Path Loss Model-Based PSO for Accurate Distance Estimation in Indoor Environments

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Abstract **—**Wireless sensor networks (WSNs) and their applications have received considerable interest in the last few years. In WSNs, accurate path loss models should be considered to achieve a successful distribution of several nodes. In this work, two path loss models are proposed to evaluate the distance between two ZigBee WSNs. First, a path loss model based on conventional Log-Normal Shadowing Model (LNSM) is derived using the collected received signal strength indicator (RSSI) of the ZigBee in real time. Second, a new path loss model based on Particle Swarm Optimization (PSO) algorithm hybridized with Polynomial Equation (PE) is proposed. The PSO algorithm is used to select the optimum coefficients of PE. These coefficients can be utilized to optimize the distance estimation error based on the curve fitting. Therefore, the new path loss model called hybrid PE-PSO is innovated in this work. The hybrid PE-PSO model considerably improves the distance estimation accuracy compared with the LNSM. Results show that the hybrid PE-PSO achieves 85% improvement in distance error compared with the traditional LNSM. The mean absolute error of 0.77 m is obtained for distance estimation, which outperforms that by state of the arts.

Index Terms**—**Indoor environment; LNSM; measurement; PSO; radio propagation; RSSI; WSN; ZigBee

I. Introduction

Wireless Sensor Networks (WSNs) have become interesting research topics in the last few years. Recent advancements in wireless communications technology have enabled the development of sensor nodes [1], [2]. WSNs can be used in several applications [3], such as healthcare and patient fall detection) [4], person tracking and monitoring [5], target tracking [6], unmanned aerial vehicles [7], disaster monitoring [8], environmental management [9], wild forest areas [10], and agriculture [11]. When the wireless signal is transmitted through a communication channel, radio wave propagation occurs. The signal strength is affected by several factors, such as reflection, diffraction, and scattering. These impermanent phenomena occur when obstacles are present in transmitting the wireless signal, such as a wall, a door, stairs, and moving people.

Path loss refers to the difference between the transmitted and received power for WSNs. Path loss models are widely used to evaluate signal attenuation [2], [12]. Several techniques are used to determine the distance between wireless sensor nodes, such as angle of arrival [13], time of arrival [14], phase of arrival [15], time difference of arrival [16], received signal strength indicator (RSSI) [17], global position system [18], and acoustic energy [19]. The RSSI method has advantages of (i) low cost [12], (ii) no requirement of extra hardware, [2], [12], [20], and (iii) no requirement of time synchronization. The signal propagation models have three types, namely, free-space model [1], two-ray ground model [21], and log-normal shadowing model (LNSM) [21]. The LNSM method is commonly used due to its simple configuration and low implementation cost that leads to no requirement of additional hardware. This method utilizes static calibration parameters to evaluate distance estimation. Therefore, this study considers LNSM. The wireless radio channel presents essential limitations in evaluating the performance of wireless communications systems when the nodes of WSN are deployed [22]. Path loss models also bring difficulty in designing and implementing a reliable wireless communication system [23]. The distance estimation based on LNSM is insufficiently accurate as well [23], [24]. Accordingly, a new method based on particle swarm optimization (PSO) is proposed in this study.

PSO is an intelligent algorithm improved in several research works [25]-[27]. It was introduced by Kennedy and Eberhart in 1995 on the basis of research in a simplified social mode [28]. PSO is proven to perform complex computations on many optimization problems based on experiments. Compared with other optimization approaches, PSO algorithm is more effective for several adjustable parameters and is easier to design. This algorithm also provides optimum solutions for different applications. Therefore, PSO has been successfully implemented in engineering areas and scientific computation applications, such as function optimization, parameter tuning, neural network training, and pattern recognition [29], [30].

This work considers the aforementioned advantages and common usage of PSO in solving optimization problems to explore a new path loss model. Our objective is to validate the use of the distance for wireless medical applications by proposing an accurate path loss model based on PSO algorithm hybridized with Polynomial Equation (PE). The new path loss model is called hybrid PE-PSO and considerably improves the distance

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estimation. The experimental results of the proposed hybrid PE-PSO model are compared with those of LNSM. The selection of the convenient path loss model enables the WSN to achieve the minimum path loss in experimental planning.

Distance measurements are conducted between the mobile and fixed nodes by using ZigBee RSSI measurements in real experiment for indoor surroundings. Statistical analyses, namely, mean absolute error (MAE), root mean square error (RMSE), and correlation coefficient (R^2), are used to evaluate the two methods (i.e., LNSM and hybrid PE-PSO). The experiment is executed in the internal corridor of the LABs building of the Electrical Engineering Technical College. The contributions of this study are as follows:

1- The path loss in indoor environments is modeled using LNSM.
2- The physical parameters at path loss, such as standard deviation, and path loss exponent are estimated.
3- A new path loss model based on PSO and PE in the real experiment is modeled for indoor environments.

II. Related Work

Estimated distance approach in WSNs is recently attracting considerable interest in scientific studies. In [31], a position estimation method for sensor node based on wavelet and artificial neural network (ANN) is presented. The proposed method is achieved in an electrical machine laboratory. The proposed technique is implemented and evaluated in real industrial environments. This approach consists of a sensor network, a PSU-Mote sensor node, an ARM7 microcontroller, and a ZigBee transceiver based on CC2500. The experimental results show that the average position error is 0.9 m.

Under a harsh indoor environment, such as multipath, non-line-of-sight, ANN is adopted to predict the position of wireless sensor nodes. ANN is receiving importance because of its fast convergence performance, rapid speed, and low cost. In [32], a method for the localization of a mobile station in an indoor environment is presented. The method uses a fingerprinting technique and wavelet-based features (WBFs). The system uses Channel Impulse Response (CIR) information as the signature and ANN as the pattern matching algorithm. Two ANN algorithms are used for the positioning system, namely, the Multi-Layer Perceptron (MLP) network and the generalized regression neural network. The WBF is extracted from the channel by the employed CIR information in the system. The CIR signature is explored first and is then applied to the ANN. However, the system exhibits low localization accuracy. The system must be enhanced by increasing (i) wavelet decomposition, (ii) the number of the truncated coefficients with their associated indices, and (iii) the number of training patterns to obtain CIR information that is close to the original CIR. The experimental results show that the average position error is 2 m.

Azenha *et al*. [33] adopted the ANN method for localization in indoor quasi-structured environments. This method uses radio frequency trilateration based on ANN (MLP type). The proposed system uses wireless hardware based on ZigBee (CC2431 chip). In addition, two types of filters are utilized in the experiment. The first filter is applied for each RSSI measurements. The second one is only applied after the sample set of RSSI measurements to ignore the measurements that contain many errors. The dimension of a training grid is 5 m × 5 m, and approximately 55 points are taken within the tested area. The experimental results show that the average position error is 2 m.

A statistics approach-based localization algorithm, such as the Kalman filter algorithm [34], [35], can be employed to predict the position of the target node. The Kalman filter algorithm is a recursive approach that tries the variance of error decrease until convergence is obtained. However, this algorithm is inappropriate for non-linear systems.

Recently, several applications based on artificial intelligence are adopted, such as PSO [36] and ANN algorithms [37], to enhance the performance of algorithms and solve the localization problem in WSNs. In [38], two PSO algorithms are adopted for the localization of sensor nodes. The first PSO determines the localized target in mobile ad hoc networks, whereas the second PSO aims to gather the sensor nodes around the target node. The simulation results in Matlab reveal that the performance of the PSO algorithm is efficient in network-centric collaborative navigation. Chuang and Jiang [39] presented a PSO-based localization technique using Wi-Fi technology for an accurate node distance estimation. The proposed scheme uses online training and correlated topology-trained data. RSSI and hop counts are employed to estimate the node distance. The range of test area is 50 m × 50 m. However, high average error is obtained. The experimental results show that the average distance error is 4 m.

Brunato and Battiti [40] presented a statistical learning theory for location fingerprinting. The proposed theory is based on the support vector machine. The proposed method based on a wireless LAN utilizes the IEEE802.11b, Wi-Fi standard. The estimated location relies on RSSI measurements. Low algorithmic complexity is used as the suitable technique. However, high localization error is recorded. The experimental results show that the average localization error is 3.04 m. Pratap *et al*. [41] used RSSI samples obtained from a mobile anchor node to evaluate the sensor node location based on polynomial modeling with LNSM. The experimental results show that the position error is 2.2 m.

Zhou and Zhang [42] determined the position of the source node by using RSSI values. Linear least squares are utilized to determine the location. The LNSM is estimated based on RSSI measurements. The simulation results show that the estimated distance error is 2.72m.

The distance accuracy of the sensor node is essential for planning a large number of applications related to low power consumption in WSNs. According to previous research works that have used LNSM and artificial intelligent techniques or algorithm, the distance or localization accuracy remains unsatisfying. Consequently, the previous drawbacks motivate us to innovate a new path loss model based on the polynomial model combined with PSO for developing an accurate distance estimation model.

III. Channel Models

A propagation path loss model, which can describe the power loss versus distance between the transmitter and the receiver in an actual environment, should be developed to effectively apply WSNs in assessing and monitoring the condition of patients. Three propagation models are known for wireless communication techniques that predict signal strength loss with distance path loss. They are discussed in the following subsections.

A. Free-space Propagation

The free-space propagation model assumes only one clear line-of-sight path between the transmitter and the receiver. The effect of the earth surface is ignored. Therefore, the receiver and transmitter antennas are located in empty environments. The free-space model is applicable to the following states: (i) the transmission distance is much larger than the carrier wavelength and the antenna size, and (ii) no impedances and reflecting surfaces between the transmitter–receiver nodes are considered [43]. The free-space propagation model is given as

$$P(dBm) = 10log\frac{P_t}{P_r} = -10log\left(\frac{\lambda^2}{(4\pi)^2L^2}\right). \quad (1)$$

where λ is the carrier wavelength, P_t is the transmitted power, P_r is the received power, and L is the distance between the transmitter and the receiver.

B. Two-ray Ground Model

The two-ray ground model depends on the idea of scattering the electromagnetic waves by reflection and refraction. Ray tracing is a method that relies on a geometric approach (Fig. 1). The two-ray ground model is applicable to the following states [43], [44]: (i) the transmission distance is within nearly a few kilometers, and (ii) the high antenna for the transmitter and the receiver is more than 50 m. The model can be useful in urban micro-cellular environments. The received power can be given as

$$P_r = P_t\,(dBm) + 10log(G_t) + 20log(H_1H_2) - 40log(D) \quad (2)$$

where H_2 is the height of the receiving antenna, H_1 is the height of the transmitting antenna, D is the distance from each other, and G_t is the antenna gain.

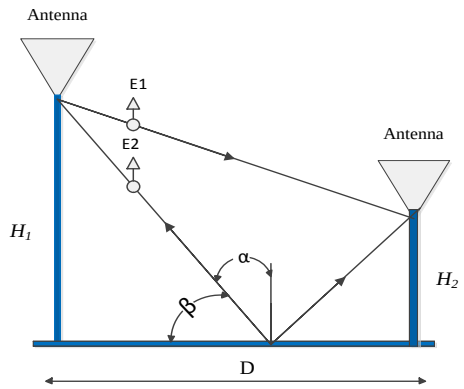

Fig. 1. Two-ray model

C. Log-normal Shadowing Model

LNSM is widely used because it is appropriate for indoor and outdoor environments. This model provides several parameters that can be configured depending on different experimental environments. LNSM can describe the relationship between the RSSI value and the communication distance, and this relationship is essential and the key of positioning technologies in WSNs [44].

The average path loss for the transmitter–receiver node is a random fluctuation [45], and it can be defined as a function of distance using a path loss exponent (n) [1], [21], [46]. The value of k depends on the particular propagation environment: the type of architecture construction, material, and infrastructure site location within a building (i.e., wall, door, and stairs) [47]. The low value of k corresponds to low signal loss. k has a high value in the presence of obstructions. Therefore, the calculation formula of LNSM can be given as

$$PL(dBm) = Pl_o + 10klog\left(\frac{d}{d0}\right) - \sigma. \quad (3)$$

where PL (dBm) is the path loss at a distance d in meters versus an increase in the distance from the transmitter in meter; Pl_o is the power received at a reference distance d_0 in 1 m [48]; k is a path loss index, which relies on particular propagation environment, and its value is large under impedance (i.e., obstacles and wall) [15]; and σ is a zero-mean Gaussian random variable (in decibels).

The first two models have private requirements for the application environments and have low accuracy [49], whereas the LNSM is the most commonly used signal loss in WSN applications. Therefore, this study uses LNSM to estimate the indoor environment parameters. In addition, the distance obtained from LNSM is compared with the estimated distance from the proposed hybrid PE-PSO.

IV. Particle Swarm Optimization Model

PSO is an intelligent algorithm improved several years ago. PSO approach is used to solve the optimization problem. PSO algorithm operates on the concept that particles change their velocity (accelerate) toward the best solution at each time [50]. These particles are classified as a swarm. Each particle (individual) flies to

vary its position in the search space depending on factors related to their recent (i) velocities, (ii) existing positions, distance between the actual position and the best position (*pbest*), and (iii) distance between the actual position and the global best position (*gbest*) [51]. The particles for (*i*th) are represented as $X_i = [X_i, X_{i2}, X_{i3} \ldots X_{id}]$; the best position (best fitness solution) is represented as $Pi= [P_{i1}, P_{i2}, P_{i3} \ldots P_{iD}]$ in d-dimensional search space [52]. Every swarm creates a new search point Xi^{n+1} as a linear combination. The best solution is obtained after the change in position is classified as *pbest*. The best solution (global) shared by all swarm particles is classified as *gbest* [51], [52]. Popular formulations of how a particle modifies its velocity and position are shown in Equations (4) and (5), respectively.

$$V_{ij}^{n+1} = W \times V_{ij}^{n} + C_1 rand1\,() \times \left(pbest\ i\,j - X_{ij}^{n} \right) + C_2 rand2\,() \times (g\ best - X_{ij}^{n}). \quad (4)$$

$$X_{ij}^{n+1} = Xi^{n} + V_{ij}^{n}. \quad (5)$$

where Vi^{n} is the previous speed vector; Vi^{n+1} is the speed vector; n is the time step; j is the index of dimension in the search space; *rand ( )* is a random number uniformly distributed between 0 and 1; and W, C_1, and C_2 are the weight-selected coefficients. The values $W = 0.7$ and $C_1 = C_2 = 2$ from Equation (4) are considered in the current study after the empirical tests to obtain fast convergence as recommended in [53].

V. Methodology

Study on the path loss model in indoor environments requires determination of the propagation parameters. The channel model in the indoor location for the wireless medical system is useful to estimate the propagation parameters, which affect in sending and receiving RSSI data packets related to a patient's condition, such as heart rate, temperature, and posture. The transmitted RSSI values are affected by several parameters (i.e., deflection, diffraction, shadowing, reflection, and scattering). This work uses the RSSI values to estimate the distance between the fixed and mobile nodes. Two methods are utilized to evaluate signal loss versus distance, which can be achieved by measuring the RSSI value in each distance. The distance is estimated using the (i) derived LNSM (as commonly used) and (ii) the PSO algorithm hybridized with PE (as a newly proposed path loss model). Each method estimates the distance between two nodes by utilizing the curve fitting (CF) method. The two methods are described in the next two sections.

A. Distance Estimation-based LNSM

The power of the transmitted signal is attenuated or affected by several deficiencies, such as diffraction, scattering, and reflection. These deficiencies are the three main modes that affect the wireless channel propagation. Most ZigBee wireless protocols support RSSI measurement because the received power is measured for each received data packet. LNSM is a popular propagation model that can fully describe the relationship between the RSSI value and the distance, especially when WSN depends on the efficiency of wireless channel models in an indoor location [1], [54]. This work evaluates the distance between the fixed and mobile nodes by RSSI measurements.

The energy of the transmitted signal between nodes in the WSN is the signal parameters, which contain the statistics that reveals the distance among those nodes. These factors can be used along with path loss and LNSM for distance calculation using Equation (3). Therefore, the RSSI value at a mobile node is evaluated as follows:

$$RSSI\ (dBm\ = PT(dBm) - PL(dBm). \quad (6)$$

where $PT\ (dBm)$ is the transmitted power from the anchor node in dBm. Then, the *RSSI* at the mobile node can be obtained from Equations (3) and (6) as

$$RSSI\ (dBm) = PT(dBm) - Pl_o - 10klog\left(\frac{d}{d0}\right) - \sigma \quad (7)$$

In this work, the RSSI values are measured using the ZigBee S2C module. k and σ can be obtained from the CF. Therefore, the distance between the anchor and the mobile nodes are estimated as shown in Equation (8).

$$d_{est\_LNSM} = 10^{-((RSSI + Pl_o + \sigma - PT)/10k)} \quad (8)$$

B. Distance Estimation-based PSO

This work predicts the estimated distance based on PSO and PE, hybrid PE-PSO, by using Matlab program version 2015. The selection of the hybrid PE-PSO model takes the advantage of predicting the swarm model using the CF. This model can be used to show the improvement in distance estimation compared with the distance estimation based on LNSM and before applying the hybrid PE-PSO (i.e., PE). First, the CF tool is used to derive the path loss model based on polynomial mathematic equation. Second, the coefficients of the obtained PE is improved using hybrid PE-PSO to realize accurate distance estimation. The mathematical expression for the PE is shown in Equation (9).

$$F(X) = P_1 X^2 + P_2 X + P_3. \quad (9)$$

where P_1, P_2, and P_3 are 0.01204, −0.24, and −21, respectively. They represent the polynomial coefficients.

The estimated distance based on the hybrid PE-PSO is shown in Equation (10).

$$d_{est\_EP\_PSO} = P_1\, RSSI^{\,2} + P_2\, RSSI + P_3. \quad (10)$$

The hybrid PE-PSO selects the optimum values of coefficients P_1, P_2, and P_3, which can be used in Equation (10) to improve the distance accuracy. The process is obtained by building the upper and lower limits of the coefficient, which are obtained previously from the PE in MATLAB. Thus, the hybrid PE-PSO achieves the next predicted distance value that relies on how far the actual

distance point is from the CF. Fig. 2 shows the flowchart of the hybrid PE-PSO.

C. Experiment Setup

The experiment is performed in the LABs building of the Electrical Engineering Technical College. Two WSN nodes are used to estimate the path loss model. The first node (transmitter node) is fixed in the beginning of a corridor, and the other node (receiver node) moves in the corridor with predefined locations, as shown in Fig.3. The low-power ZigBee S2C module is selected as the WSN. This module is a new version of the XBee products. For this feature, the ZigBee provides convenient range sensing with low power consumption, low cost, high scalability, and low complexity; moreover, it contains an RSSI indicator without extra hardware [15], [53].

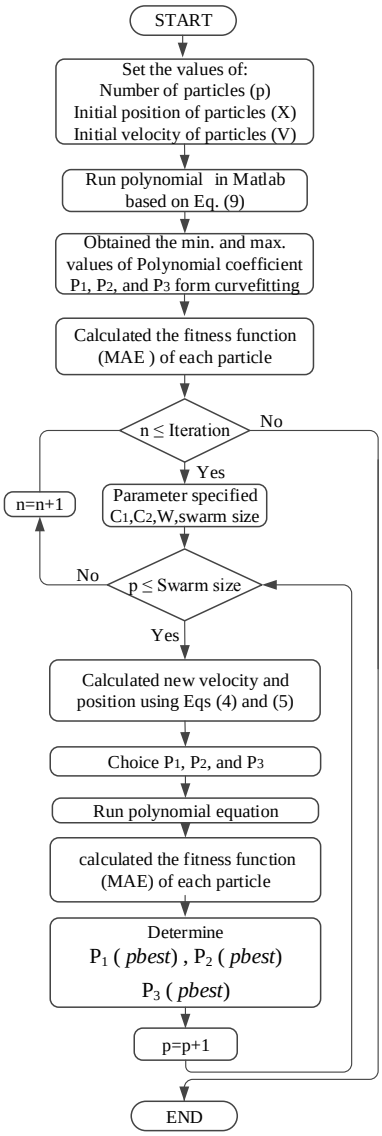

Fig. 2. Flowchart of the hybrid PE-PSO

Fixed and mobile nodes are supplied by battery power (1300 mAh/3.7 V). The mobile node connects to a personal computer via a USB port (Fig. 4). The total number of tested locations is 16 positions because of the limited area in the corridor. A total of 1,600 samples are gathered, and a hundred samples are gathered for each position. The measurements are achieved in the normal movement of students in the corridor by considering the impairments that affect the signal propagation. The corridor has an area of 33 m ×3 m (Fig. 3). The maximum distances between the fixed and mobile nodes are 30 m. The two nodes are located at a height of 1.5 m from the ground to avoid the Fresnel zone. The mobile node moves away from the fixed node by 2 m for the 16 predefined positions (Fig. 3).

The fixed node transmits the packets to the mobile node. The RSSI values are recorded using a laptop based on the X-CTU software [55]. The RSSI values are received at the 16 predefined locations with the measurements at 1 m as the reference distance d_o.

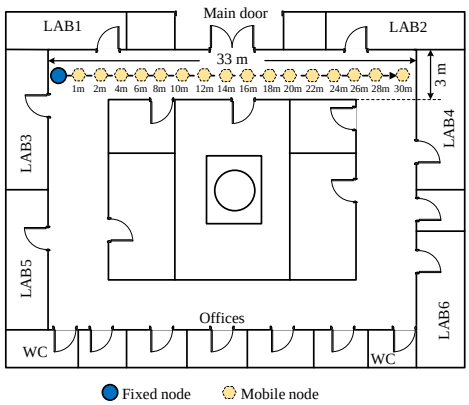

Fig. 3. Indoor experimental setting.

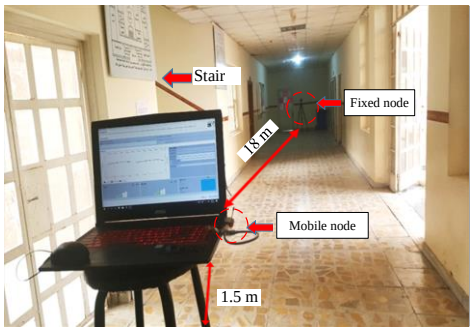

Fig. 4. Network during testing.

VI. Results and Discussion

A. RSSI Measurements

The RSSI measurements at the mobile node for each position are recorded based on X-CTU (Fig. 5). The RSSI measurements are plotted with respect to the number of samples. The figure illustrates a hundred samples for each position. The RSSI values fluctuate due to the signal propagation in the wireless channel. The fluctuations of the RSSI values produce a substantial error in distance estimation when the LNSM is used. Therefore, a new path loss model based on hybrid PE-PSO is proposed. The new model considerably improves the distance estimation accuracy compared with the LNSM.

Fig.6. shows the variances of RSSI at a predefined distance as blue squares and the averaged RSSI as black

diamond points. The averaged RSSI is varied between −34 and −55.88 dBm for 1 and 30 m, respectively. Low variances from 4–8 m are observed. However, high variances are noted from 10–30 m due to the presence of obstacles: stairs, windows, door, and student's movements. The values increase with the increase in distance. Fig. 5 illustrates that the farthest location is 30 m; at this distance, the RSSI is −55.88 dBm. This RSSI value is greater than the receiver sensitivity (i.e., −100 dBm) of the XBee S2C. Thus, the received data packets by the mobile node are expected to be delivered without losses. In medical applications, signal losses are expected due to the reflection and absorption in the body of the patients. Under low sensitivity of the mobile node, the XBee S2C wireless technology can be used in wireless medical applications for a wireless body sensor network. In this case, the patient can move freely without data packet losses.

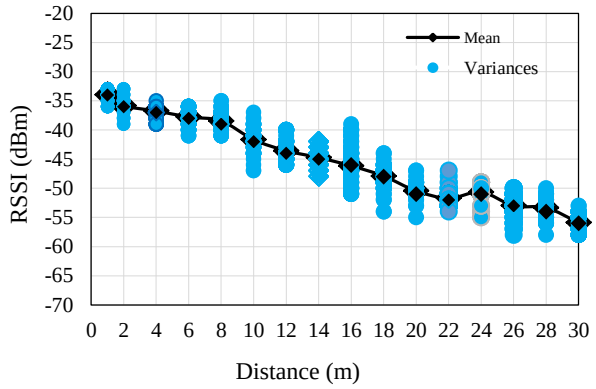

Fig. 5. RSSI values at 16 positions versus number of samples.

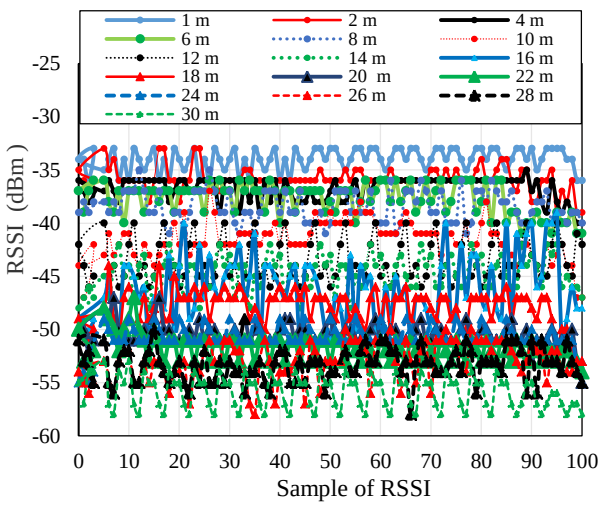

Fig. 6. Variances of RSSI values with distance.

B. LNSM Parameter Measurements

The LNSM parameters are estimated on the basis of the measurements of the averaged RSSI for predefined indoor locations. The relationship between the measured averaged RSSI and the logarithmic scale of the predefined positions is schemed for indoor environments to obtain the LNSM and related parameters (Fig. 7).

The standard deviation σ and path loss exponent k can be acquired using the linear fit line over the curve in Fig 7. Subsequently, the estimated regression line can be modeled by

$$Y = -15.183x - 29.327. \quad (11)$$

The rewritten equation is

$$RSSI = -15.183\log(d) - 29.327. \quad (12)$$

By comparing Equation (7) with (12), Equation (13) can be obtained.

$$PT - Pl_o - \sigma = -29.327. \quad (13)$$

where PT = 5 dBm is the transmitted power of XBee S2C model; and Pl_o is −34 dBm, which is the measured RSSI at a reference distance of 1 m. The standard deviation σ is 0.327, and the path loss exponent k is 1.51 (Table I). Table 1 shows a close agreement between theoretical and practical path loss exponent and Pl_o values.

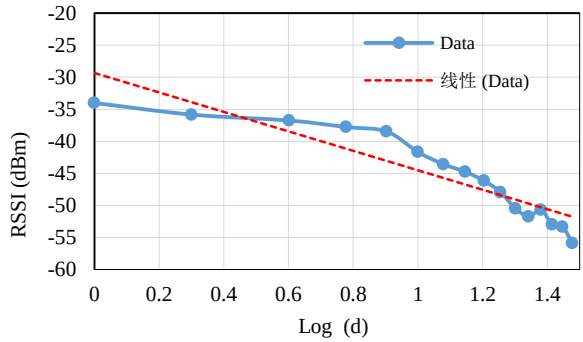

Fig. 7. Curve fitting based on LNSM

TABLE I: THEORETICAL AND MEASURED LNSM PARAMETERS FOR INDOOR SURROUNDINGS

Parameters	Symbol	Units	Indoor Environments	
			Measured	Theoretical
Path loss at l_o	Pl_o	dBm	34	36
Reference distance	do	m	1	1
Path loss exponent	k	—	1.51	1.6–1.8 [53]
Standard deviation	σ	dB	0.327	2 [53]

C. Distance Estimation Based on LNSM

The distance between the two ZigBee nodes (i.e., constant and mobile) can be estimated from Equation (8). The measured LNSM parameters in Table I are obtained using Equations (8) and (12). The estimated distance based on LNSM can be expressed as in Equation (14).

$$d_{est\_LNSM} = 10^{-(\mathrm{RSSI}+29.327)/15.183} \quad (14)$$

Therefore, the absolute distance error d_{error_LNSM} can be evaluated by Equation (15).

$$d_{error\_LNSM} = |d_{act} - d_{est\_LNSM}| \quad (15)$$

where d_{act} is the actual distance. It is predefined in the experiment in the internal corridor and is measured using a distance meter.

On the basis of Equation (14), the actual distance based on meter measurements (*x-axis*) and the estimated distance based on LNSM (*y-axis*) can be plotted (Fig. 8). The correlation coefficient (R^2) of determination between the estimated and actual distance is 0.87, which indicates no perfect match between the two distances. Fig. 9 shows the absolute error relative to the actual distances. Fig. 9 demonstrates that the error of estimated distance increases with the increase in distance to 20 m. The minimum and maximum errors are computed at 1 m (at a distance of 1 m) and 26 m (at a distance of 30 m), respectively. However, the average error of 5.263 m is calculated using the LNSM method. This error is relatively large. Therefore, hybrid PE-PSO improves the distance estimation error.

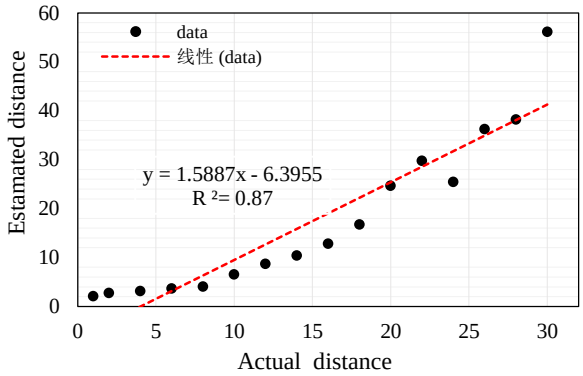

Fig. 8. Correlation between estimated and actual distances based on LNSM.

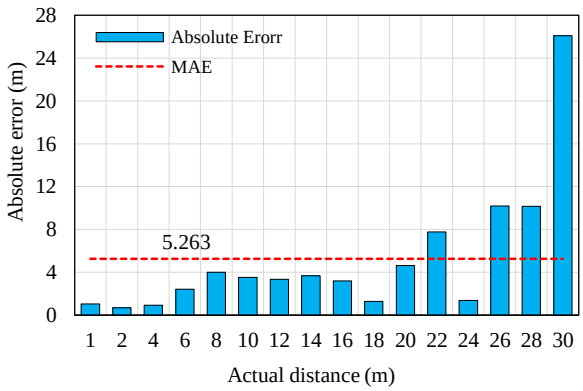

Fig. 9. Absolute error relative to actual distance based on LNSM.

D. Distance Estimation based on Hybrid PE-PSO Algorithm

The hybrid PE-PSO algorithm is applied to find the optimum values of the PE coefficients (P_1, P_2, and P_3) for improving the distance estimation accuracy. The number of iterations of the hybrid PE-PSO is set to 1000 to obtain the minimum fitness function (i.e., MAE). However, the MAE becomes constant after 66 iterations [53]. Its value is 0.7724 m, which is the same as that by the fitness function of the hybrid PE-PSO (Fig. 10). After applying the hybrid PE-PSO algorithm (Fig. 2), the obtained coefficients are P_1 equal to 0.0106, P_2 equal to −0.3743, and P_3 equal to −23.96. Therefore, these values can be substituted in Equation (10) to yield Equation (16).

$$d_{est\_PE\_PSO} = 0.0106\, RSSI^{\,2} - 0.3743\, RSSI - 23.96 \qquad (16)$$

To investigate the performance of the hybrid PE-PSO algorithm, the relationship between the RSSI values and the distances before and after applying PE-PSO can be established as shown in Fig. 11a and Fig. 11b, respectively, which correspond to Equations (9) and (16). Fig. 11a shows a divergence between the data (blue circle points) and linear fit (red line). The figure illustrates that the correlation coefficient (R^2) is 0.9859. By contrast, Fig. 11b presents a perfect match between the data and linear fit with the value of R^2 of 1. The use of hybrid PE-PSO substantially improves the performance of the polynomial model, which leads to a paramount enhancement in distance estimation accuracy. A relationship between the actual and estimated distances can be established (Fig. 12).

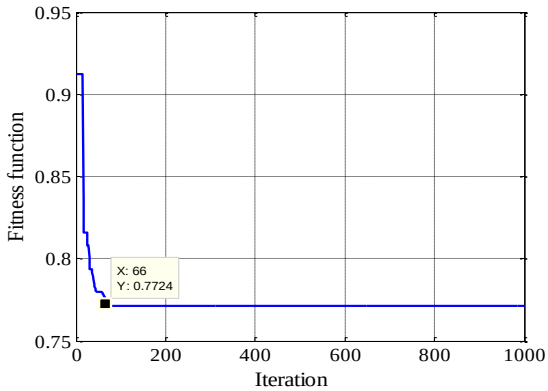

Fig. 10. Performance of fitness function for hybrid PE-PSO.

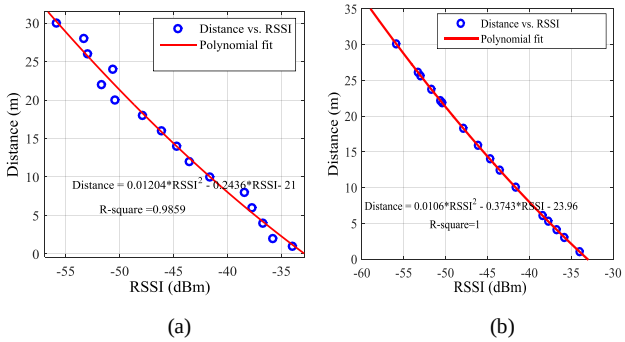

Fig. 11. Performance comparison (a) before applying hybrid PE-PSO and (b) after applying hybrid PE-PSO.

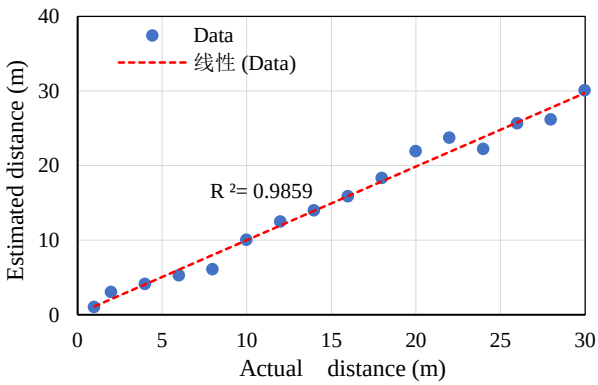

Fig. 12. Correlation between estimated and actual distances based on hybrid PE-PSO.

The figure demonstrates a close agreement between both distances with the correlation coefficient of 0.9859. The errors of the estimated distance based on hybrid PE-PSO (obtained from Equation (17)) can be plotted relative to the actual distance (Fig. 13).

$$d_{error\_PE\_PSO} = \left|d_{act} - d_{est\_PE\_PSO}\right| \quad (17)$$

The figure shows that the minimum and maximum errors vary between 0.02 and 1.9 m. However, the average distance estimation error is increased to 0.774 compared with that of the LNSM method (Fig. 13). The equation parameters before and after applying the hybrid PE-PSO are compared in terms of polynomial coefficient, correlation coefficient, and RMSE (Table II).

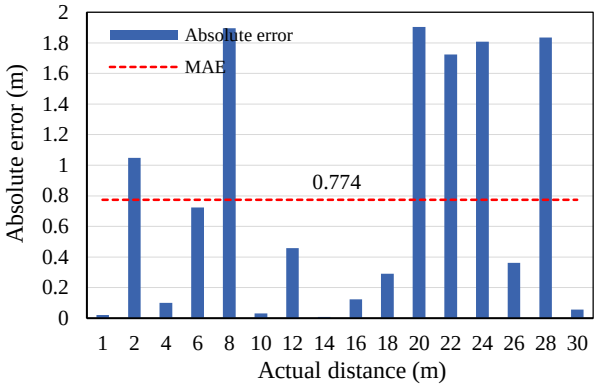

Fig. 13. Absolute error relative to the actual distance based on hybrid PE-PSO.

TABLE II. COMPARISON OF PARAMETERS BEFORE AND AFTER APPLYING HYBRID PE-PSO

Model	Polynomial coefficient			Correlation coefficient	Root mean square error	Fitting distance equation
	P_1	P_2	P_3	R^2	RMSE	$F(x) = p_1x^2 + p_2x + p_3$
Before applying hybrid PE-PSO	0.012	−0.24	−21	0.9859	1.202	$d=0.012*RSSI^2-0.2436*RSSI-21$
After applying hybrid PE-PSO	0.0106	−0.374	−23.96	1	1.06×10^{-14}	$d=0.0106*RSSI^2-0.3743*RSSI-23.96$

E. Comparison Results between Hybrid PE-PSO and LNSM

This section compares PE-PSO and LNSM to confirm the performance of the proposed hybrid PE-PSO in terms of three statistical analyses (i.e., MAE, mean square error (MSE), and RMSE), as shown in Fig. 14. The RMSE and MAE errors are calculated using Equations (18) and (19), respectively [56, 57].

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (error)^2} \quad (18)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{n}|e_i| \quad (19)$$

Fig. 14 shows that high distance estimation errors occur when LNSM is adopted. However, the error based on hybrid PE-PSO is better than that based on LNSM for the considered statistical analyses. The figure also shows that MAE, RMSE, and MSE increase by 85%, 86%, and 98%, respectively, when the hybrid PE-PSO algorithm is considered. Apparently, the distance error based on LNSM cannot satisfy the accuracy requirement, whereas the results based on hybrid PE-PSO are accurate. The correction coefficient is also used to fit the model as a CF in the output for linear regression analysis and to estimate the distance related to the actual distance. The correlation coefficient is 0.98 for hybrid PE-PSO, whereas the value is 0.87 for LNSM. Obviously, the hybrid PE-PSO achieves better performance than LNSM in terms of the correlation coefficient.

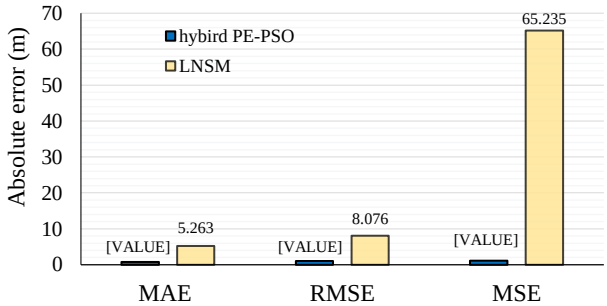

Fig. 14. Comparison between LNSM and hybrid PE-PSO.

From the analysis above, we can deduce that the polynomial model based on hybrid PE-PSO considerably improves the distance estimation accuracy compared with the LNSM. Therefore, the hybrid PE-PSO algorithm introduces an optimum solution that can be employed as a path loss model in an indoor wireless channel and may be adopted in several indoor environments.

F. Comparison with Previous Works

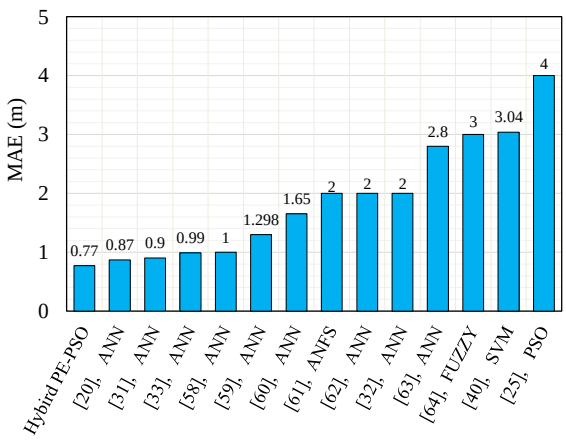

Fig. 15. Comparison of hybrid PE-PSO with previous studies for indoor environments.

The hybrid PE-PSO is compared with related previous works to confirm the proposed path loss model. MAE is employed to evaluate the distance estimation error relative to the previous articles. Thirteen reliable studies

[20], [25], [31]-[33], [40], [58]-[64] have been compared with the current work in terms of MAE. These studies are similar to our work on indoor environments, adopted wireless technologies (i.e., ZigBee), and artificial intelligent or optimization algorithm. They are also based on collected RSSI for distance estimation or localization. These works have used ZigBee as the WSN because of its low cost, low extra hardware, and smooth implementation. The results in Fig. 15 show that the hybrid PE-PSO algorithm outperforms the previous works. Specifically, the MAE of our work has lower error (i.e., 0.77 m) than that of the other studies.

VI. Conclusions

In this work, two path loss models are presented to evaluate the distance between the fixed and mobile nodes. The first model is based on a traditional LNSM, whereas the second model based on hybrid PE-PSO is innovated. This study mainly aims to estimate the distance between two nodes in the WSN for medical applications. The experiment is conducted in the LABs building of the Electrical Engineering Technical College. We verify the performance of our proposed path loss model by comparing the results of the estimated distance of the two models in terms of MAE, RMSE, and MSE. The results show that the hybrid PE-PSO model is superior to LNSM in terms of distance measurement accuracy. The analysis results show that the distance estimation error (i.e., MAE) based on EP-PSO is improved by 85% compared with that of the model based on LNSM. The correlation coefficient is 0.98 for hybrid PE-PSO, whereas the value is 0.87 for LNSM. Obviously, the hybrid PE-PSO achieves better performance than LNSM in terms of the MAE, RMSE, MSE, and the correlation coefficient. We can deduce that the hybrid PE-PSO algorithm introduces an optimum solution that can be employed as a path loss model for accurate distance estimation in environments and can be adopted in several wireless medical applications when the patient moves indoors without data packet losses.

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