three crop locations.

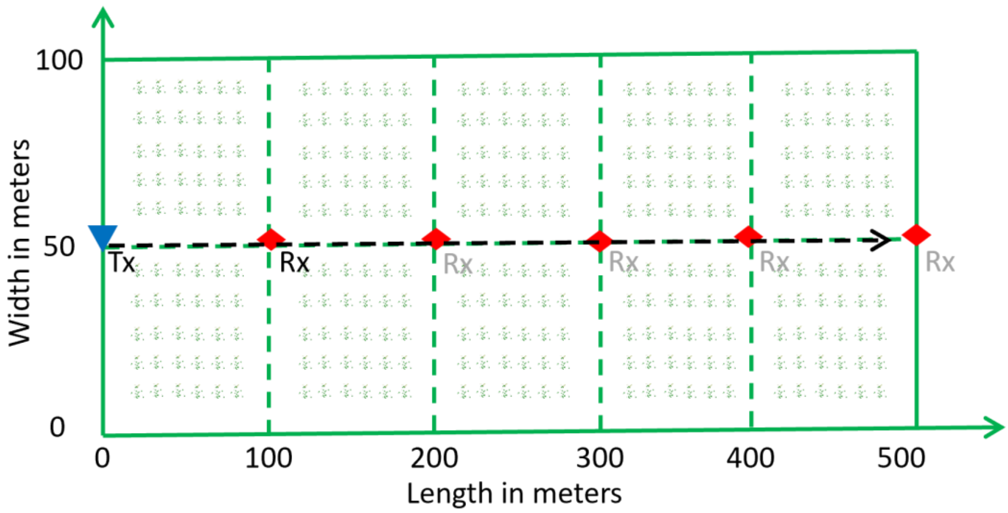

Figure 2. Setting the signal strength measurement area in rice fields, especially in the case of Adan rice.

Fig. 3 shows how to determine signal strength data (in dB) for signals received at the receiver antenna (Rx) in the form of RSSI. This RSSI comes from 2.4GHz RF measurements from the vector signal analyzer (VNA) to the Rx as a spectrum signal analyzer (SSA). Both devices use omnidirectional antennas with a gain of 0dBi (G_t and G_r) and have a transmit power (P_t) of around 10dBm (≈ 0.01watt). A personal computer (PC) or laptop is used to calculate PL from measurement data in RSSI and PL from empirical models. The data of transmit power, working frequency, and antenna gain in the RF measurement system are summarized in Table 1. The placement of both equipment during measurements from the ground is adjusted to the condition of the plant height in 3 conditions, i.e., the seedling, growth, and maturity periods, which also determines the height of the Tx and Rx antennas as h_t and h_r. From the measurement data of signal strength (P_r), transmit power (P_t), and the gain of both antennas. PL can be determined as PL_m with the formula

$$PL_m = P_t + G_t + G_r - P_r \tag{1}$$

where the units for P_t, P_r, G_t, and G_r are dBm, dBm, dBi, and dBi, respectively.

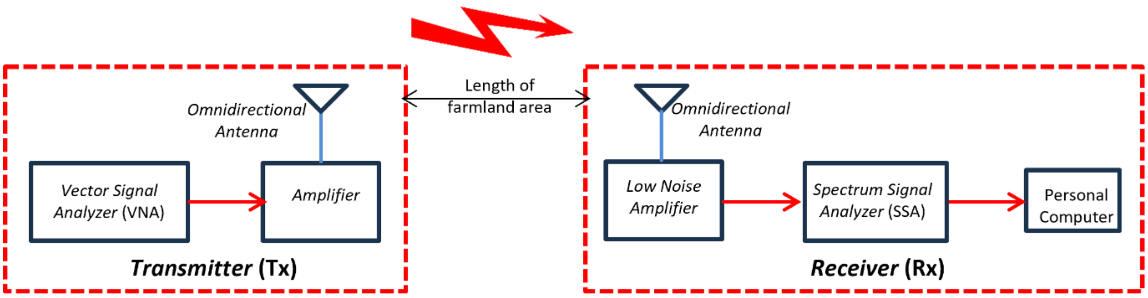

Figure 3. RF measurement configuration on farmland.

Table 1. Parameter settings for RF measurements

System Parameters	Value
Frequency (GHz), f	2.4
Transmit power (dBm), P_t	10
Antenna type	Omnidirectional
Tx and Rx antenna gain (dBi), G_t and G_r	0
Measurement parameter (dBm), P_r	RSSI

Pathloss in Eq. (1) is calculated by involving aspects such as the height of the crop, the distance between Tx-Rx, the planting period of the crop, and the type of environmental vegetation. North Kalimantan, Indonesia, has a fairly high average rainfall. According to a study reported by [19], rainfall has a significant effect on the propagation of high-frequency radio waves, especially in Indonesia, which generally has a tropical climate with high rainfall and the location of the research area which is, in fact, an area on the equator so that rain attenuation also increases the high PL. In the study reported by [12], rain attenuation contributes positively to increasing the PL of the empirical model, which increases the attenuation described in Section 2.2. Rain attenuation in dB is expressed by [12]

$$A_r = kr^{\alpha} \tag{2}$$

where r denotes the rain rate in mm/h, and both k and α depend on the frequency distribution of rainfall size. Suppose it is assumed to use horizontally polarized antenna propagation at a frequency of 2.4GHz. In that case, the k and α values are respectively 0.0001321 and 1.1209 [12], so by using Eq. (2) for a rain rate of 140mm/h, a rain attenuation of 14.73dB is obtained. However, if using statistical data from BPS North Kalimantan 2023 [26], the average rain rate is around 243.78 mm/h, so the rain attenuation is around 12.04dB. After the PL_m determination

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process, it is continued by comparing it with the PL from theoretical calculations using models commonly used in the environment with the influence of vegetation, leaves, and trees, including Weissberger (W), ITU-vegetation (ITU), COST-235, Egli, and FITU-R, whose expressions are given in Section 2.2.

To test and validate the PL obtained from measurement results (PL_m) and empirical calculation results (PL_e) based on existing models, the root-mean-square-error (RMSE) and coefficient-of-determination (R^2) parameters are used to test statistically, which are respectively given by the expression [10].

$$RMSE = \sqrt{\frac{1}{n}\sum_{n=1}^{N}(PL_e - PL_m)^2} \tag{3}$$

and

$$R^2 = \frac{\sum_{n=1}^{N}(PL_e - \widehat{PL_m})^2}{\sum_{n=1}^{N}(PL_m - \widehat{PL_m})^2} \tag{4}$$

where n indicates the amount of measurement data and $\widehat{PL_e}$ as the average of PL. Suppose the calculation result in Eq. (3) has a small value, in that case, it indicates a PL model that can be used as a reference to predict and estimate PL as a characteristic that matches the propagation of radio waves in the vegetation, likewise with R^2 in Eq. (4) where if the value is close to or equal to 1, the empirical PL model can be used as PL to predict the characteristics of radio wave propagation through WSN applications in the planting environment of the agricultural crops. This happens because the empirical PL model is said to have variations that are almost similar to PL from the measurement data.

2.2. Empirical Pathloss Models

Here are some empirical models of PL, and if the calculation result of RMSE is small and R2 is close to one, then the model will be used and agreed upon as a PL model to predict the characteristics of radio wave propagation in the vegetation. Furthermore, the PL model will also be optimized with the PSO method to become the best modified PL model for the type of plant and its vegetation. In this paper, several empirical models are applied specifically for PL involving trees, vegetation, and soil conditions, such as Weissberger (W), ITU-vegetation (ITU), COST-235, Egli, and FITU-R. These empirical models have been recommended for calculating PL by studies [12], [23]-[25] in the agricultural field.

2.2.1. Free Space (FS) Pathloss

This PL model in dB is a simple model of the working frequency of the wireless system (f) in Hz and the distance (d) in meters between Tx and Rx, which is formulated with [10].

$$PL_F = 20log_{10}(f) + 20log_{10}(d) - 147.56 \tag{5}$$

2.2.2. Two-ray (TR) Pathloss

This model includes the influence and reflection of two rays, i.e., the ground ray and the line-of-sight (LOS) ray, which are expressed by the expression [25].

$$PL_{TR} = 40log_{10}(d) - 20log_{10}(h_t) - 20log_{10}(h_r) \tag{6}$$

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2.2.3. Weissberger Pathloss

This model is used for paths with signals with a frequency (*f*) in GHz whose propagation is obstructed by dense, leafy, and dry trees in dB with a vegetation depth of *d* in meters, which is stated by [10].

$$PL_W = \begin{cases} 0.45f^{0.284}d \text{ for } 0m < d \leq 14m \\ 1.33f^{0.284}d^{0.588} \text{ for } 14m < d \leq 400m \end{cases} \tag{7}$$

2.2.4. ITU-Vegetation Pathloss

This PL model is intended for Tx or Rx close to a small group of trees so that the signal propagates through the trees with a depth (*d*) in meters expressed by [10].

$$PL_{ITU} = 0.2f^{0.3}d^{0.6} \tag{8}$$

with the condition $d < 400$m.

2.2.5. COST-235 Pathloss

This PL model is for trees with a depth of *d* in meters expressed in dB with [10].

$$PL_C = 15.6f^{-0.009}d^{0.26} \tag{9}$$

2.2.6. Egli Pathloss

This PL model is expressed in dB for the working frequency *f* in MHz and involves the presence of the surrounding terrain factor with the expression [24].

$$PL_E = PL_F + 20log_{10}\left(\frac{f}{40}\right) \tag{10}$$

2.2.7. FITU-R Pathloss

This PL model applies to VHF signals with a maximum short foliage depth of around 400m with a depth *d* in meters expressed in dB with [23], [25].

$$PL_{FITU} = 0.39f^{0.39}d^{0.25} \tag{11}$$

2.3. Particle-Swarm-Optimization Method for Pathloss

According to [13], PSO is a heuristic approach to solving optimization problems. Some particles, called swarms, can regulate the speed of optimization calculations that provide the best results. To determine the optimal solution, particle modifications are carried out involving parameters such as the best position (p_b) *and the best global position* (g_b) *where the position of the ith particle (pi) and the velocity of the ith* particle (v_i) for i = 1, 2, ..., I. The iterative equation of the PSO method for iteration index n = 1, 2, ..., N, which determines the solution by setting v_i and p_i is expressed as

$$v_i^{n+1} = wv_i^n + c_1r_1(p_b - p_i) + c_2r_2(g_b - p_i) \tag{12}$$

with

$$p_i^{n+1} = p_i + v_i^{n+1} \tag{13}$$

where w is the inertia weight, c_1 and c_2 denote the scaling constants, and r_1 and r_2 are random vectors with values between 0-1. The formulation in Eqs. (12)-(13) is used to estimate the PL from the empirical model with the smallest RMSE value of all empirical PLs against the PL of the measurement data.

Before PSO optimization is carried out on the PL model that has the smallest RMSE, first determine the empirical PL model from Eqs. (5)-(11), which has a trend close to the PL of measurement data as indicated by the smallest RMSE value. Furthermore, the PL model is optimized using the PSO method, which aims to generate coefficients from the PL model so that it has a trend close to the measurement PL, which is indicated by a smaller RMSE or R2 approaching 1. This adopts the steps of PL model optimization by [14], which is carried out for mobile communication systems. The basic process of the PSO method consists of initialization, constraint assignment, fitness evaluation of all particles, and selection, as in Fig. 4.

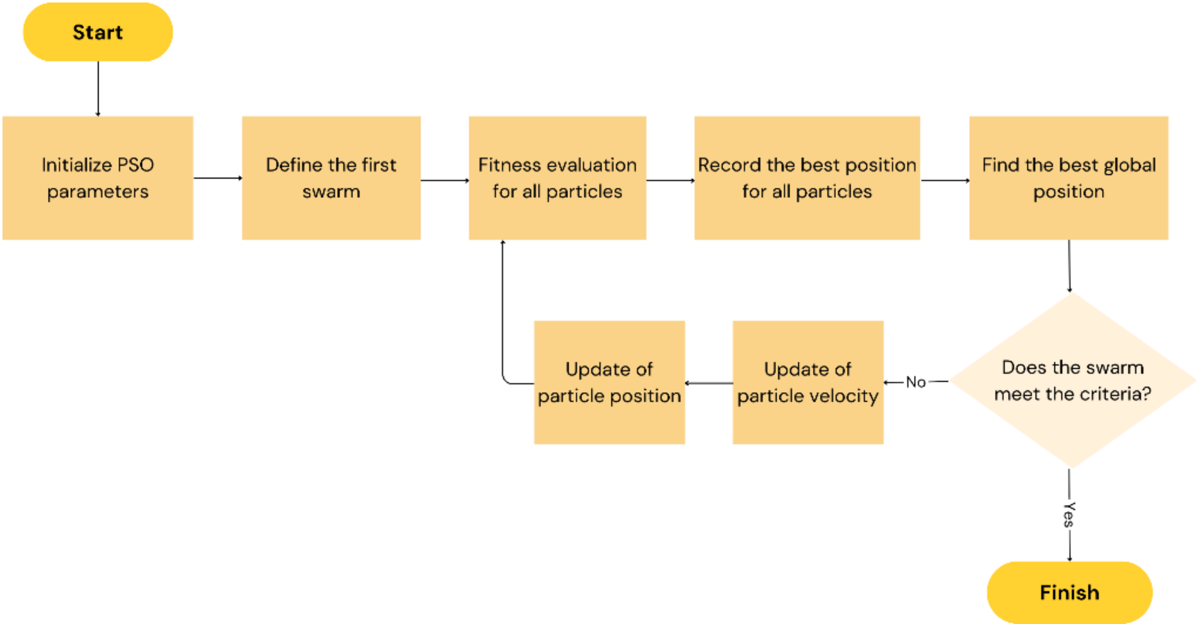

Figure 4. Flowchart of PSO method.

3. RESULTS AND DISCUSSION

This section presents the results of experimental measurements along with their analysis and discussion, which include (a) the results of signal strength measurements in the form of RSSI for the three types of plants during the seedling, growth, and maturity stages, (b) determining the PL_m from measurements using Eq. (1) with the data in Table 1 and RSSI (P_r) obtained from the RF measurement results in point (a), (c) then the PL_m is compared with theoretical calculations for the PL_e models in Eqs. (5)-(11) with and without involving rain attenuation in Eq. (2), and (d) determining the empirical PL model that has the smallest RMSE and R^2 against the PL data from RF measurements with Eqs. (3)-(4) will be used as a modified PL model using the PSO method. It can then be recommended as a PL model for agricultural WSN systems at the research location and its surroundings.

3.1. Signal Strength Measurement in Agricultural Plants

Fig. 5 shows the results of RSSI measurements with the RF system for agricultural crops in three planting conditions for Adan rice, corn, and peanuts in Figs. 5(a), 5(b), and 5(c), respectively. All RSSI values decrease with increasing vegetation depth, which is proportional to the distance between the Tx and Rx antennas. In Fig. 5(a), the RSSI measurement data on Adan rice plants, the receiver sensitivity during the seedling, growth, and maturity periods is -82dBm, -89dBm, and -95dBm, respectively. RF measurements can still be done with vegetation depths up to 500m. RSSI at maturity is lower because rice plants at that age already have many dense leaves when compared to RSSI at seedling and growth periods. According to

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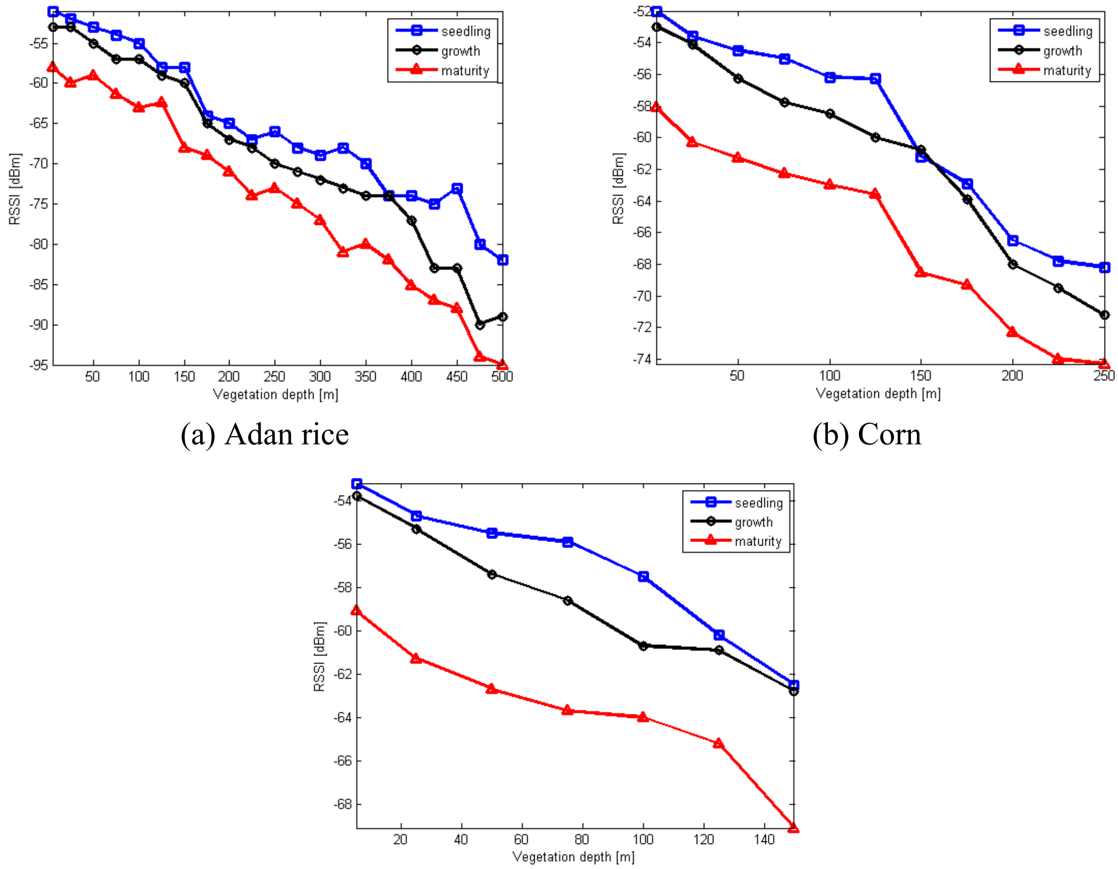
[20], the number of leaves at maturity is 108, more than the growth period where the number of leaves is 9. This happens because the signal emitted by the sensor node at Tx is mostly absorbed by vegetation, such as leaves from Adan rice. In the seedling period, the RSSI is measured relatively high compared to other planting periods because the depth of the plants is still sparse, and the trees are still relatively small. However, during the seedling period, there is still a reduction in the transmitted signal from the sensor node originating from the land surface where the conditions are wet and watery so that it reflects the transmitted signal. These results strengthen the study [10], which only measured the RSSI of agricultural crops such as corn, rice, and peanuts in two planting conditions, namely the growth and maturity periods only, and the results showed that the growth period had a relatively high RSSI compared to the maturity period.



(a) Adan rice (b) Corn

(c) Peanuts

Figure 5. RSSI measurements during seedling, growth, and maturity periods for agricultural crops.

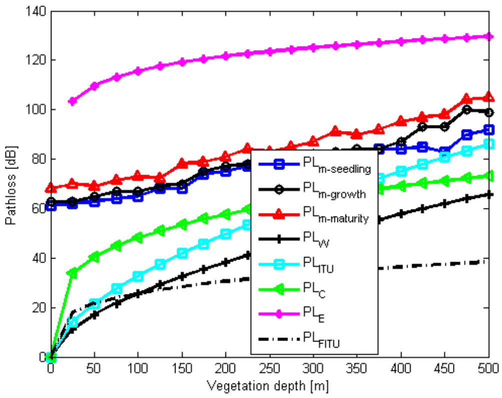
The RSSI measurement results on corn plants in Fig. 5(b) have a similar phenomenon to the RSSI measurement on Adan rice plants. However, because the length of the plant field is lower than the length of the Adan rice field, which is only 250m, the receiver sensitivity obtained successively at the seedling, growth, and maturity periods are -68.2dBm, -71.2dBm, and -74.3dBm. Compared to Adan rice plants at a vegetation depth of 250m, the RSSI of the three planting conditions is -66dBm, -70dBm, and -73dBm, respectively. This indicates that corn plants have denser and thicker vegetation than Adan rice, so signal absorption by vegetation, i.e., from trees and leaves, is relatively greater than that in Adan rice. This result has also been proven previously in a study by [10]. According to a study [21] on corn, the number of leaves is 3 strands per tree during the seedling period, and the stem diameter is around 0.29 cm. During the maturity period, the number of leaves is 25 strands more than during the seedling period, and the stem diameter is, on average, 3 cm.

RF measurements in peanut plants (see Fig. 5(c)) also have an RSSI level phenomenon as in RSSI measurements in Adan rice and corn. Receiver sensitivity obtained successively at seedling, growth, and maturity periods are -62.5dBm, -62.8dBm, and -69.1dBm, respectively, where the depth of plant vegetation is around 150m. For RSSI values on Adan rice with the same vegetation depth in the three measured planting conditions, around -64dBm, -65dBm, and -69dBm, respectively. It can be seen that during the maturity period, the RSSI received by the Rx node of the peanut plant is weaker than that of the rice plant because it is influenced by the depth of the peanut plant, which has dense leaves, and the reflection from the soil surface where the maximum planting height of peanuts is lower by around 45cm [22] compared to Adan rice up to 150cm.

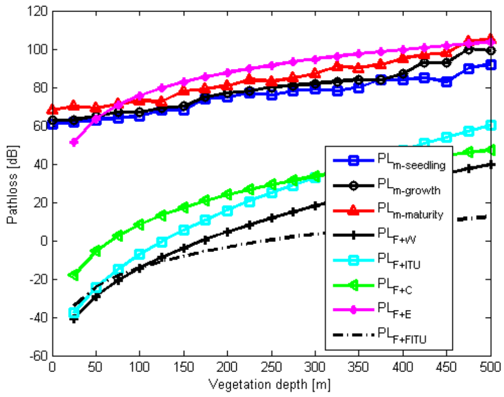
3.2. Pathloss in Agricultural Crops

Based on Eq. (1), the PL of RF measurement results can be calculated through the RSSI signal strength obtained in Fig. 5 for all agricultural crops. In Fig. 6 for Adan rice plants, the PL of measurement data and PL from empirical models have been presented. In contrast, Fig. 6(a) shows the PL of measurements and PL of empirical models without the addition of PL from the Free-Space (PLF) model and PL from the Two-ray (PLTR) model, Fig. 6(b) shows the PL of measurements and PL of empirical models with the addition of PLF. Fig. 6(c) shows the PL of measurements and PL of empirical models with the addition of PL_{TR}. The three empirical PL determination conditions are used to calculate the empirical PL model that matches the PL measurement data in agricultural plants. This method has been investigated by [25] for tomato agricultural plants in greenhouses, and the aim is to determine the PL model that approaches the measurement PL model because the signal from the Tx node comes from various signal propagation paths.

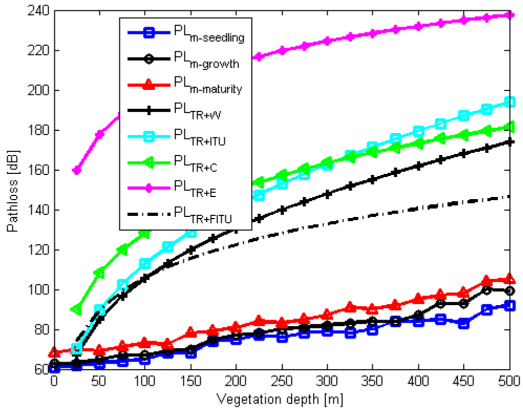
At a glance, it can be seen in Fig. 6(a) that the empirical PL model that is closest to the trend of the RF measurement PL is the COST-235 PL model, where this empirical model is very close to the measurement PL data. At the same time, other empirical models have a range far below the measurement data, such as PL from ITU (PLITU), Weissberger PL (PLW), and PL from FITU (PLFITU), and above the measurement data, such as Egli PL (P_{LE}). In addition to PL from PLF, the PLE model that approaches the three conditions of measurement PL and other empirical PL is below the measurement PL, as shown in Fig. 6(b). In addition to path losses with PLTR, all empirical model PLs are above the measurement PL shown in Fig. 6(c). Thus, for the next PL calculation, to optimize the PL model with the PSO method, the COST-235 PL model in Fig. 6(a) is selected. As described in the last paragraph in Section 2.3, the PL model that has the smallest RMSE against the PL measurement is optimized by the PSO method. This is also supported by the study reported by [14]. To strengthen the determination of a suitable model for optimization, the RMSE value of the empirical PL model (PL_e) and the measured PL (PL_m) is calculated, and the one with the smallest RMSE value is selected, as was done by [14]. Based on the same approach to Adan rice plants in Fig. 6(a), the results of PL calculations from measurement data and empirical models are presented in corn and peanut plants, as in Fig. 7(a) for corn and Fig. 7(b) for peanut plants. It can be seen from Figs. 7(a)-(b) that the empirical PL model that approaches the trend of RF measurement PL is the COST-235 PL model.



(a)

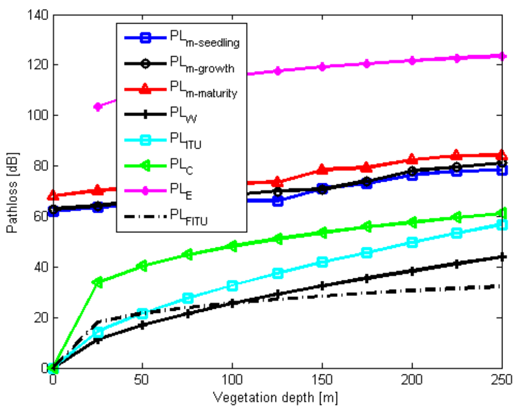


(b)

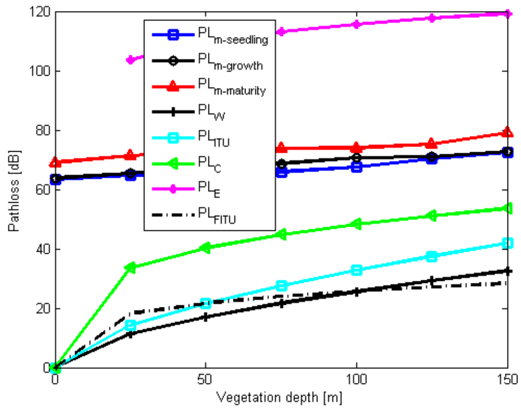


(c)

Figure 6. Calculation of PL measurements and empirical PL models of Adan rice plants for (a) without adding PL_F and PL_T, (b) adding PT_F, and (c) adding PL_T.



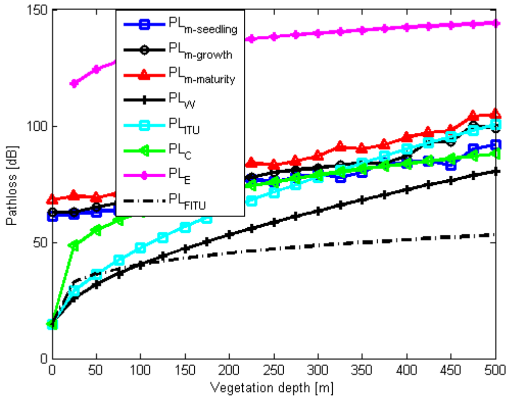
(a)



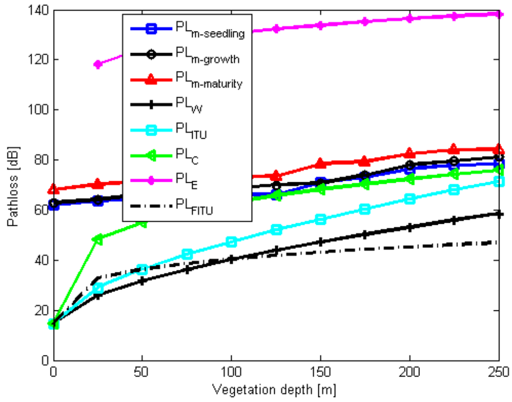
(b)

Figure 7. Calculation of PL measurements and empirical PL models of crops: (a) corn and (b) peanuts.

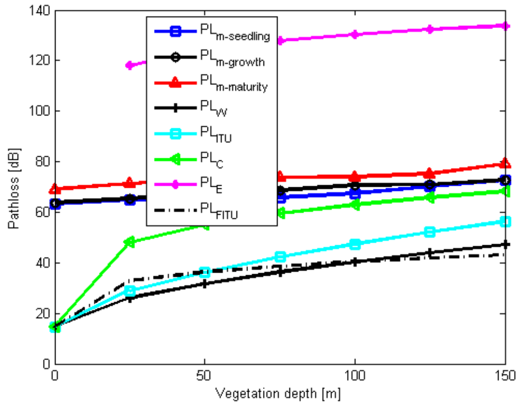
To find an accurate PL model of the type of agricultural crops, land, and its environment, it is also advisable to consider the influence of weather, especially the presence of rain attenuation, because it is known that the research location is an area with high average rainfall as reported by [26] with an average of around 243.78 mm/h. A study that has reported the involvement of rain attenuation is [12], where rain attenuation influences fruit farming land on the propagation of 2.4GHz frequency radio waves.



(a) Adan rice



(b) Corn



(c) Peanuts

Figure 8. Calculation of PL measurement and PL empirical model of agricultural crops with the influence of rain for (a) Adan rice, (b) corn, and (c) peanuts.

It can be seen in Fig. 8 that the involvement of rain attenuation is also applied to the calculation of the empirical model PL. Rain attenuation at a location with a certain rainfall is calculated using Eq. (2), and then the results are added to the existing empirical model PL. Without involving the influence of the Free-space model PL and Two-ray PL and only with the PL shown in Fig. 6(a) and Fig. 7, the results of the PL calculation with rain attenuation are completely shown in Fig. 8, where there is an increase of around 14.7dB. It can be seen from these results that the COST-235 model PL is a strong candidate for continued optimization with the PSO method for the three types of plants that cover the three planting seasons.

3.3. Performance of RMSE and Pathloss Determination Coefficient with PL Measurement Results

The performance of PL, which is no less important for comparing PL measurement results, proposed PL, and PL results from empirical model calculations, is determining the accuracy of data predictions from both PL determinations, i.e., by determining RMSE [10], [12], [14], [23]. RMSE is one of the statistical parameters in modeling data, which is calculated using Eq. (3). Table 2 shows the results of the RMSE calculation of the PL of all empirical models, the proposed model against the PL of measurement data from the three plants presented in Figs.

6(a) and 7 previously. The model indicated as appropriate and suitable for estimating measurement data is the theoretical model with the lowest RMSE value [10], [18].

It can be seen from Table 2 that the PL model COST-235 is the right model to be used as a basis for estimating PL measurement data in wireless wave propagation systems, such as WSN systems, from three types of plants, including their planting conditions. This is based on the model's RMSE value, which is the lowest value compared to other models of PL measurement results. When compared with the RMSE value on corn and peanut plants, the RMSE on Adan rice plants is lower because the observation data is more, so the variation of empirical model prediction errors with measurement data shows a small value. By involving the influence of weather, such as rain attenuation, the RMSE value is presented in Table 3 for the three types of plants where the PL results have been shown in Fig. 8. The RMSE results in Table 3 show that the PL COST-235 model the smallest RMSE value of the PL models, so this result strengthens that this model continues to be optimized with the PSO method. Both results in Tables 2 and 3 show that the effect of rain attenuation for tropical areas such as those experienced by this data collection location is appropriate and appropriate to be included in the calculation and modeling of radio wave propagation.

Table 2. Comparison of RMSE in PL measurements and empirical models for agricultural crops

Type	**Planting period**	**RMSE**				
		W	**ITU**	**COST**	**E**	**FITU**
Adan rice	Seedling	34.06	23.99	**17.24**	45.83	45.03
	Growth	37.29	26.37	**20.79**	42.45	48.82
	Maturity	42.59	31.29	**26.12**	37.13	54.19
Corn	Seedling	40.95	33.19	**20.13**	46.56	43.43
	Growth	42.69	34.88	**21.83**	44.75	45.21
	Maturity	47.59	39.73	**26.69**	39.89	50.07
Peanuts	Seedling	45.11	39.09	**22.94**	45.48	43.61
	Growth	46.67	40.65	**24.46**	43.90	45.16
	Maturity	51.73	45.68	**29.51**	38.91	50.23

Table 3. Comparison of RMSE in PL measurements and empirical models for agricultural crops with rain attenuation

Type	**Planting period**	**RMSE**				
		W	**ITU**	**COST**	**E**	**FITU**
Adan rice	Seedling	20.01	13.79	**4.22**	60.49	30.40
	Growth	22.92	14.28	**6.87**	57.06	34.27
	Maturity	28.10	18.15	**11.76**	51.71	39.61
Corn	Seedling	26.43	19.31	**6.48**	61.23	28.76
	Growth	28.15	20.86	**7.79**	59.43	30.53
	Maturity	33.03	25.57	**12.39**	54.56	35.39
Peanuts	Seedling	30.53	24.75	**8.97**	60.16	28.93
	Growth	32.08	27.28	**10.32**	58.57	30.47
	Maturity	37.12	31.24	**15.18**	53.56	35.54

3.4. PSO Modified Pathloss Performance

After seeing the RMSE data in Tables 2 and 3, the optimization process with PSO was applied to the COST-235 PL model, which had the lowest RMSE compared to other empirical PL models. This procedure has been carried out by [13] and [14] by determining the values of the coefficients of a PL formulation based on the PSO method against Eq. (9), which is a candidate for modification, and the formulation is rewritten as

$$PL_{C-PSO} = \gamma_1 f^{\gamma_2} d^{\gamma_3} \tag{14}$$

and if we take into account rain attenuation, then it becomes

$$PL_{C-PSO} = \gamma_1 f^{\gamma_2} d^{\gamma_3} + \gamma_4 \tag{15}$$

where γ_1, γ_2, γ_3, and γ_4 are the coefficients of the PL model of COST-235 optimized by the PSO method.

In Eqs. (14)-(15), the complete coefficients before the PSO method is applied can be seen in Table 4. For the application of PSO using Eqs. (12)-(13) then the values of w, c_1, and c_2 are given as 0.5, 1.5, and 1.5, respectively. These numbers control the performance of PSO during the iteration process to produce a modified formulation of PL COST-235 with the latest RMSE value, which is smaller than before this method was applied. After conducting simulations and evaluations of the PSO method with PL measurement data and PL model COST-235 from the three types of plants and their planting periods, the results were obtained in Tables 5 and 6, respectively, for PSO performance without and with rain attenuation.

Table 4. Coefficients of the COST-235 path loss model without the PSO method

COST-235 PL Parameters	COST-235 PL coefficient without PSO	COST-235 PL coefficient with rain attenuation and without PSO
γ_1	15.6	15.6
γ_2	-0.009	-0.009
γ_3	0.26	0.26
γ_4	0	14.7

Table 5. Coefficients, RMSE, and R^2 of the COST-235 path loss model with the PSO method

Type	Planting period	Coefficient			RMSE		R^2	
		γ_1	γ_2	γ_3	Without	With	Without	With
Adan rice	Seedling	19.5	-0.015	0.27	17.24	3.61	0.18	0.94
	Growth	19.3	-0.014	0.28	20.79	3.34	0.21	0.95
	Maturity	19.1	-0.013	0.29	26.12	3.24	0.15	0.96
Corn	Seedling	22.1	-0.028	0.29	20.13	2.07	0.05	0.67
	Growth	21.8	-0.028	0.28	21.83	2.02	0.06	0.68
	Maturity	21.2	-0.023	0.28	26.69	2.01	0.06	0.71
Peanuts	Seedling	22.8	-0.028	0.29	22.94	2.07	0.07	0.69
	Growth	22.4	-0.028	0.28	24.46	2.02	0.08	0.71
	Maturity	22.2	-0.023	0.28	29.51	2.01	0.08	0.75

Table 5 shows the application of the PSO method on the COST-235 PL model, where, in general, there are changes in the coefficients of the COST-235 PL model in Table 4. It also appears that by applying this method, it can be seen that the RMSE performance of all types of plants and their planting periods has decreased drastically in the RMSE value of around 11%, where the details for Adan rice, corn, and peanuts are 16%, 10%, and 8%, respectively. Meanwhile, the performance of the determination coefficient (R^2) of all types of plants and their planting periods has increased quite significantly by around 8.98 times, with the details for Adan rice, corn, and peanuts being 5.38, 12.18, and 9.37 times, respectively. Indeed, the results of the increase in RMSE and R^2 performance are not like those in the study reported by [13], where R^2 reached a perfect value of 1 because the PL model before optimization already had an R^2 above 0.90. In this research case, the previously optimized model has a very small R^2 below 0.5. This is because the COST-235 PL model starts from 0 and then approaches the PL value, which is very much determined by the working frequency of the WSN system and the distance between Tx and Rx. Furthermore, the factor of a lot of data can affect the performance of the PL optimization model. This is supported by evaluating the RMSE and R^2 performance for Adan rice, whose values are relatively better than those of corn and peanut plants.

The results of the performance of RMSE, coefficients, and R^2 in Table 6 with the PSO method involving rain attenuation show the same phenomenon as the condition without rain attenuation in Table 5, i.e., an increase in RMSE, changes in the values of the coefficients, and approaching the value of 1 for R^2. Due to the involvement of the rain attenuation factor, the RMSE value of the measurement data and the empirical PL model is smaller than without rain attenuation. The RMSE results with the PSO method involving rain attenuation from all types of plants and their planting periods showed a very drastic decrease in the RMSE value of around 61%, where the details for Adan rice, corn, and peanuts were 60%, 66%, and 58%, respectively. Meanwhile, for the performance of the determination coefficient (R^2) of all types of plants and their planting periods, there was a significant increase of around 10.5 times, with the details for Adan rice, corn, and peanuts being 1.28, 4.2, and 26.05 times, respectively.

Table 6. Coefficients, RMSE, and R^2 of the COST-235 pathloss model with the influence of rain and the PSO method

Type	**Planting period**	**Coefficient**			**RMSE**		**R^2**	
		γ_1	γ_2	γ_3	**Without**	**With**	**Without**	**With**
Adan rice	Seedling	18.1	-0.014	0.25	4.22	4.08	0.60	0.90
	Growth	18.4	-0.015	0.26	6.87	4.38	0.75	0.91
	Maturity	19.3	-0.015	0.26	11.76	2.30	0.85	0.97
Corn	Seedling	17.8	-0.019	0.26	6.48	5.02	0.31	0.81
	Growth	17.5	-0.019	0.27	7.79	5.29	0.26	0.84
	Maturity	18.2	-0.019	0.28	12.39	6.62	0.13	0.88
Peanuts	Seedling	20.5	-0.010	0.22	8.97	5.38	0.07	0.83
	Growth	20.5	-0.010	0.23	10.32	5.31	0.05	0.94
	Maturity	16.6	-0.013	0.29	15.18	9.28	0.02	0.95

Based on the analysis related to the role of the PSO method in optimizing PL in the COST-235 model, there is an increase in the performance of both RMSE and R2 for conditions without and with rain attenuation. In general, it can be said that the PSO method works well and effectively in optimizing this PL, so several modification models of the COST-235 PL can be obtained for the three types of plants covering the planting period, both during the seedling period, growth, and maturity. If associated with a similar radio wave propagation study in agriculture by [13] with alfalfa plants, this PSO method seems to apply to any plant and any location, but by also considering vegetation factors, the surrounding environment, weather conditions, and the selection of empirical models that are appropriate for these conditions.

4. CONCLUSION

This paper presents calculations, evaluations, and analyses related to radio wave propagation, especially signal strength and path loss measured on Adan rice, corn, and peanuts agricultural land for 2.4GHz agriculture-WSN applications in North Kalimantan, Indonesia. Several empirical models are provided to find candidate models optimized by the PSO method, including Weissberger (W), ITU-vegetation (ITU), COST-235, Egli, and FITU-R. Various factors are taken into consideration in determining the appropriate PL model in the study, including the planting period of the three types of agricultural crops (seedling, growth, and maturity periods), the depth of vegetation between Tx and Rx, the height of the Tx and Rx antennas from the ground according to the planting period of the three types of crops, environmental conditions, and the effect of rain attenuation. Based on the results of the RMSE calculation without and with rain attenuation, the COST-235 PL model provides the lowest RMSE of the other empirical PL models. Thus, this model continues to be optimized with the PSO method, which produces changes in the exact coefficients of the parameters in the COST-235 PL model. As a result, the modified COST-235 PL model with PSO significantly improves the RMSE value, which is very low, and the coefficient of determination (R2), which is almost 1. In the future, it is expected that farmers can implement and plan this WSN application for local plant cultivation and replace conventional and manual plant growth monitoring systems so that the agricultural process becomes more effective and efficient and also helps preserve the environment. Further studies of this wave propagation modeling by considering other empirical models, including hybrid methods involving numerical optimization, and considering the effects of seasonal and weather variations involving real-time and long measurement times, different observation and measurement locations, and practical implications for farmers.

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