Optimizing 2.4GHz Wireless Networks in Shrimp Ponds with Particle Swarm Optimization

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ABSTRACT

This paper focuses on enhancing wireless sensor networks (WSNs) for monitoring water quality in aquaculture, specifically shrimp ponds, by improving pathloss (PL) models. Radio wave propagation in such environments is challenging due to unpredictable signal attenuation caused by factors like distance, antenna height, terrain, vegetation, and weather conditions. Reliable PL modeling is essential for optimizing network performance. The research evaluates the performance of theoretical PL models, including ITU, Fitting-ITU (FITU), and Weissberger, by comparing their predictions with actual 2.4GHz radio frequency (RF) measurements. Statistical metrics such as root-mean-square error (RMSE) and the coefficient of determination (R^2) were used to assess model accuracy. Initial results showed significant discrepancies, with an average RMSE of 28.7dB and an R^2 of only 5%. To address these issues, the study employed modification techniques (quadratic and cubic polynomial adjustments) and optimization methods, particularly particle swarm optimization (PSO). These approaches refined the theoretical models, aligning them more closely with real-world data. The optimized PSO model reduced the RMSE to 8.34dB and further to 1.89dB, while improving R^2 from 5% to 95.6%, demonstrating a near-perfect fit. This study highlights the critical role of PSO and similar techniques in bridging the gap between theoretical predictions and practical applications, ensuring more reliable WSN performance in aquaculture environments. The findings contribute to the development of robust, high-accuracy models tailored to the unique challenges of aquaculture settings.

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1. INTRODUCTION

According to the FAO, the fisheries sector, particularly shrimp farming, has shown a steady upward trend since 1961, with shrimp consumption growing at an average rate of 3.0%, surpassing the population growth rate of approximately 1.6% [1], [2]. Additionally, a BPS report indicates that shrimp catches reached 19,341 tons in 2023 [3], while shrimp farming in the province is projected to produce 9,240 tons by 2024 [4]. This growing demand for shrimp highlights the urgent need for strategies and initiatives to enhance and accelerate shrimp farming production to meet market needs.

The growing demand for shrimp fishery products has not been matched by the production capacity and efficiency of the fisheries industry. This shortfall arises primarily from the reliance on human operators who manually monitor various aquaculture environmental variables. To address this issue, adopting smart fisheries equipped with wireless sensor network (WSN) applications offers a viable solution. WSN technology is widely utilized for monitoring and early detection in diverse areas such as forest fires, agricultural lands, hillsides, industrial processes, and flood detection [5]. When integrated with IoT (WSN-IoT) [6], [7], it can be further combined with control systems [8] for applications such as a monitor for air pollution in smart city applications [9], [10], [11], as guiding the hajj process [12], assisting military training [13], protecting agricultural products from wildlife threats [14], [15], and supporting industrial monitoring [16], [17], [18], [19]. In shrimp farming, WSN systems serve not only to monitor water parameters like temperature, humidity, and acidity but also to track surrounding environmental conditions. This dual function helps safeguard the ecosystem and mitigate climate change impacts. Given the increasing limitations on available land and infrastructure, implementing WSN in shrimp farming has become essential for improving efficiency and ensuring sustainability.

The WSN system relies on a wireless network where maintaining network connectivity is a crucial requirement for its continuous operation. This connectivity is directly influenced by factors such as signal strength, interference, and attenuation. One of the major challenges is the instability and unpredictability of the received signal strength, which affects the network's connectivity. Several factors contribute to this issue, including pathloss (PL) caused by phenomena like reflection, refraction, absorption, and signal scattering. In light of these challenges, this paper examines PL in radio wave propagation, specifically focusing on WSN applications in shrimp ponds. Key factors affecting PL include mangrove vegetation, foliage, the refractive index of brackish water, and the characteristics of the surrounding terrain. Understanding propagation characteristics and their management with accuracy and precision is critical for successfully transmitting and receiving aquaculture data, such as for remote sensing applications. Consequently, an in-depth exploration of studies like [17], which focus on PL in pond environments, becomes essential. Various studies have examined PL across different fields. For instance, [20] measured signal strength to determine PL in agricultural settings with crops like corn, rice, and peanuts; [21] analyzed PL variations based on different stages of corn growth; and [22] conducted PL calculations in fruit farming. These studies utilized different empirical models: [20] employed ITU-vegetation, Weissberger, and COST-235 models for a 2.4GHz WSN system; [21] applied the log-normal distribution method; and [22] incorporated rain attenuation in PL calculations. These findings highlight the importance of investigating radio wave propagation in WSN systems tailored to pond fisheries. Given the unique environmental and vegetation characteristics of such areas, developing a generalized PL model applicable to all pond environments is a critical goal.

This paper presents an evaluation and analysis of the propagation of 2.4GHz WSN radio waves from signal strength measurements in shrimp ponds to determine and recommend appropriate PL models. This is a key contribution of this paper that has not been reported in previous studies. Various methods are employed to achieve accurate PL modeling, including polynomial modifications and heuristic optimization techniques like particle swarm optimization (PSO), which are used to derive statistically optimized PL parameters. A review of the literature reveals that both polynomial and PSO methods have been infrequently applied in PL modeling, particularly in the context of shrimp pond fisheries. For example, [23] utilized a cubic polynomial approach for modeling PL in tomato greenhouse farming, while [24] applied a similar approach for cellular communication systems in Oman. The PSO method, on the other hand, has been more commonly used for PL modeling in fields such as grassland agriculture [25], cellular communication systems [26], [27], and millimeter-wave communication systems [28]. This method has demonstrated its capability in enhancing statistical metrics like root-mean-square error (RMSE) and the coefficient of determination (R^2), as noted in [27]. These techniques aim to produce PL models that align accurately with environmental conditions. In this study, various approaches are explored to refine empirical PL models, such as ITU, FITU, and Weissberger, while accounting for the impact of rainfall attenuation. To evaluate and analyze PL performance effectively, field-measured RF data are compared against theoretical predictions from models like ITU, FITU, and Weissberger, focusing on critical statistical parameters such as RMSE and R^2. This approach involves assessing how well the theoretical models replicate the measured PL by considering the specific environmental conditions, such as vegetation density, terrain type, and antenna height. For instance, the ITU model incorporates vegetation depth and frequency dependence, making it suitable for predicting signal attenuation in environments with dense mangroves or aquatic vegetation [29]. Similarly, the FITU model extends the ITU framework by fine-tuning the coefficients to account for localized vegetation characteristics, such as canopy spread and leaf structure, ensuring better accuracy in semi-dense foliage conditions [30]. The Weissberger model, on the other hand, is designed for dense forested areas, emphasizing the non-linear attenuation effects caused by thick and dry foliage [31]. By calculating the RMSE, researchers can quantify the deviation between measured and predicted PL, where a lower RMSE indicates a better model fit. The R^2 value complements this analysis by measuring how well the model explains the variability in the measured data. An R^2 value close to 1 suggests high predictive reliability of the model. These statistical evaluations help identify the most appropriate PL model for a specific application, such as designing WSNs for shrimp ponds, where environmental factors like high rainfall and varying vegetation significantly impact signal propagation [32].

This paper introduces a novel approach by evaluating and analyzing signal strength and pathloss (PL) while considering multiple influencing factors, including the distance between the transmitter and receiver (Tx-Rx) of the WSN system, variations in Tx-Rx antenna height, and the conditions of the signal propagation path. Measurements were conducted in shrimp pond environments located in North Kalimantan, Indonesia. The propagation paths examined include those passing over pond water obstructed by mangrove vegetation, paths along pond embankments with moderately dense mangrove coverage, and paths along embankments without vegetation, consisting of hard clay surfaces. Additionally, the refractive index of the water surface was factored in, as it contributes to the occurrence of multiple signal propagation rays, as discussed in [33], [34]. This study also employs modified radio wave propagation modeling techniques, such as polynomial and PSO methods, tailored for aquaculture-WSN applications. These findings are compared to prior studies, such as [35], which focused on measurements in tropical regions known for their high rainfall and significant rain attenuation effects, as highlighted in [36].

The structure of this paper is as follows: Section 2 outlines the methodologies applied, covering the research stages, materials, an overview of empirical PL models, the use of polynomial methods for PL modification, and the application of PSO techniques for optimization. Section 3 details the results of the study and includes a discussion of signal strength measurements, PL calculations, RMSE performance, and the performance of PL modifications and optimizations using the PSO method. Finally, Section 4 concludes the study with key findings and insights.

2. METHODS

This section describes and explains the process and stages related to the measurement area and data collection methods, descriptions of each of the empirical PL models commonly used in radio propagation with vegetated locations, and descriptions related to the polynomial and PSO methods as one of the optimization techniques for accurate system modeling in this study which is shown in Fig. 1 and explained in the next subsection.

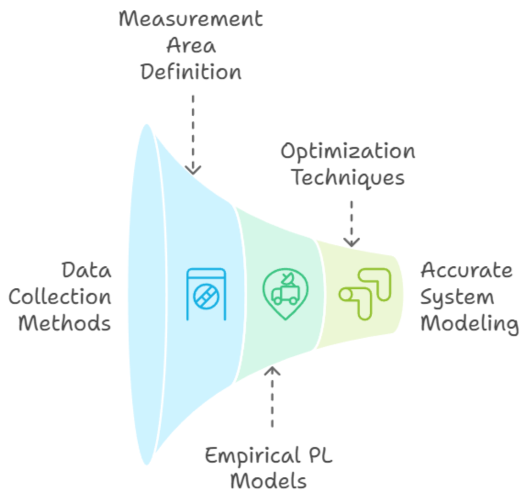

Fig. 1. Flowchart of the radio propagation modeling process

2.1. Location, Configuration, and Data Collection for RF Measurements

The selection of the measurement location was based on the significance of shrimp fisheries as a primary commodity in aquaculture within North Kalimantan, Indonesia. A single site was chosen to represent typical pond conditions for experimentation, as illustrated in Fig. 2 (marked by a red pointer on the map). This site is situated in Tana Tidung Regency, Sesayap Hilir District, at latitude 3.418241 and longitude 117.427562. According to [37], shrimp ponds in North Kalimantan primarily cultivate tiger and vaname shrimp, covering approximately 149,958 hectares (62%). However, production has declined by about 50–60 kg per hectare, attributed to factors such as land-use changes, environmental pollution, and traditional manual pond management practices. To address these challenges, adopting WSN technology is proposed as a potential solution.

The RF signal strength at the shrimp pond site was measured as the received signal strength indicator (RSSI, P_r), taking into account various factors, including the conditions of the radio wave propagation paths. Since mangrove vegetation is present at the location, its impact on the RF measurements was also considered. According to [38], the average height of wild mangrove plants ranges from 1–5 meters to as high as 10–15 meters. Additionally, a study by [39] described these plants as having small, densely clustered, pointed leaves and growing in compact formations. RF signal strength measurements were conducted for each type of propagation path in the shrimp pond, as illustrated in Fig. 3. The pond features three distinct paths: (A) a route through pond water with sparse mangrove vegetation, (B) a path along pond embankments surrounded by moderately dense mangrove vegetation, and (C) a path along pond embankments consisting of hard clay surfaces. The radio wave propagation path scenarios are illustrated in Fig. 4.

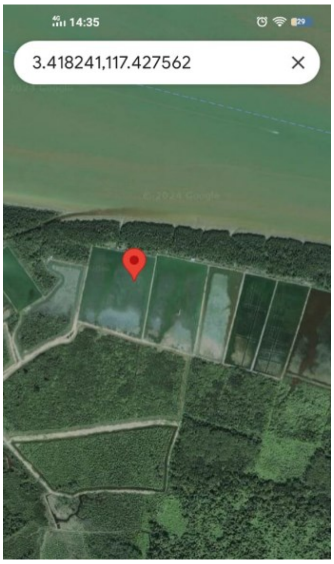

Fig. 2. Geographic coordinates of shrimp pond measurement sites

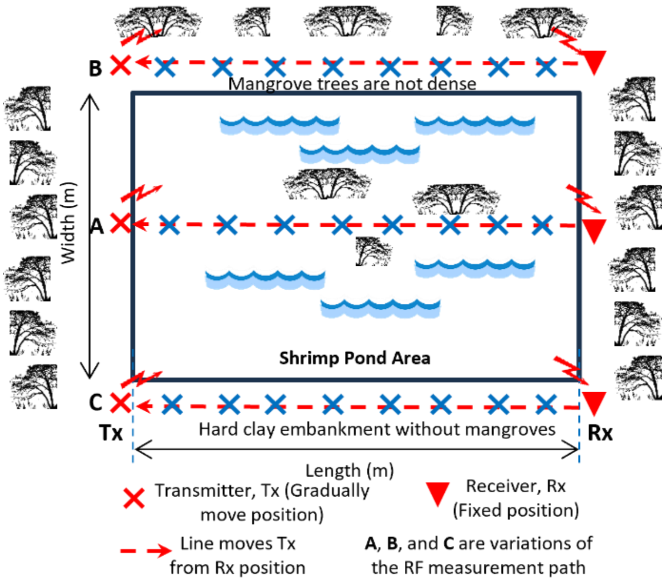

Fig. 3. Configuration of the RF measurement area for shrimp pond environments

At the shrimp pond measurement site, the setup includes a combination of Tx and Rx antennas positioned at specific heights above the ground, denoted as h_t and h_r, respectively. Two height configurations were used: one where the antennas were positioned below the height of the mangrove vegetation, approximately 50 cm from the ground, and another where they were slightly above the vegetation, at a height of around 4 meters. The 50 cm height was chosen to minimize signal attenuation caused by reflections from the ground surface along a propagation path exceeding 100 meters. In contrast, the 4-meter height was achieved by mounting the antennas on poles to ensure Line-of-Sight (LoS) conditions between the Tx and Rx, as noted in [17], despite differences in vegetation types and pond dimensions. While mango and coconut trees were reported as vegetation in other ponds measuring about 27 m × 69 m, the measurement area in this study was approximately 120 m × 280 m. At the site, the Rx position was kept stationary, while the Tx location was adjusted incrementally up to 20 meters along the pond's length. This adjustment was necessary since data processing was carried out on a Personal Computer (PC) connected to the Rx, making it important to maintain the Rx in a fixed position, as depicted in Fig. 5. In the wireless sensor network (WSN) configuration, the Tx served as a sensor node, while the Rx functioned as the sink node.

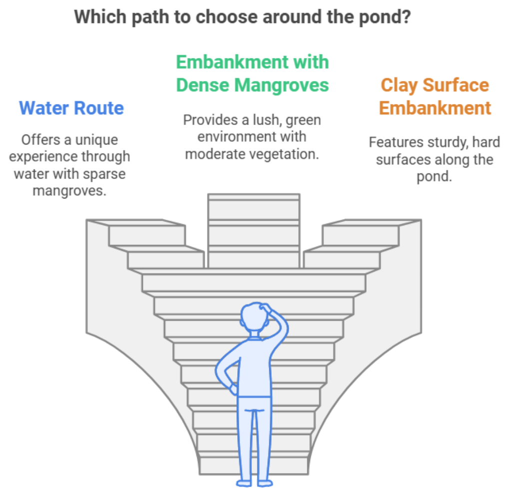

Fig. 4. Various scenarios of radio wave propagation paths in shrimp ponds

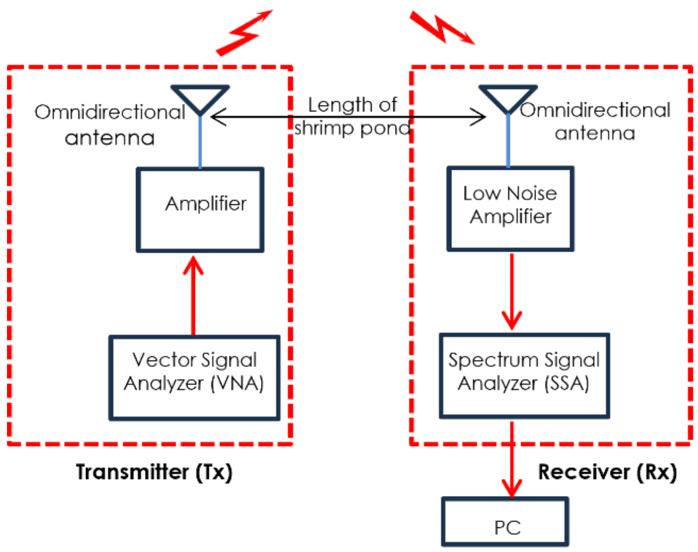

Fig. 5. Setup of RF measurement system in the shrimp pond environment

Fig. 5 illustrates the process of collecting signal strength data (in dBm) for the RSSI signals received by the Rx antenna. The RSSI values are derived from the measurement of 2.4GHz RF signals at the Rx using a spectrum signal analyzer (SSA), with the transmitter being a vector signal analyzer (VNA). Both the transmitting and receiving antennas are omnidirectional, featuring a gain of approximately 0 dBi (G_t and G_r), and the transmit power is set at 10 dBm (roughly 0.01 watts). A PC is employed to calculate and simulate both the measured PL and the PL predicted by empirical models. Table 1 provides a detailed summary of the RF measurement system parameters, including transmission power, operating frequency, antenna gain, and other relevant settings.

From the measurement data of signal strength (P_r), transmit power (P_t), and antenna gain, both can be calculated as PL_m using the formula

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

where P_t, P_r, G_t, and G_r are expressed in dBm, dBm, dBi, and dBi units, respectively.

Table 1. Configuration of Parameters for RF Measurements

Parameter	Value	
Frequency, f	2.4	GHz
Transmit power, P_r	10	dBm
Antenna type	Omnidirectional	
Antenna height, h_T & h_R	0.5 & 4	M
Tx and Rx antenna gain, G_T & G_R	0	dBi
Measurement Parameter, P_R	RSSI	dBm

The computation of PL in (1) incorporates several factors, including the height of the Tx-Rx antennas, the distance between them, the characteristics of the propagation path, and the surrounding vegetation. As highlighted by [36], North Kalimantan, Indonesia, experiences substantial rainfall, which significantly affects the propagation of high-frequency radio waves. Additionally, being located in the equatorial region with a tropical climate, the area experiences rain attenuation that further contributes to an increase in PL. In the findings reported by [22], rain attenuation was identified as a key factor in the elevated PL of the empirical model, which aligns with the additional attenuation effects discussed in Section 2.2 of [22]. Rain attenuation, measured in dB, is determined using the formula provided in [22].

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

In this calculation, r represents the rain rate in mm/h, while k and α are constants that depend on the rainfall distribution at a specific frequency. For radio wave propagation at 2.4GHz with horizontally polarized antennas, the constants k and α are assigned values of 0.0001321 and 1.1209, respectively, as per [22]. Using (2), the rain attenuation is calculated to be approximately 14.73 dB. However, based on statistical data from the North Kalimantan BPS in 2023 [40], which recorded a rain rate of around 243.78 mm/h at the study location, the rain attenuation is slightly lower at approximately 12.04 dB. After determining the measured PL (PL_m), these results are compared with theoretical PL (PL_t) derived from empirical models such as ITU, FITU-vegetation, and Weissberger, which account for the effects of vegetation, leaves, and trees.

After obtaining PL_m and PL_t, to validate them statistically, the RMSE and R^2 parameters can be used as done by [20]. The RMSE and R^2 expressions are formulated, respectively with

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

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

In this context, n represents the total number of measurement data points, and $\widehat{PL_t}$ denotes the average measured PL. If the RMSE value calculated using (3) for a specific empirical PL model is the lowest, that model can serve as a reliable reference for predicting PL characteristics in shrimp pond environments. Additionally, R^2, as defined in (4), determines the suitability of an empirical PL model as a reference if its value is close to or equal to 1. A higher R^2 indicates that the empirical model's data closely align with the measured PL values.

2.2. Theoretical Pathloss Models

This section outlines several empirical PL models commonly utilized to estimate the characteristics of radio wave propagation, such as those used in fisheries-WSN communication systems. If a model yields a low RMSE and an R^2 value nearing one, it can be adopted as a modified PL model for predicting radio wave propagation in vegetative environments. To further enhance RMSE and R^2 values, the PL model is refined through polynomial methods and optimized using the PSO technique to achieve statistically superior parameters. This study employs several empirical models tailored for PL, accounting for factors like trees, vegetation, and soil conditions, including ITU, FITU-vegetation (FITU), and Weissberger (W). These models have been recommended in studies such as [22], [41], which highlight the impact of surrounding vegetation on PL calculations.

2.2.1. ITU Pathloss

This PL model (measured in dB) is utilized when the Tx and Rx are positioned near each other, with a sparse grouping of trees in between. In this scenario, the signal traverses the trees at a depth (d) in meters, and the model is expressed as described in [20].

$$PL_{ITU} = 0.2f^{0.3}d^{0.6} \tag{5}$$

2.2.2. FITU Pathloss

This PL model, measured in dB, is applicable for environments with relatively short vegetation and a maximum foliage depth (d) of approximately 400 meters. The model is mathematically expressed as outlined in [41].

$$PL_{FITU} = 0.39f^{0.39}d^{0.25} \tag{6}$$

2.2.3. Weissberger Pathloss

This model is used for radio wave propagation, measured in dB, at a frequency (f) in GHz when the signal is obstructed by dense, dry, and leafy vegetation. The vegetation depth (d) in meters is incorporated into the formulation as presented in [20].

$$PL_W = 1.33f^{0.284}d^{0.588} \tag{7}$$

2.2.4. Polynomial and PSO Approaches for Pathloss

The polynomial method is a type of non-linear analysis used for modeling PL measurements based on the distance between Tx-Rx or the vegetation depth (d). The resulting curve can take a quadratic form, representing the second order of d, as shown in (8), or a cubic form, representing the third order of d, as indicated in (9) [42].

$$PL_Q = \beta + \gamma d + \delta d^2 \tag{8}$$

$$PL_C = \beta + \gamma d + \delta d^2 + \varepsilon d^3 \tag{9}$$

with the constants β, γ, δ, and ε determined through the following expressions

$$\beta n + \gamma \sum d_i + \delta \sum d_i^2 + \varepsilon \sum d_i^3 = \sum PL_i \tag{10}$$

$$\beta \sum d_i + \gamma \sum d_i^2 + \delta \sum d_i^3 + \varepsilon \sum d_i^4 = \sum d_i PL_i \tag{11}$$

$$\beta \sum d_i^2 + \gamma \sum d_i^3 + \delta \sum d_i^4 + \varepsilon \sum d_i^5 = \sum d_i^2 PL_i \tag{12}$$

$$\beta \sum d_i^3 + \gamma \sum d_i^4 + \delta \sum d_i^5 + \varepsilon \sum d_i^6 = \sum d_i^3 PL_i \tag{13}$$

Based on research reported by [25], [43], dan [44], Particle Swarm Optimization (PSO) is a heuristic method used to address optimization problems. In this approach, individual elements referred to as particles form a swarm, and the calculation speed can be adjusted to achieve optimal results. The process of finding the best solution involves updating particle positions based on specific parameters, including the particle's personal best position (p_b) and the global best position (g_o). The position and velocity of each particle are denoted as p_i and v_i, respectively, where $i = 1, 2, ..., I$. The iterative process for PSO, which updates v_i and p_i for each iteration $n = 1, 2, ..., N$, is defined mathematically as shown in [45].

$$v_i^{n+1} = wv_i^n + c_1r_1(p_b - p_i) + c_2r_2(g_b - p_i) \tag{14}$$

with

$$p_i^{n+1} = p_i + v_i^{n+1} \tag{15}$$

In this context, w represents the inertia weight, c_1 and c_2 are scaling coefficients, and r_1 and r_2 are random vectors with values ranging between 0 and 1. The equations in (14) and (15) are utilized to predict path loss (PL) from various empirical models, ensuring that the resulting PL achieves the lowest RMSE value when compared to the measured data. The algorithm of this method applied to PL optimization is listed in detail in Algorithm 1.

Algorithm 1: Pseudocode of Path Loss Optimization Algorithm using PSO

Input:
  I = swarm size
  N = problem dimension (positions k_1, k_2, ..., k_n) n_{max} = maximum number of iterations
  c_1, c_2 = acceleration constants ($0 \leq c_1 \leq 2$, $0 \leq c_2 \leq 2$), $w_{max} = 0.9$ (initial inertia)
  $w_{min} = 0.3$ (final inertia)
  $PL(k_1, k_2, ..., k_n)$ = path loss function for positions

Output:
  g_o = best solution (position) that minimizes path loss

1. Start:
    Initialize swarm randomly:
    For each particle i from 1 to I:
      Initialize particle position p_i
      Initialize particle velocity v_i randomly
      Initialize personal best position $p_{bi} = p_i$
      Evaluate path loss function: $f(p_i) = PL(k_1, k_2, ..., k_n)$
      Set $p_{bi} = p_i$ jika $f(p_i)$ is the best so far
      end for
2. Define g_o as the particle with the minimum fitness value.
3. As long as $n \leq n_{max}$ do:
    Calculate inertia weight: $w(n) = n_{max} - (n_{max} - n_{min}) * (n / n_{max})$ for each particle i from 1 to I do:
      Update particle velocity in (14) to update particle position in (15)
      Evaluate fitness function: $f(p_i) = PL(k_1, k_2, ..., k_n)$
      Update personal best position:
      If $f(p_i) < f(p_b)$ then $p_b = p_i$
      Update global best position:
      If $f(p_i) < f(p_b)$ then $g_o = p_b$
      end for
      Increase iterations: $n = n + 1$
      Check stopping criteria (maximum iterations reached or solution has converged).
4. Done
5. Return go and minimized path loss value $PL(g_o)$

The empirical PL model with the smallest RMSE value is chosen for further modification and comparison using both the polynomial method and the PSO optimization approach. The goal is to identify which PL model provides the most accurate statistical parameters, making it the most appropriate and reliable for modeling radio wave propagation in shrimp pond fisheries. This model can then serve as a reference for designing and planning an effective WSN system in the area.

3. RESULTS AND DISCUSSION

This section outlines the measured results and provides a detailed analysis through the following steps: (a) presenting signal strength measurements for all path scenarios in graphical form, (b) calculating based on the measurement results using (1) for RSSI values derived from RF measurements and the data in Table 1, (c) determining the PL using empirical models from (5)-(7) and polynomial models from equations (8)-(9), which include rain attenuation calculated using (2), and comparing them with PL_m, and (d) calculating the RMSE for the results in step (c), where the model with the lowest RMSE is identified as a candidate for further optimization using the PSO method. The PL model modified through PSO, with an R^2 value approaching 1, is then recommended as the most suitable model for predicting radio wave propagation in WSN systems for shrimp pond fisheries at the research site and similar environments.

3.1. RSSI as Signal Strength in Shrimp Ponds

Fig. 6 illustrates the measured signal strength in shrimp ponds for the three different propagation path scenarios. Overall, the RSSI values decrease as the distance between the Tx and Rx antennas increases. The figure also highlights that in scenario B, where the Tx-Rx antenna is positioned 0.5 m above the ground, the receiver sensitivity has a lower threshold of approximately -85 dBm. Under these conditions, signal propagation remains feasible across the entire pond length of up to 280 meters. RSSI on path B is lower because there is mangrove vegetation that weakens the signal received by the Rx antenna from the Tx when compared to other paths, in line with the study reported by [17], [46], which shows that in ponds surrounded by vegetation, signal attenuation occurs compared to when no vegetation is present. According to the studies by [38], [39],

[47], and [48], mangrove plants grow in dense clusters, have thick leaves, and are more than 15 m high from the ground surface, which makes them a significant source of attenuation in radio wave propagation. This phenomenon arises because the signal emitted by the Tx sensor is largely absorbed by the vegetation, particularly the leaves of the trees. In path A, the measured RSSI remains relatively strong, as the mangrove vegetation is present but less dense compared to path B. Conversely, in path C, which traverses embankments with uneven clay surfaces, the transmitted signal experiences attenuation due to the effects of irregular reflections from the ground dispersing in multiple directions.

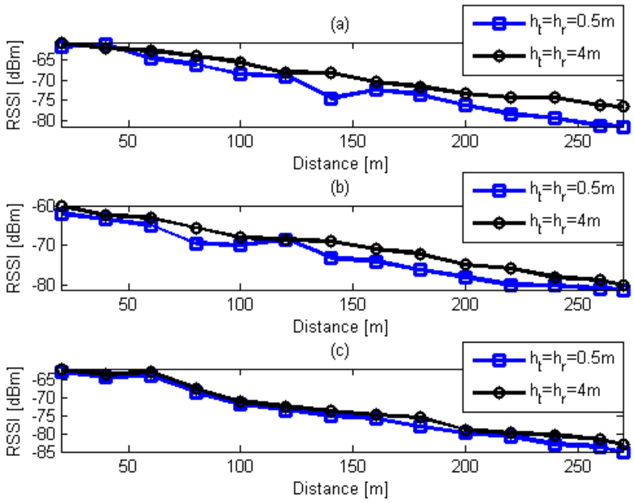

Fig. 6. RSSI for variations in Tx-Rx antenna height with: (a) path passing through pond water with little mangrove vegetation, (b) path passing through pond embankments with fairly dense mangrove vegetation, and (c) path with pond embankments consisting of hard clay surfaces

3.2. Pathloss Performance in Shrimp Ponds

Based on RSSI data for all path scenarios in Fig. 6, then by using (1) and Table 1, the measurement PL ($p_{\cdot m.}$) can be calculated, the results of which are presented in Fig. 7. While for the empirical PL model, use (5)-(7) and include the rain attenuation that has been calculated with (2) for the measurement location. From the measurement data, Quadratic PL (PL_Q) and Cubic PL (PL_C) can also be generated using (8)-(9) where the formulation of polynomial PL for both path scenarios is given in Table 2. Determining an accurate PL model for WSN applications in shrimp ponds should also consider the influence of weather such as rain attenuation, which has been done by [22] in fruit farming areas on the propagation of 2.4GHz radio waves.

Table 2. PL Formulation with Quadratic and Cubic Polynomial Methods for Each Scenario in Shrimp Ponds

Type	Tx-Rx antenna height (m)	Quadratic (PL_Q)	Cubic (PL_C)
A	0.5	$68.369 + 0.1051d - 0.00007d^2$	$68.748 + 0.0921d + 0.00003d^2 - 0.0000002d^3$
	4	$68.36 + 0.0828d - 0.00006d^2$	$69.662 + 0.0382d + 0.0003d^2 - 0.0000008d^3$
B	0.5	$68.752 + 0.1443d - 0.0002d^2$	$67.639 + 0.1824d - 0.0005d^2 + 0.0000007d^3$
	4	$68.835 + 0.0806d - 0.00002d^2$	$68.417 + 0.0949d - 0.0001d^2 + 0.0000003d^3$
C	0.5	$69.532 + 0.1248d - 0.0001d^2$	$70.091 + 0.1056d + 0.00003d^2 - 0.0000003d^3$
	4	$68.534 + 0.1261d - 0.0001d^2$	$69.006 + 0.1099d - 0.000009d^2 - 0.0000003d^3$

In general, from Figs. 7(a)-(f), it is evident that the ITU PL model (PL_{ITU}) [49] exhibits a trend that closely aligns with the PL of RF measurements. In contrast, the PL of other empirical models, such as FITU PL (PL_{FITU}) [50] and Weissberger PL (PL_W) [31], falls significantly below the measurement data. For PL_Q and PL_C, their patterns closely match PL_m, as the values of both PLs are derived directly by referencing. Thus, for the next stage of PL calculations, modifications are performed using the RMSE method and optimization with the PSO method, leading to the selection of the ITU PL model in Fig. 7. This selection is justified by determining the RMSE value of the three empirical PLs (PL_e) against PL_m and then choosing the PL with the smallest RMSE value, as demonstrated in studies such as [26].

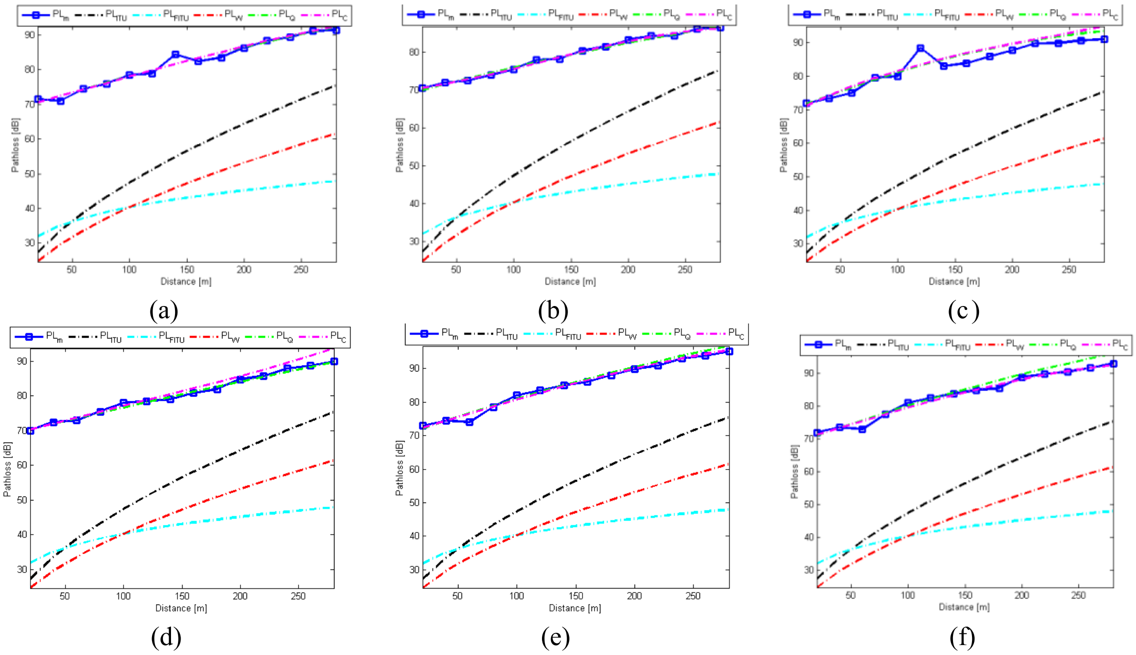

Fig. 7. PL on RF measurements and empirical models for scenarios: (a). A with Tx-Rx antenna height of 0.5m, (b). A with Tx-Rx antenna height of 4m, (c). B with Tx-Rx antenna height of 0.5m, (d). B with Tx-Rx antenna height of 4m, (e). C with Tx-Rx antenna height of 0.5m, and (f) C with Tx-Rx antenna height of 4m

3.3. RMSE and R^2 Performances of All Pathloss

In path loss (PL) modeling, performance serves as a key criterion for comparing measurement PL, modified PL proposals, and empirical model PLs. This comparison is based on identifying the PL model with the lowest RMSE, a method supported by prior research such as [20], [22], [26], and [35]. Table 3 summarizes the calculated RMSE and R^2 values for the PL of various empirical models, including quadratic and cubic polynomial PL (PL_Q and PL_C), in relation to the measured PL for shrimp ponds, as depicted in Fig. 7. The theoretical model with the smallest RMSE is deemed most suitable for estimating the measurement data [20], [34].

It can be seen from Table 3 that the ITU PL is the most suitable model to proceed to the modification and optimization stage for estimating data from PL measurements in the WSN system for shrimp ponds. This conclusion is based on the RMSE value of the ITU PL model, which is the lowest compared to other models. For the two polynomial PL models, PL_Q and PL_C, there is no need for modification and optimization as their RMSE values are below 6 dB, with averages of 1.21dB and 1.18dB, respectively. According to the study by [24] and [51], PL modification is required only if the RMSE exceeds 6 dB. This is further supported by the R^2 results for the polynomial PL models, which exceed 0.9, with averages above 0.97 (97%).

Table 3. Comparison of RMSE and R^2 between Measurement PL against Empirical and Polynomial PLs

Type	Tx-Rx antenna height (m)	RMSE (dB)					R^2				
		ITU	FITU	W	Q	C	ITU	FITU	W	Q	C
A	0.5	**28.42**	40.01	36.50	**1.08**	**1.10**	0.05	0.03	0.03	**0.97**	**0.98**
	4	**26.11**	37.05	33.84	**0.41**	**0.03**	0.04	0.02	0.02	**0.99**	**0.99**
B	0.5	**30.19**	41.63	38.22	**2.22**	**2.48**	0.04	0.02	0.03	**0.92**	**0.92**
	4	**27.14**	38.47	35.08	**0.60**	**1.68**	0.04	0.03	0.03	**0.99**	**0.99**
C	0.5	**30.97**	42.79	39.20	**1.17**	**0.89**	0.05	0.03	0.03	**0.98**	**0.98**
	4	**29.75**	41.42	37.89	**1.78**	**0.94**	0.05	0.03	0.03	**0.98**	**0.98**

Generally, the polynomial method provides the best statistical parameters to estimate the measured PL, as reported by [25], [52], even before the optimization process is carried out. This is also evident in Table 3, and based on the guidelines by [24], the ITU PL model can be modified using RMSE by adding all ITU PL formulations in Fig. 7 to each path scenario, along with their respective RMSE values. The modified PL formulation is presented in Table 4. This modification is necessary because the trend of the ITU PL model before modification falls below the measured PL. As shown in Table 4, after modification, the ITU PL achieves an RMSE reduction of 30%, with an average RMSE of approximately 8.34dB, compared to pre-modification values. However, the R^2 value remains below the desired threshold, approaching 0.90, with an average of about 0.20 (20%).

Table 4. Formulation of Modified ITU PL with RMSE for Each Scenario in Shrimp Pond

Type	Tx-Rx antenna height (m)	Modified ITU PL	RMSE (dB)	R^2
A	0.5	$0.2f^{0.3}d^{0.6} + 28.42$	8.01	0.22
	4	$0.2f^{0.3}d^{0.6} + 26.11$	9.44	0.14
B	0.5	$0.2f^{0.3}d^{0.6} + 30.19$	8.72	0.19
	4	$0.2f^{0.3}d^{0.6} + 27.14$	8.57	0.18
C	0.5	$0.2f^{0.3}d^{0.6} + 30.97$	7.49	0.25
	4	$0.2f^{0.3}d^{0.6} + 29.75$	7.83	0.23

3.4. Performance of Pathloss with PSO

As discussed in Section 3.3, the ITU PL model was selected for optimization using the PSO method due to its lowest RMSE value. This optimization approach, previously introduced in studies [25], [26], and [27], involves determining the coefficients of the PL model to be adjusted using the PSO algorithm as defined by (14)-(15). Initially, the coefficients were as shown in Table 5, and after optimization, they were updated to the values presented in Table 6.

Table 5. Coefficients of ITU PL Model with Rain Attenuation without PSO

ITU PL model parameters	Coefficients
λ_1	0.2
λ_2	0.3
λ_3	0.6
λ_4	14.7

Table 6. Coefficients, RMSE, and R^2 of the ITU PL Model with PSO and Rain Attenuation in Shrimp Pond

Type	Tx-Rx antenna height (m)	Coefficient			RMSE (dB)		R^2	
		λ_1	λ_2	λ_3	Without	With	Without	With
A	0.5	17.7	0.083	0.142	28.42	**1.98**	0.05	**0.99**
	4	20.1	0.069	0.128	26.11	**1.73**	0.04	**0.92**
B	0.5	23.1	0.060	0.129	30.19	**1.96**	0.04	**0.97**
	4	24.1	0.044	0.136	27.14	**1.79**	0.04	**0.95**
C	0.5	25.8	0.041	0.139	30.97	**1.94**	0.05	**0.91**
	4	25.8	0.041	0.139	29.75	**1.91**	0.05	**0.99**

It can be seen in Table 6 that by applying the PSO method to the ITU PL model, there is a significant change in the values of its coefficients, RMSE, and R^2. The results also show that by adopting this approach, the RMSE performance across all radio wave propagation path scenarios has drastically improved, with RMSE reductions of approximately 7%dB or 21.47 times and an average of 0.96. Based on this observation, the PSO method demonstrates exceptional capability in predicting PL, as evidenced by the significant enhancement in statistical parameters before and after optimization, in agreement with the findings of [53] and [54] using a similar approach. To provide a comprehensive comparison of all the modified and optimized PL models proposed in this study, including the ITU PL model, Quadratic PL, Cubic PL, RMSE-modified PL, and ITU PL with the PSO method, the results are summarized in Fig. 8. This figure consolidates the formulations presented in Table 2, Table 4, and Table 6 for clarity and evaluation.

It can be seen in Fig. 9 by using variations in swarm size, namely 10, 20, 30, 40, and 50, then the RMSE versus iteration graph is obtained where the iteration size is from 1 to 100. Based on the study [55] that to achieve the best error value is obtained when the number of swarms increases. This can be seen from the whole Fig. Fig. 9(a)-(f) the best RMSE value is obtained when the swarm size approaches 50. At this swarm size, the RMSE value is obtained after PSO optimization as shown in Table 6.

This study demonstrates that the PSO method is both effective and efficient in optimizing the ITU PL, enabling the development of several modification models applicable to various radio wave propagation scenarios in shrimp ponds. Beyond its established utility in cellular communication systems, the PSO method proves versatile, showing potential for optimizing PL in fisheries, particularly in shrimp farming. Furthermore, based on previous research and the findings of this study, the PSO method appears adaptable for broader applications in fisheries, regardless of location, provided factors such as vegetation, environmental conditions, weather, and suitable empirical models are taken into account.

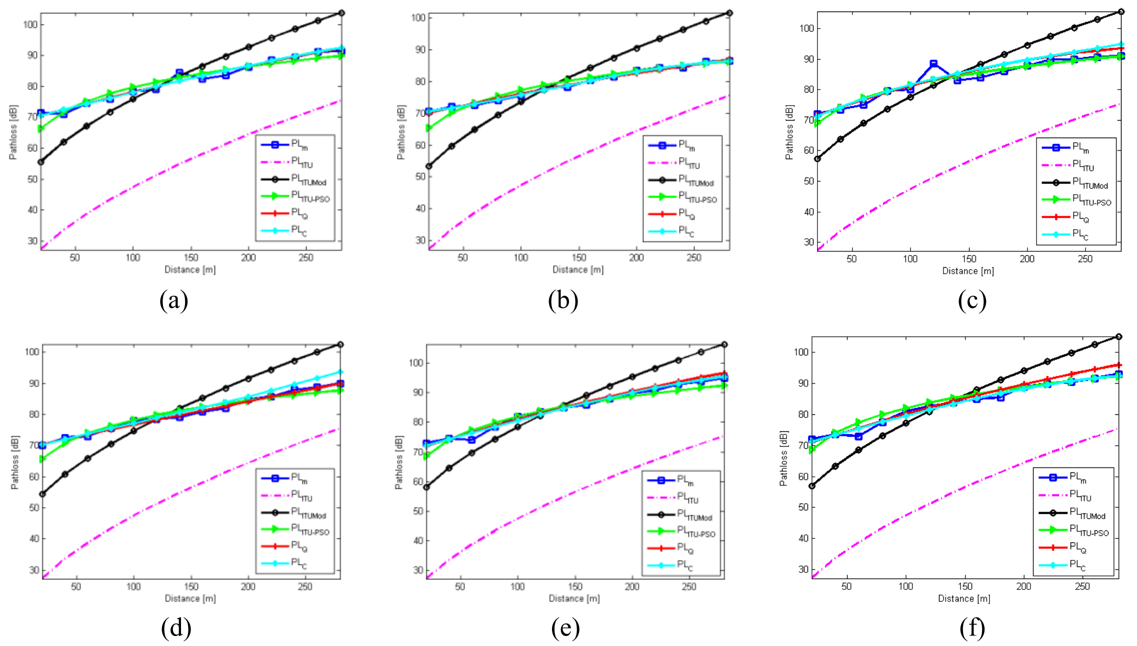

Fig. 8. Comparison of PL measurements against all PL modification variants for the scenarios: (a). A with Tx-Rx antenna height of 0.5m, (b). A with Tx-Rx antenna height of 4m, (c). B with Tx-Rx antenna height of 0.5m, (d). B with Tx-Rx antenna height of 4m, (e). C with Tx-Rx antenna height of 0.5m, and (f) C with Tx-Rx antenna height of 4m

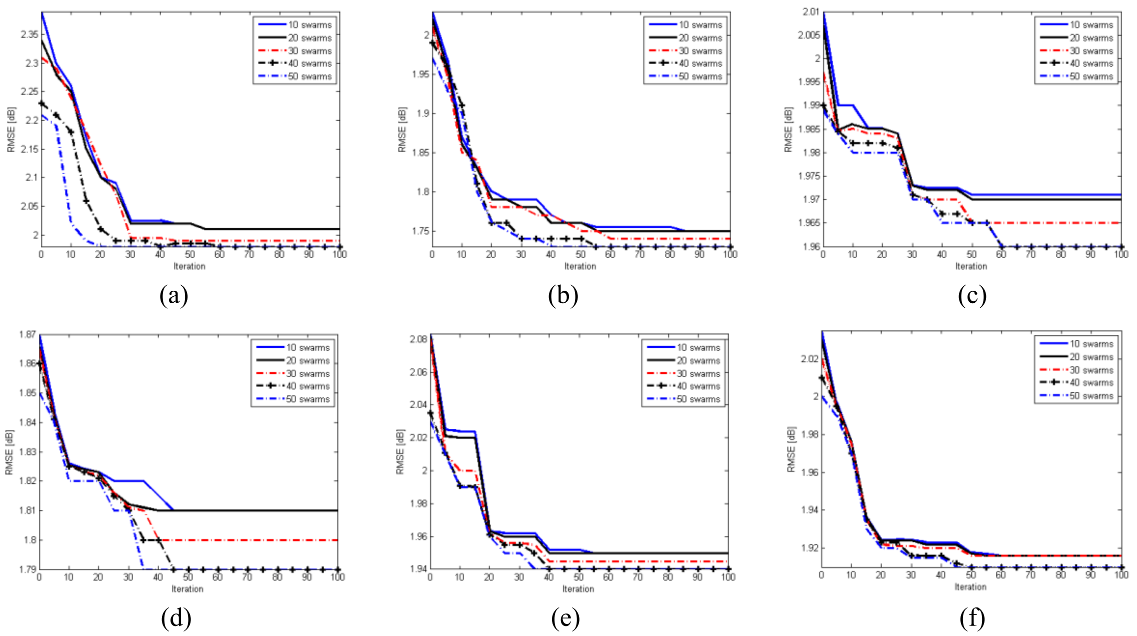

Fig. 9. RMSE versus iterations for varying swarm sizes across scenarios: (a). A with Tx-Rx antenna height of 0.5m, (b). A with Tx-Rx antenna height of 4m, (c). B with Tx-Rx antenna height of 0.5m, (d). B with Tx-Rx antenna height of 4m, (e). C with Tx-Rx antenna height of 0.5m, and (f) C with Tx-Rx antenna height of 4m

4. CONCLUSION

This paper has thoroughly detailed the calculations, evaluations, and analyses related to radio wave propagation, specifically focusing on signal strength and pathloss measurements in shrimp ponds for 2.4GHz aquaculture-WSN applications in North Kalimantan, Indonesia. Several empirical models, including ITU, FITU, and Weissberger (W), were assessed to identify candidate PL models optimized using the PSO method. Key factors influencing the selection of the appropriate PL model included the distance between the transmitter and receiver (Tx-Rx), the height of the Tx-Rx antenna from the ground, environmental conditions, and the impact of rain attenuation. Based on RMSE calculations that accounted for rain attenuation, the ITU PL model demonstrated the lowest RMSE compared to other models and was further refined using the PSO method. This optimization yielded significant improvements in coefficients, RMSE values, and the R^2 parameters of the ITU PL model. The evaluation results show that by adopting this approach, the RMSE performance across all radio wave propagation path scenarios has been drastically improved, with a reduction in RMSE of about 7%dB or 21.47 times and an average of 0.96 compared to without the approach. The higher the swarm size, the better the RMSE value can be achieved, where in this research the average of the scenarios created was obtained, so the swarm size of 50 gave the best RMSE results. Moving forward, it is anticipated that shrimp farmers can adopt this WSN application to enhance local shrimp farming operations, replacing traditional and manual monitoring methods with a more efficient and environmentally friendly approach. Future research on wave propagation modeling could explore additional empirical models, hybrid optimization techniques such as genetic algorithms or ant colony methods, and incorporate seasonal and weather variations through extended real-time measurements in diverse locations, ensuring practical benefits for farmers.

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