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MULTI-STAGE OPTIMIZATION OF IEEE 802.11 ACCESS POINTS PLACEMENT USING PARTICLE SWARM OPTIMIZATION BASED ON PATH LOSS

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***ABSTRACT*:**

Indoor placement is critical factor in enhancing the performance of wireless networks especially in smart healthcare environments requiring accurate localization and consistent connectivity. This study proposed a multi-stage optimization framework using the Particle Swarm Optimization (PSO) algorithm to optimize the placement of IEEE 802.11 Access Points (APs) based on empirical Path Loss (PL) modelling. Initially Received Signal Strength Indictor (RSSI) data is collected across four zones in a hospital environment. A zone-specific long distance PL model is derived by optimizing the PL exponent and the standard deviation using PSO under both Line of Sight (LoS) and non Line of Sight (NLoS) conditions. Subsequently a second PSO stage determines the optimal AP location to maximize coverage and minimize interference by maximizing Signal to Interference Ratio (SIR) using the optimum PL parameters in the previous stage. The accuracy of measurement data was evaluated by calculating the mean-square error (MSE) between real PL and theoretical PL, as well as the real PL and optimized PL model. The results demonstrate that the measurement data is accurate and the optimized PL model can reduce MSE and build a reliable dataset. The minimum MSE is achieved in zone 1 which is equal to 0.28 dB. On the other hand, the optimum AP locations provide a high coverage area with less interference

Keywords: *Received Signal Strength Indictor (RSSI), WiFI, Path Loss(PL), Particle Swarm Optimization (PSO), Signal to noise ratio (SIR), coverage area , interference, Mean Square Error (MSE).*

INTRODUCTION

The proliferation of wireless technologies in smart environments , particularly healthcare facilities , necessitates robust indoor communication strategies [1, 2]. Traditional wired network are being replaced by WiFi based architecture for their ease of deployment and maintenance. However optimizing AP placement in complex indoor setting is challenging due to multipath effects , human movements, and architecture constraints that cause signal degradation [3].

The 2.4GHz industrial, scientific, and medical (ISM) bands remains apopular choise for indoor WiFi due to its compatibility and range characteristics. In practice , APs are often deployed arbitrarily, leading to redundant coverage in some areas and signal voids (blank zones) in others . moreover , interference from overlapping signals and structural obstacle leads to suboptimal network performance [4][5].

To address these limitations , this study presents a a data-driven , PSO based optimization framework comprising multistage. the presented approach investigates the behavior of RSSI propagated from the installed WiFi and calculate the empirical PL at a 2.4 GHz network in four corridor indoor environments. then evaluate the reliability of the measurement data using MSE between them. The proposed optimum PL models for each environment are based on the empirical PL by optimizing long-distance PL model parameters, PL exponent (n), and Standard deviation(σ). Using the optimum PL model's parameters, the APs location is optimized to reduce interference

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and provide a high coverage area. To find the best locations for the APs, the optimization procedure takes into account a variety of variables, including the length of the corridor, the quantity of APs, and the PL parameters. This work contributes to the development of effective and dependable wireless communication infrastructures by combining the advantages of PL modeling and PSO to offer a comprehensive solution for Wi-Fi APs location optimization in corridor environments. The rest of this paper is organized as follows: in section 2 related work will be discussed. Some important aspects of indoor communications and optimization will be highlighted in sections 3 and 4, respectively. The methodology will be illustrates in section 5. The results and evaluation of the proposed model are presented in section 6. Finally, the conclusion and future work will be set out in section 7.

RELATED WORKS

Previous studies explored various models for indoor PL prediction such as the authors in [6] present an indoor estimation PL model to improve estimation accuracy in the environment. The authors used a WiFi signal at 2.4 GHz to 2.4835 GHz in an indoor environment considering the multiwall model. They used an Adaptive Neuro-Fuzzy Inference System (ANFIS) to predict PL as an output. At the same time, the inputs were distance, no. of walls between AP and RP, frequency, and wall material then compared the results with measurement data. The Root Mean Square Error (RMSE) between the estimated and measurement data was 2.7302 dB. The authors in [7] optimize the PL Floating Interception (FI) by simulating an office environment and calculating PL using a ray tracing algorithm at 39GHz. They work to minimize the error of shadow fading of the FI model to 0.6dB in the LOS scenario. The authors in [8] evaluate the measured PL in a three corridors environment at 2.4 GHz with the theoretical PL. They used the linear regression method to predict PL exponent to calculate theoretical PL. They found that the highest difference between theoretical and measured PL is 8.74 dB. In [9] the PL exponent has been estimated utilizing deep deterministic policy gradient learning, in an indoor environment. The authors used collected RSSI in the environments from three Zigbee nodes. They also measure distance empirically and compare it with three distances calculated from the RSSI equation. And then calculate the error between them that is equal to 0.43m. Another work in [10] presents an adaptive model (ADAM) to optimize the long-distance PL model using Bluetooth technology. The introduced model was applied in a real environment that achieved an average error of 2.93m. The geodesic PL model is proposed to optimize PL parameters in ship and office environments using DASH-7 sensors at 868 MHz. The authors in [11] optimized five WiFi APs' signal quality in a floor plan using a genetic algorithm. The proposed network was able to increase coverage area to 80% and improve signal quality from -45 to -65 dBm. APs location optimization was highlighted in [12] to enhance coverage area and service quality in several room environments. The optimized signal quality ranged between -47 and -87dBm. The authors in [13] used binary PSO (BPSO) to select the best position of three WiFi APs in lab and room environments to propose APs Distribution Optimization Algorithm Coverage Solution (APD-CS) Algorithm. They used ray tracing propagation model to evaluate signal quality at -40dBm, -45dBm -50dBm , -55dBm and -60dBm. The highest accuracy was achieved at 97.6% at -55dBm.

INDOOR COMMUNICATIONS CHARACTERISTICS

Multipath Phenomena

It represents the phenomena wherein the AP and the receiver communicate multiple copies of the original signal. When human bodies, objects, obstacles, and barriers are present, multipath propagation occurs, which significantly affects indoor wireless communication.

Path loss (PL)

Before actual deployment, accurately estimating coverage and carefully adjusting installation site antenna heights are crucial factors in optimizing network performance. As a result, accurate radio propagation characteristic modeling is essential for designing and optimizing WiFi networks. The properties of radio propagation have been extensively researched worldwide. In the context of cellular and wireless sensor networks, numerous field measurements have been conducted in a range of indoor and outdoor environments. In general, a wide range of parameters, including distance, frequency band, typical antenna heights, topography, and the presence of obstructions, buildings, hills, mountains, people, and other features, influence the PLy. However, other elements like wall thickness and type, floor plans, and building materials must be taken into account for the indoor environment. Research institutions and standard organizations have produced several PL models, such as Okumura-Hata, Cost 231-Hata, Bertoni-Walfisch, ITU Advanced, WINNER II, WINNER+, and 3GPP Spatial Channel Model, Log-normal Okumura-Hata, Stanford University Interim (SUI) developed for IEEE 802.16d model, and Ericsson model [14]. The Log-normal PL model is commonly used to reflect indoor radio signal

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propagation, but this model does not reflect the obstacle-induced attenuation between the AP and Receiver Points (RPs) [15]

$$PL(d)dB = PL(d_0) + 10n\log(\tfrac{d}{d_0}) + \sigma \quad (1)$$

Where $PL(d_0)$ is average PL at the separation distance d_0 =1, d is the distance between the transmitter position and each receiving point, n is PL exponent, and σ is standard deviation

Received Signal Strength (RSS)

Regarding the characteristics of multipath propagation, received power (P_r), which denotes the diminishing signal power during the transfer between the transmitter and the receiver, is another crucial quantity that warrants attention. P_r can be computed using the following formula at d distance [16]:

$$\Pr(d) = P_t - PL(d) \quad (2)$$

Where P_t is power transmission.

PARTICLE SWARM OPTIMIZATION

Eberhart and Kennedy created the PSO algorithm in 1995 as a random optimization technique. This tactic draws inspiration from social psychology as well as the dynamic behaviors of fish schools, birds, and insects. The PSO approach stands out as a widely utilized technique for addressing continuous and nonlinear optimization challenges [17].

Our approach's goal is to select optimum parameters of the long-distance PL model using measurements data to use it for producing predictions of optimum APs locations that give high coverage area with less interference. The proposed approach for optimizing PL using a fitness function may be readily applied in an actual case study. In the optimality research space, every particle in the swarm represents a possible solution. Let $Xi(t)$ represent the position and $Vi^{\rightarrow}(t)$ denote the velocity of the particle Pi at time t, as defined by the equation [17].

$$x_i^{t+1} = (x_i^t * w) + (c1*u1*P_{best}^t - P_i^t) + (c2*u2*P_{gest}^t - P_i^t) \quad (3)$$

$$P_i^{t+1} = P_i^t + x_i^{t+1} \quad (4)$$

where x_i^{t+1} is the velocity of next iteration, x_i^t is the velocity of i iteration, w is the weight that control the effect of the current velocity on the velocity of the next iteration, P_{pbest}^t is the best position i particle , the P_{gbest}^t is the best position in the swarm c1 and c2 are used to control the effect of P_{pbest}^t and P_{gbest}^t , and u1 and u2 are random numbers between 0 and 1.

METHODOLOGY

Experimental setup

The study was conducted on the sixth floor of a hospital building, characterized by concrete flooring, brick walls, glass windows with metal frames, and metal-framed doors. The experimental area comprised four zones, designated as zone 1, 2, 3, and 4, as depicted in Figure 1. The installed WLAN operated at 2.4 GHz with a bandwidth of 6 MHz. The separation distance between two RPs is 1 m along zone 1, 2, and 4, with 26, 20, and 22 RPs respectively, positioned at a height of 1 m. These RPs were designed to receive RSSI data from the four APs. The experimental design ensured that each AP maintained LOS with two zones while experiencing NLOS conditions with the remaining two, as illustrated in Figure 1. At each RP, RSSI samples were collected using netspot software installed on an HP laptop with specifications: an Intel Core i7-12650H processor, 16 GB of RAM at 2.30 GHz, with an NVIDIA GeForce GTX 1050 graphics card, and a 64-bit Windows 10 operating system. At each RP, 24 samples were collected in four orthogonal directions, capturing signals from the APs in all four zones. A total of 2,112 samples were aggregated across all zones Figure (1) show the positions of APs in the installed network the RPs in each zone and the direction of moving the receiver in each zone. The yellow points represent the APs, blue points are the RPs in Zone 1, purple points are the RPs in Zone 2, orange points are the RPs in Zone 3, and cyan points are the RPs in Zone 4. Black arrows represent the directions of RPs direction.

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The equipment used in the experiments clarified in Figure (2) including the 4 APs and the RP represented by the labtop. Table (1) list the configuration of these equipment

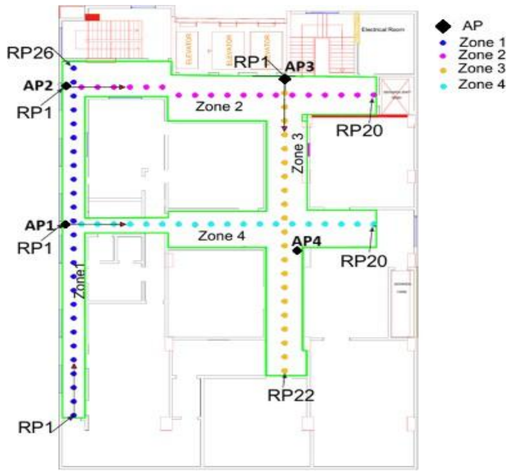


Figure 1:floor layout and Measurement setup.

(a) (b) (c) (d) (e)

Figure 2:experimental equipment in the experimental site: (a) AP1, (b)AP2, (c)AP3, (d)AP4, (e) RP.

Table 1:experimental set up specifications

Parameter	Configuration
Zone 1 (corridor 1)	2*26m
Zone 2 (corridor 2)	2.5*20m
Zone 3 (corridor 3)	2.5*22m
Zone 4 (corridor 4)	2.5*20m
Communication protocol	802.11n
No. Channels	6
Channel Bandwidth	20MHz
Frequency	2.4 GHz
Transmitter height	1.5m
Transmitter gain	5dBi
Transmitter and receiver antenna	Omni-direction
Transmission power	20dBm
RP height	1m
Receiver gain	3dBi

Proposed Mode

This study aims to present multi-stage to minimize interference between installed APs in four zones and maximize the coverage area in these zones passing through three stages including:

1. **Initial Stage** : this stage is foundation of the proposed framework on comprises the following steps:

a. Setup initial network: The test scenario consists of four WiFi APs deployed in an indoor environment, each in one outlying zone.

DOI: 10.46121/pspc.53.2.26

b. RSSI measurement and Data Collection

The RSSI values are collected from the APs across multiple RPs along each zone. The RPs are spaced according to the zone lengths to capture a comprehensive dataset for each section.

$$RPs = \begin{bmatrix} RSSI_{1,1} & RSSI_{1,2} & RSSI_{1,3} & RSSI_{1,n} \\ RSSI_{2,1} & RSSI_{2,2} & RSSI_{2,3} & RSSI_{2,n} \\ RSSI_{3,1} & RSSI_{3,2} & RSSI_{3,3} & RSSI_{3,n} \\ RSSI_{m,1} & RSSI_{m,2} & RSSI_{m,3} & RSSI_{m,n} \end{bmatrix} \quad 5$$

PL Model Optimization Stage

This stage focuses on optimizing the PL model parameters using RSSI data. A long-distance PL model is selected depending on the RSSI characteristics of the environment. A PL model is provided for each zone utilizing the measured RSSI values as empirical data for PL. PSO was employ to refine PL parameters (e.g., PL exponent and Standard deviation) for each zone to create a PL model for each zone. Gaussian distribution and Standard deviation' ranges for simple indoor environment are listed in Table 2 [18].

Table 2: PL parameters for indoor environment at 2.4GHz

scenario	PL exponent	Standard deviation
LoS	1.6-1.8	3-6
NLoS	3-4.5	6-10

These values are adjusted using the PSO algorithm by minimization of the error, in terms of MSE which is expressed in equation (6) to create a PL model for each zone. The aim is to reduce the MSE between the empirical and estimated PL for each RP. This phase produces ideal values for PL parameters that precisely represent the conditions in each zone.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(PL_{emp} - PL_{est}\right)^2 \quad 6$$

Where PL_{emp} is the empirical PL at each receiver PL_{est} is PL estimated by PSO , and N is number of receiver at each zone.

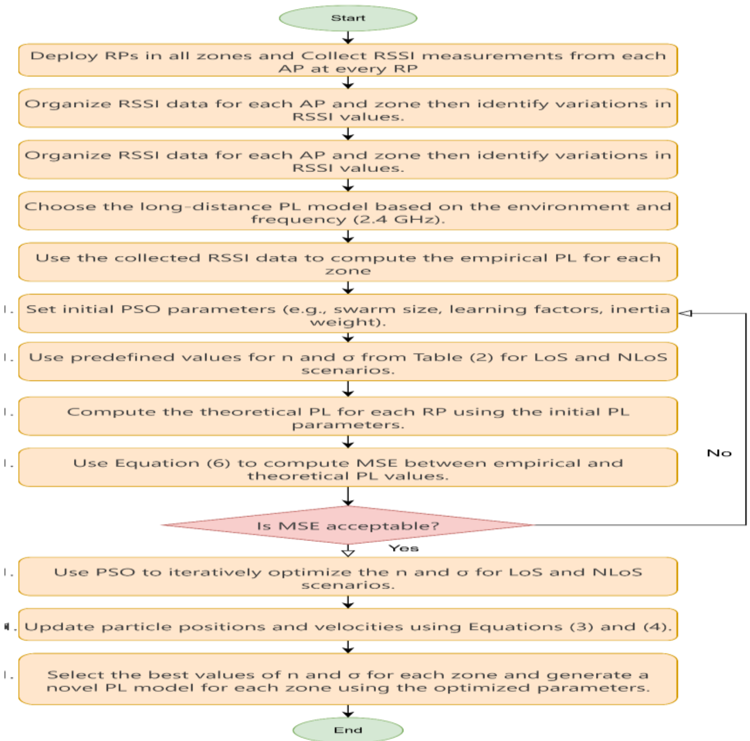


Figure 3: flowchart of proposed PL model for each zone.

AP Locations Optimization Stage:
Using the optimized PL model, a second PSO optimization has been implemented to distribute the APs by reducing interference caused by multiple APs and enhancing the coverage area at each zone. The RSSI and interference as the basis for its fitness function, aiming to keep RSSI values above the threshold (e.g., -60 dBm) and ensure minimal overlap and interference among APs. Formally, the optimization problem is given equation by

$$fitness\_function(Xi) = -(\alpha * f_{coverage} + \beta * f_{SIR}) \quad (7)$$

$$X_i = \left\{ AP1_{x,y}, AP2_{x,y}, AP3_{x,y}, AP4_{x,y} \right\} \quad (8)$$

Where α and β are weights to balance between the interference and the coverage functions. In this study, α and β are equal 0.5 to balance between the SIR and coverage area. The minus sign is to reverse PSO work and minimize the cost function. The first part of the fitness function:

$$f_{SIR} = \frac{\sum_{i=1}^{N} SIR_i}{N} \quad (9)$$

Where N is number of receivers at each zone. SIR are calculated at each receiver by:

$$SIR_i = \frac{M}{\sum_{k=1, k\neq m}^{K} \Pr_k} \quad (10)$$

Where M is the maximum signal strength P_r in mWatt. P_{rk} is the PR at each RP measured in mWatt. The second part of fitness function is

$$f_{coverage} = \frac{C}{N} \quad (11)$$

Where

$$C = \begin{cases} 1, if\ ...RPs >= RSSI_{threshold} \\ 0 \end{cases} \quad (12)$$

Where $RSSI_{threshold}$ which is -60 in this study.
With some constraint

$$fitness\_function = \begin{cases} \infty, f_{SIR} \leq SIR_{threshold} \\ 0, otherwise \end{cases} \quad (13)$$

$$SIR_{threshold} = 1.5$$

To guarantee not overlapping the APs, in this study we used the constraint:

$$d_{APs} = \begin{cases} \infty, if \ldots d_{APs} \prec \min\_distance \\ 0 \end{cases} \quad (14)$$

Where minimum distance between two APs is 5m.

DOI: 10.46121/pspc.53.2.26

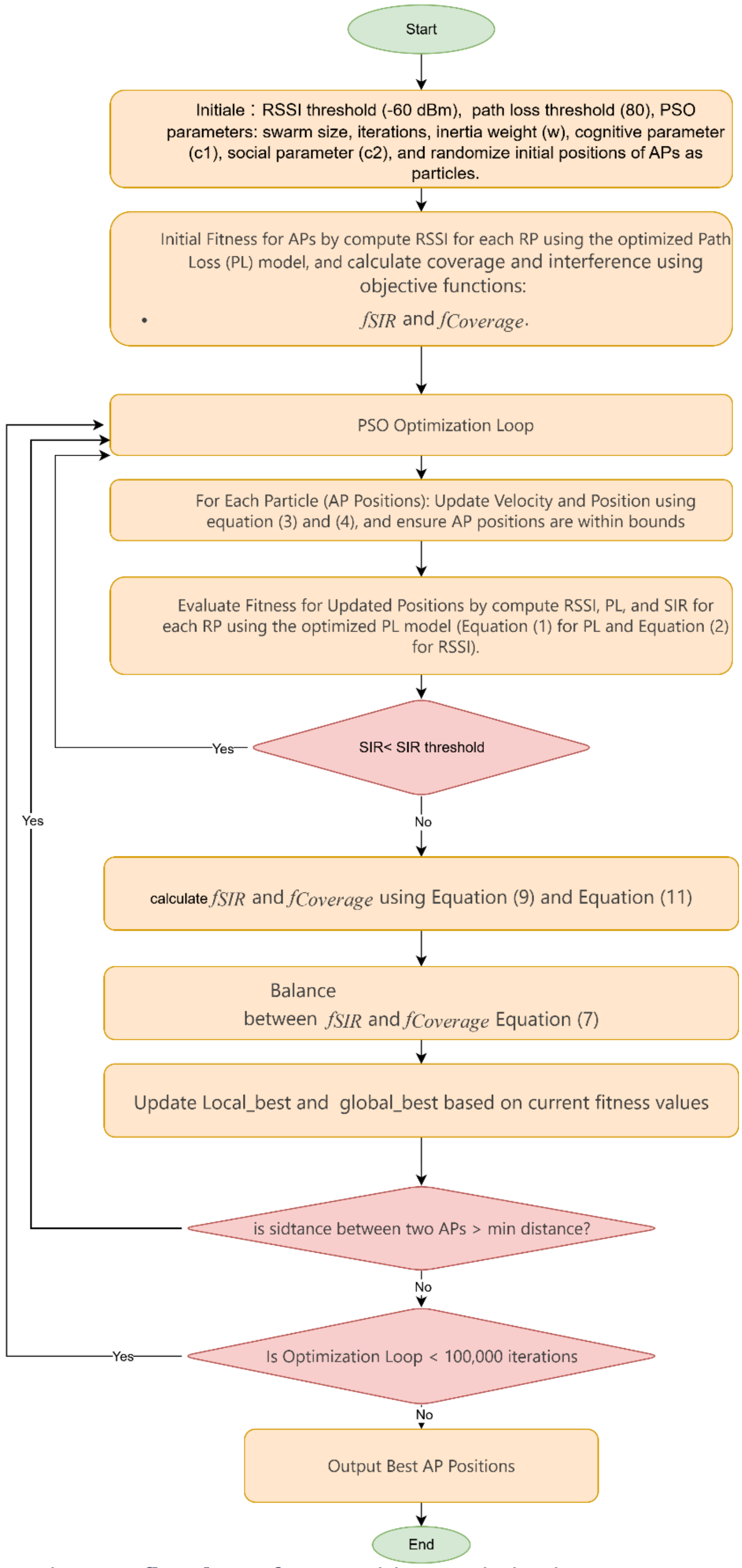


Figure 4: flowchart of APs positions optimization process .

Combining both flowcharts, here's an integrated methodology for optimizing the network's PL model parameters and AP locations in a single flowchart format:

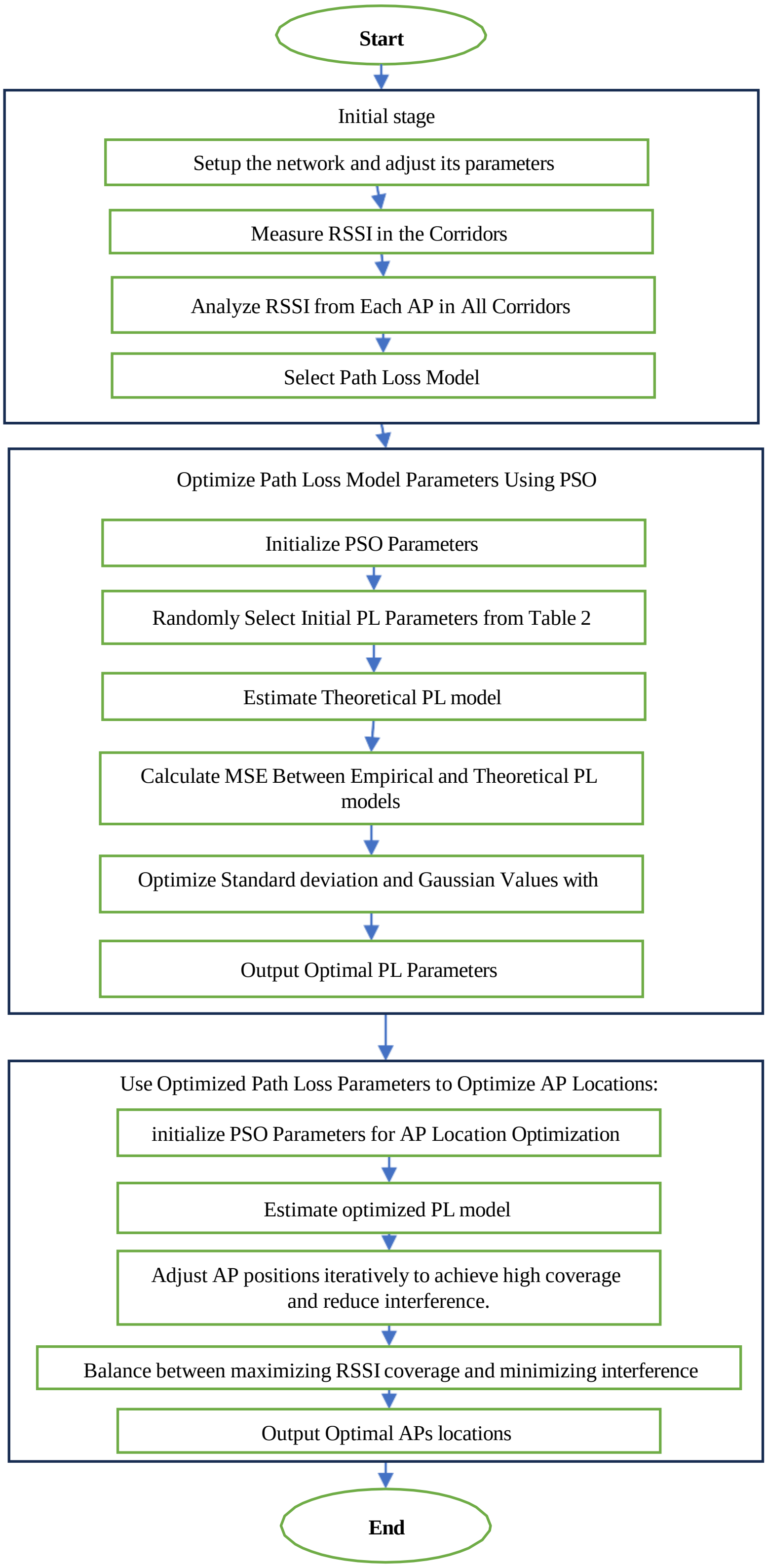


Figure 5: flowchart of the proposed work.

DOI: 10.46121/pspc.53.2.26

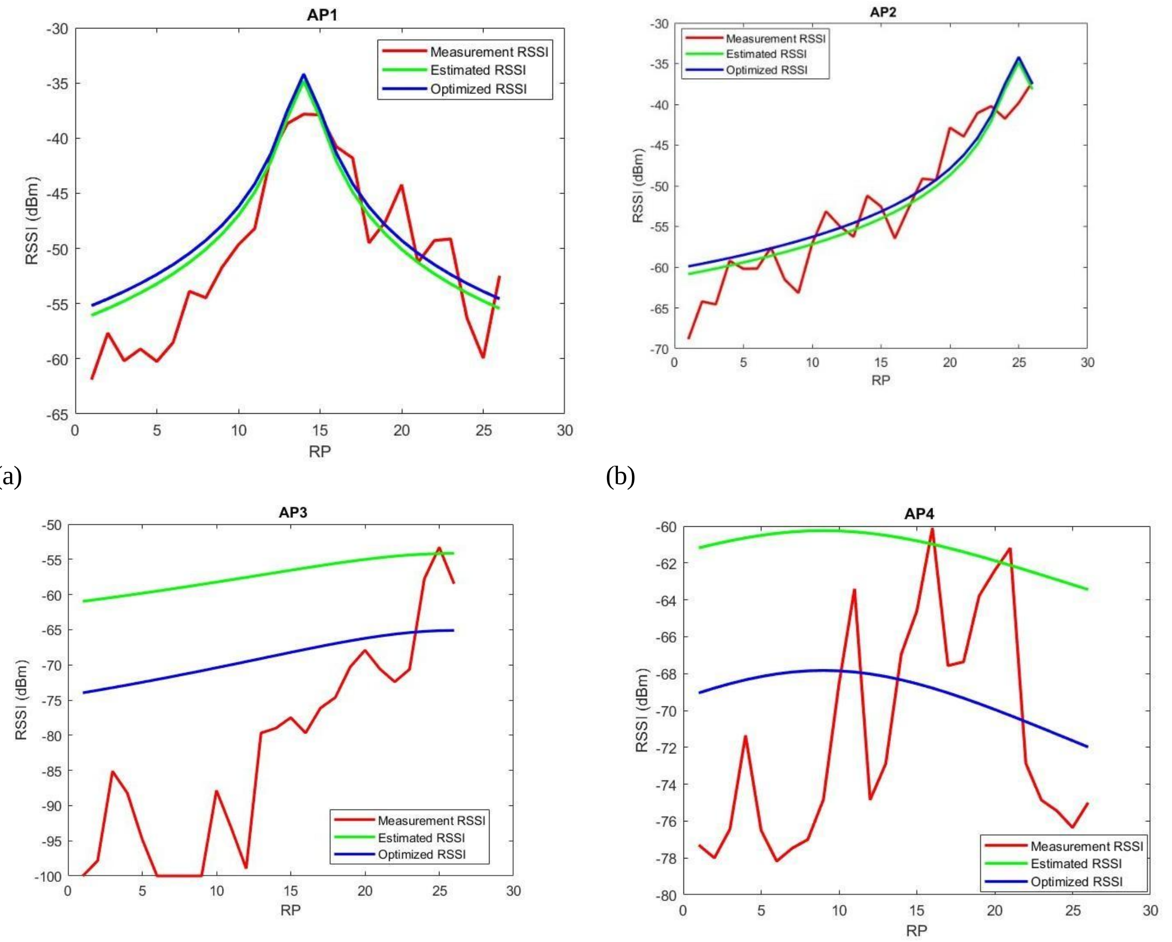
Power System Protection and Control
ISSN:1674-3415

RESULTS AND DISCUSSIONS

The results of the proposed work are divided into two sections, first one includes the results of evaluating the accuracy of measurement data by comparing it with theoretical data and data resulted by the optimized PL model. While the second section focus on the results of the optimized network highlighting the improved AP locations to enhance the coverage and reduce interference between them.

PL model optimization

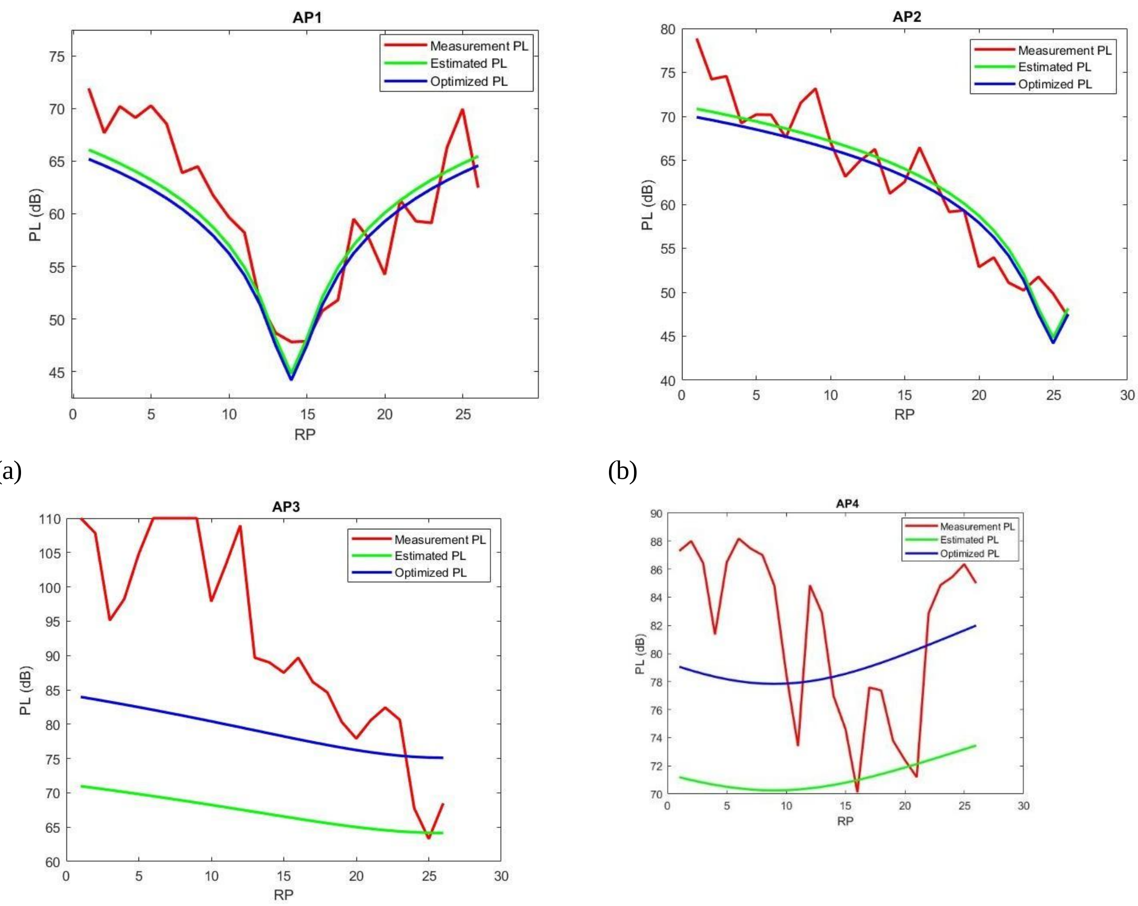
The PL of the installed network was calculated based on the measured data and compared with the long-distance PL which was derived using equation (2). The comparison was conducted to evaluate the accuracy of the measurement data for each zone across the four APs. After applying PSO and creating the optimized PL model for each zone, the RSSI at each RP was updated to reflect the changes in PL parameters. Figure (6) expounded the RSSI at each RP in zone 1 from all APs, it can be noted that the AP1 and AP2 covered the zone whereas AP3 and 4 covered some RPs. On the other hand, the optimized RSSI results from the novel PL model for zone 1 the close to the real RSSI.



(a) (b) (c) (d)

Figure 6:comparison between RSSI of measurement, optimized model, and theoretical model of the installed network in zone 1 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

Also, Figure (7) explain the real, estimated and novel PL of RP in zone 1.

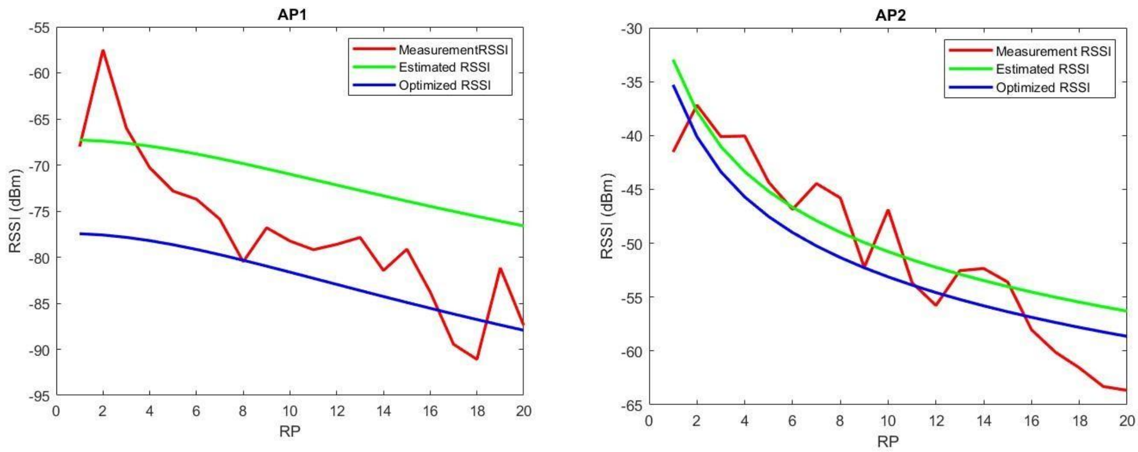


(a) (b)

(c) (d)

Figure 7: PL of the installed network in zone 1 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

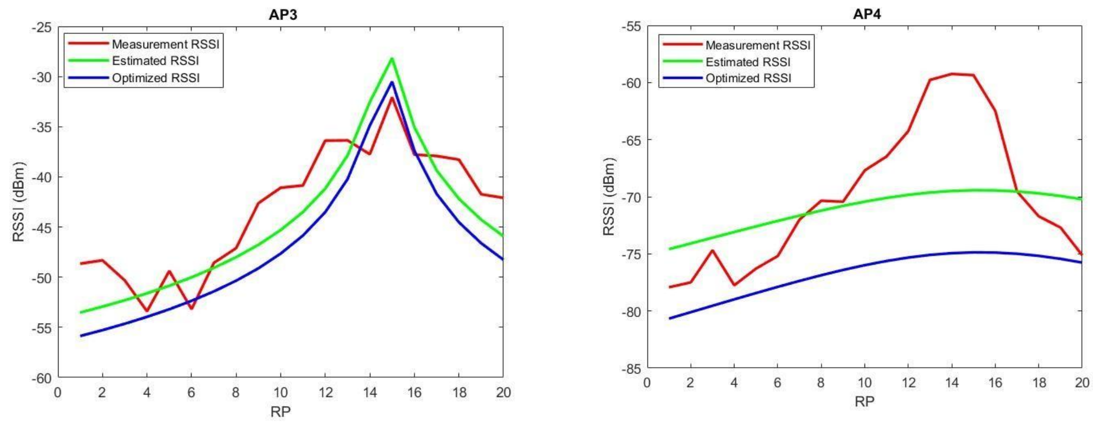
The RSSI at each RP in zone2 are demonstrated in Figure (8) . AP2 and AP3 are covered this zone with good coverage area. In figure (8), the PL of these APs are illustrated.



(a) (b)

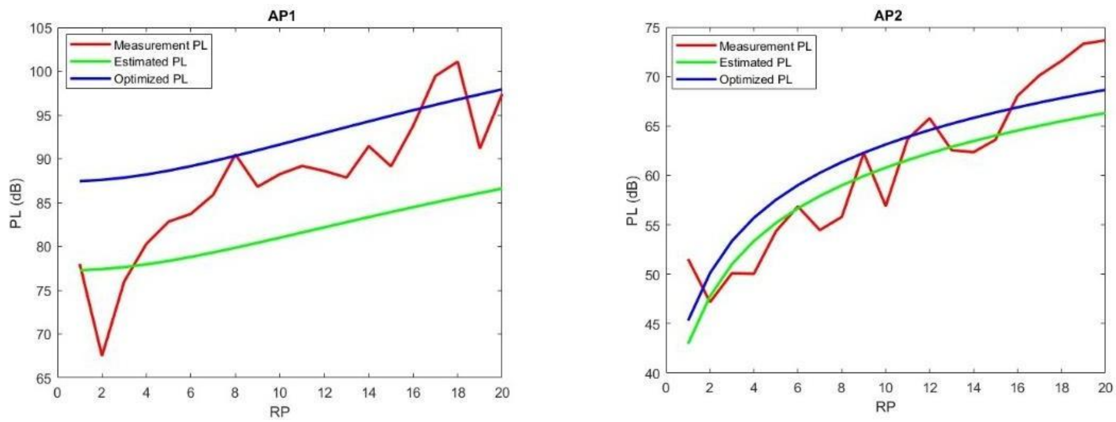
DOI: 10.46121/pspc.53.2.26

Power System Protection and Control
ISSN:1674-3415

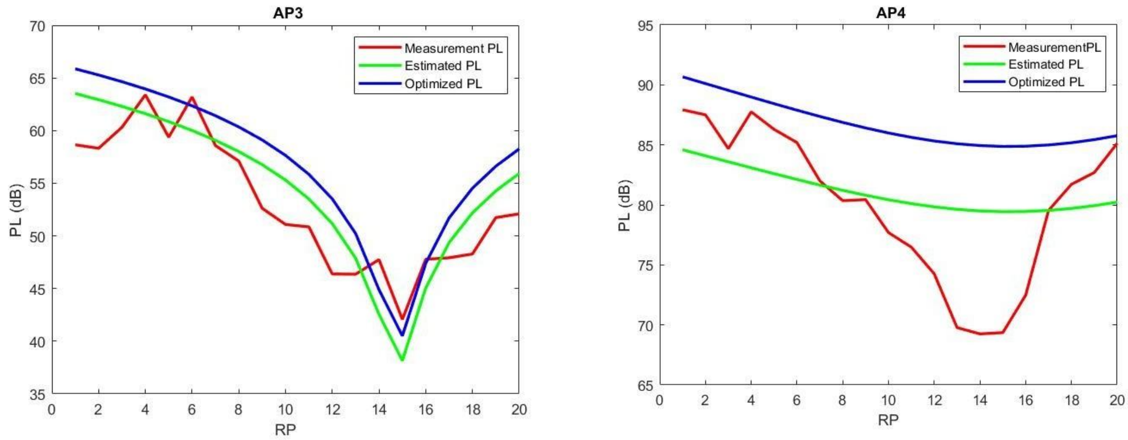


(c) (d)

Figure 8:comparison between RSSI of measurement, optimized model, and estimated model of the installed network in zone 2 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.



(a) (b)



(c) (d)

Figure 9: PL of the installed network in zone 2 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

The RSSI in zone 3 and the PL are explained in Figure (10) and figure (11) respectively.

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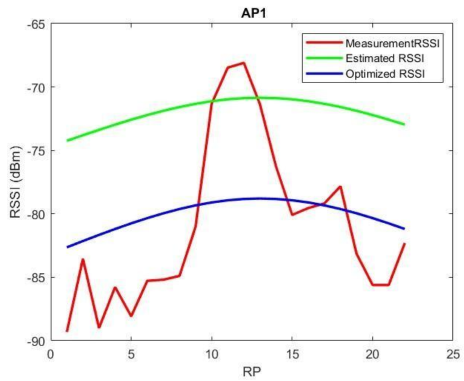
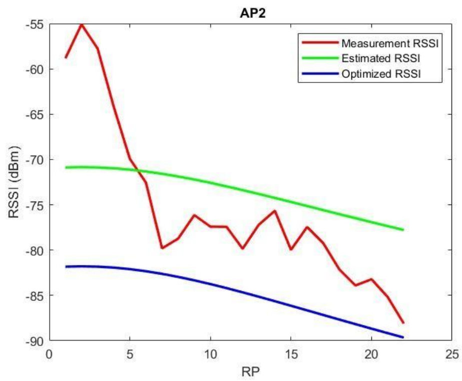
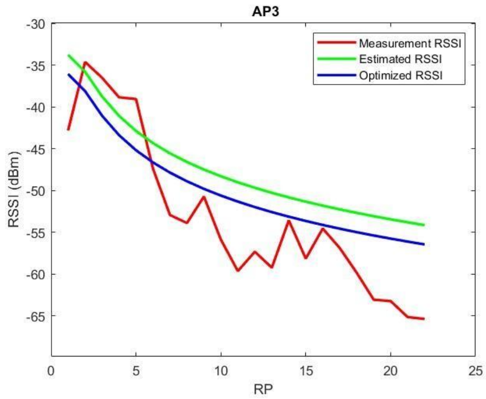
Power System Protection and Control
ISSN:1674-3415



(a)



(b)



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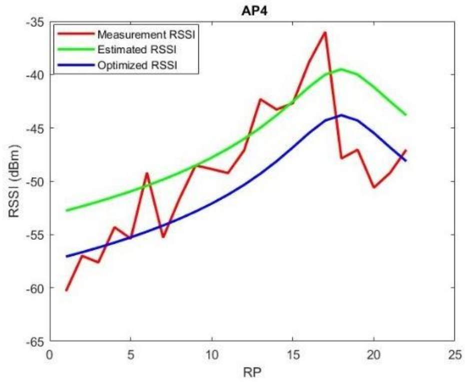
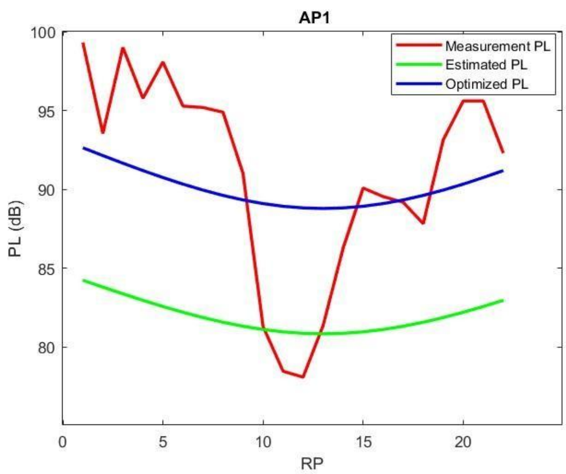
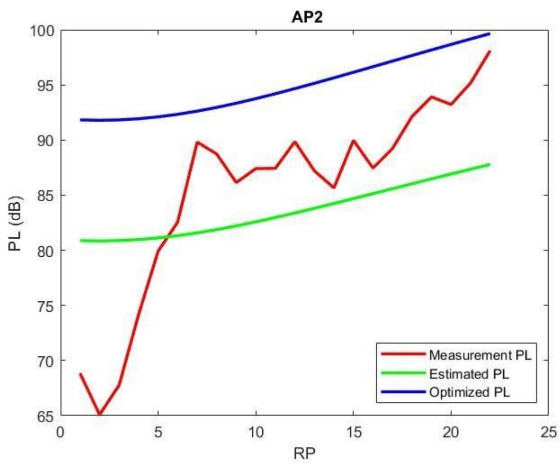


(d)

Figure 10:comparison between RSSI of measurement, optimized model, and theoretical model of the installed network in zone 3 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.



(a)



(b)

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Power System Protection and Control
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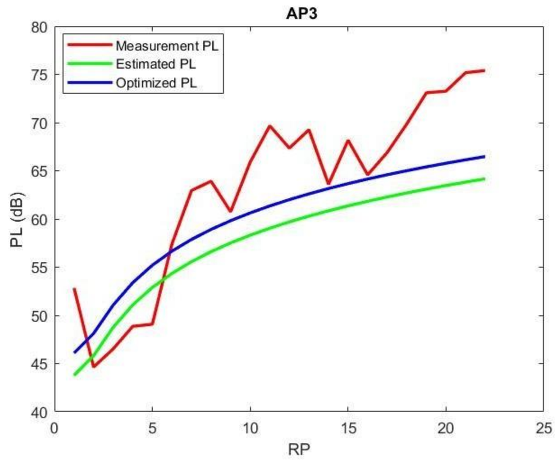

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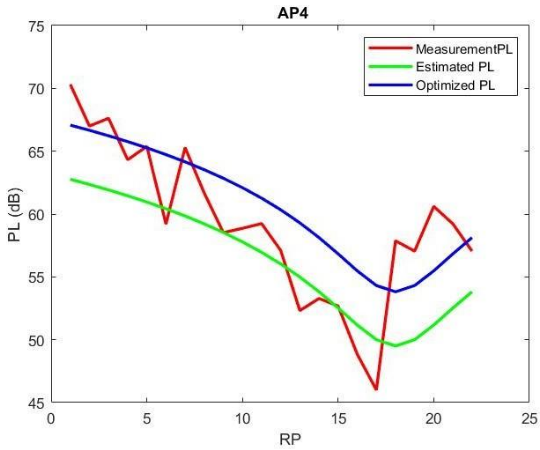
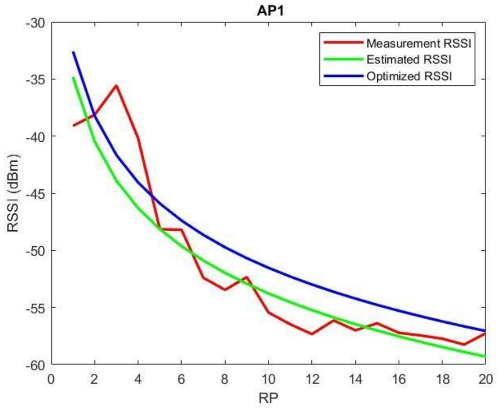


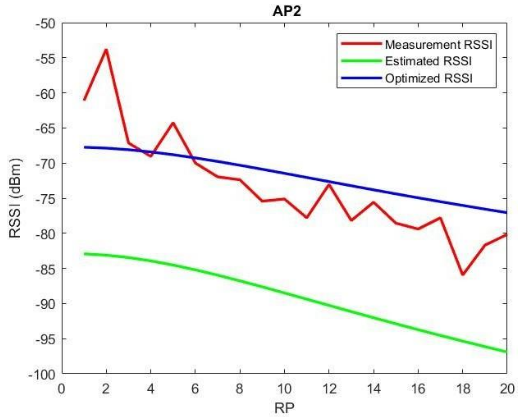
(d)

Figure 11: PL of the installed network in zone 3 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

Finally, the coverage area of zone 4 in terms of RSSI and PL are illustrates in Figure (12) and figure (13), respectively.



(a)



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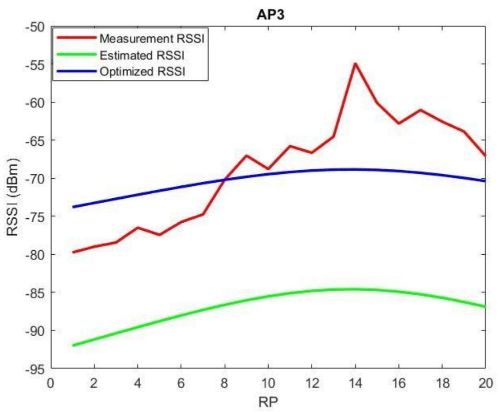
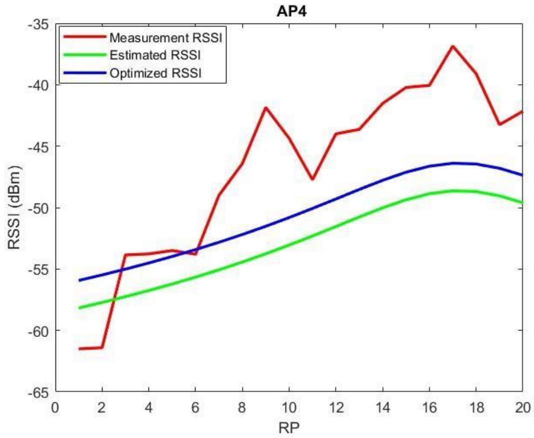


(c)



(d)

Figure 12:comparison between RSSI of measurement, optimized model, and theoretical model of the installed network in zone 4 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

DOI: 10.46121/pspc.53.2.26

Power System Protection and Control
ISSN:1674-3415

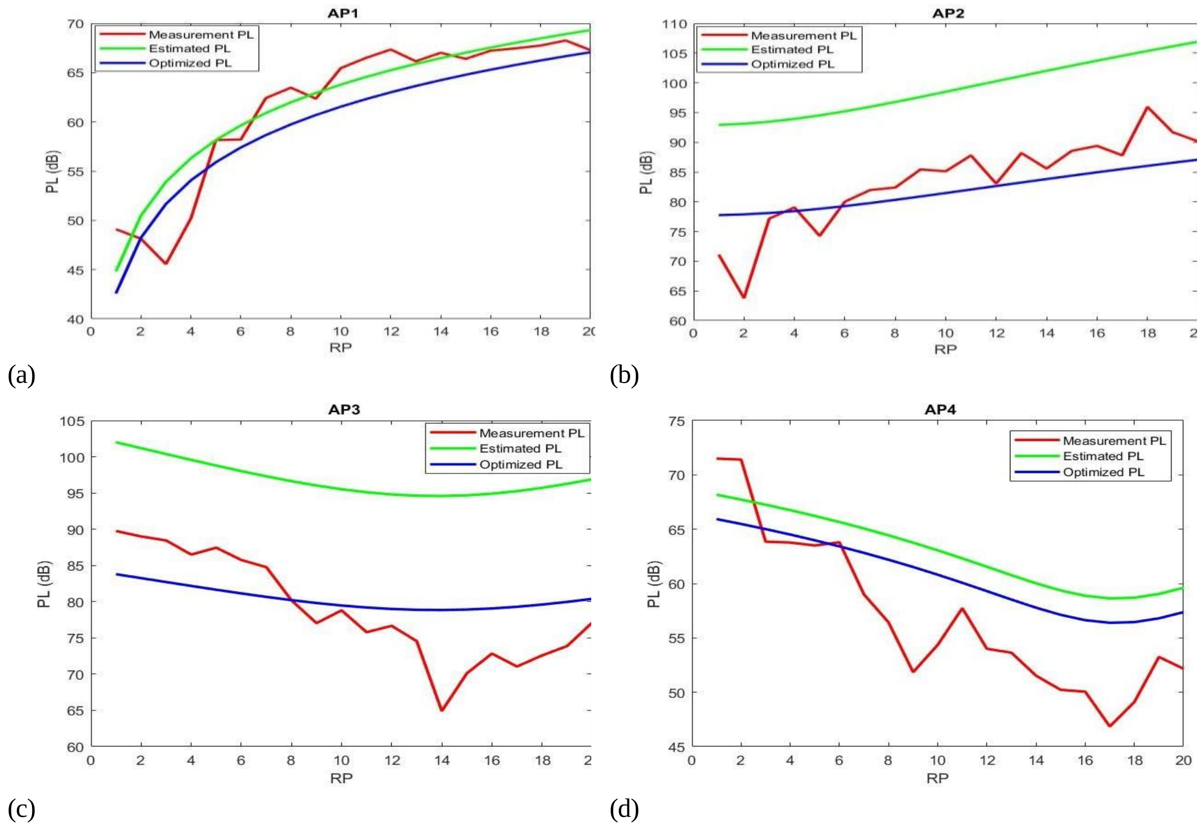


Figure 13: PL of the installed network in zone 4 from: (a) AP1(b) AP2 (c) AP3 (d) AP4.

The optimized PL model shows a strong correlation with the empirical RSSI data validating its effectiveness in capturing realostic signal behavior. The optimized PL model is created by optimizing the parameters of the long distance PL model for each zone for all APs Using PSO. the optimized PL model represented the novel PL model for each zone. The fitness function of the proposed model in terms of MSE decreased significantly for all zones as clarified in Figure (14).

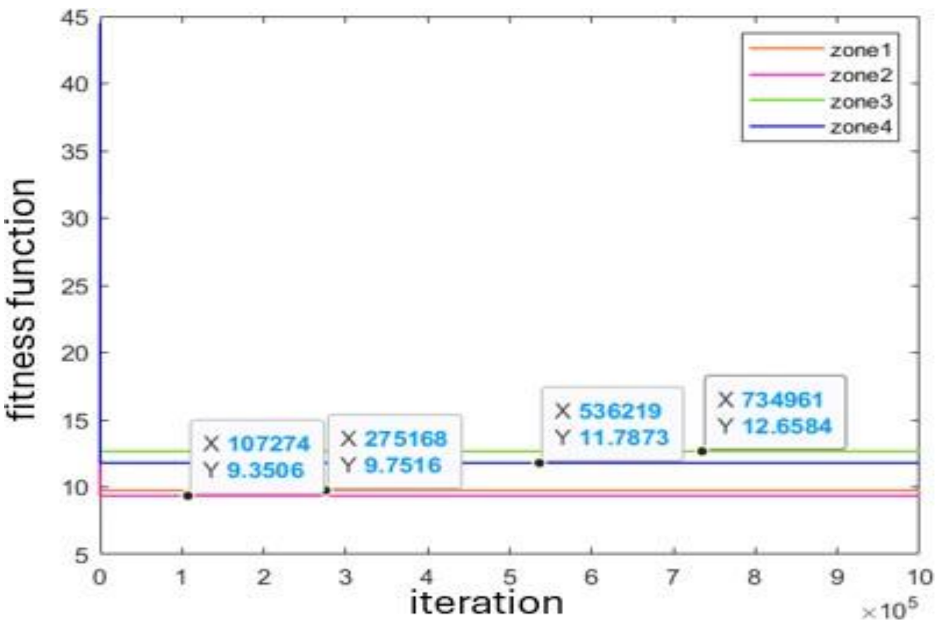


Figure 14: fitness function of PSO for all zones.

Power System Protection and Control
ISSN:1674-3415

The optimized parameters which are listed in Table (3) are selected from the range of them in Table (2). In zone 1, AP1, and AP2 are LoS with the RPs while AP3 and AP4 are NLoS with RPs. AP2 and AP3 are LOS with RPs in zone 2 whereas AP1 and AP4 are NLoS with them. Whereas AP3 and AP4 are LOS with RPs in zone 3 and AP1, AP2 are NLoS with them. Finally, AP1 and AP4 are LOS with RPs in zone 4, and AP2, and AP3 are NLoS with them.

Table 3: optimized parameters for optimized PL models for each zone in LoS and NLoS scenarios.

scenario	LoS		NLoS	
PL parameters	n	σ	n	σ
zone1	1.8	5.54680353828335	3.51026000032416	9.64060822034534
zone2	1.76556084990013	6	3.2223	9.91317242147897
zone3	1.8	5.06724408616220	3.52886216348056	6.89233478681771
zone4	1.64545022544877	3	3.99921812085644	9.35302164644985

The MSE between real PL and theoretical PL was calculated to evaluate the accuracy of real data whereas the MSE between real PL and optimized PL model was calculated to compare with MSE between measured PL and theoretical PL for each AP in all zones as illustrated in Figure (15). It can be noted that the RPs located in the intersection areas between zones are LoS with the APs in other zones increasing MSE values such as RPs (24, 25, 26) in zone LoS with AP3, RPs (13,14,15) in zone 2 are LoS with AP4, RPs (11,12,13) in zone 3 are LoS with AP1, and RPs (14,15,16) in zone 4 are Los with AP3. On the other hand, it can be observed that the MSE values reduced significantly compared to pre-optimization values. This reduction illustrates the accuracy of the optimized PL model in fitting the real data, improving the predictions for RSSI and PL for the APs location optimization stage.

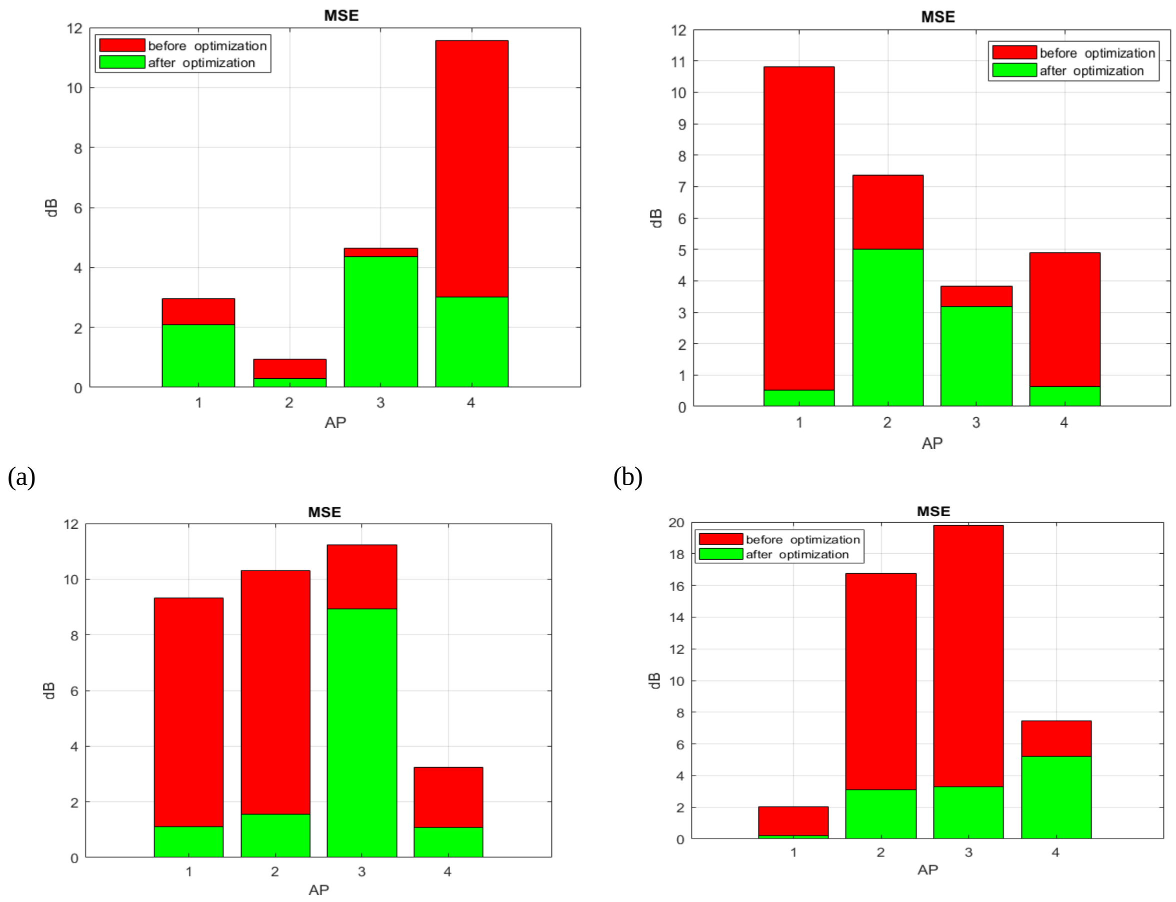


Figure 15: MSE of PL for: (a) zone1 (b zon2 (c) zone3 (d) zone4.

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APs locations optimization

The optimized Pl model is utilized to calculate the PL and determine the optimal locations for all APs. This guarantees that each RP receives a strong RSSI signal from at less from one AP. The fitness function of the proposed model strikes a balance between maximizing coverage area and minimizing interference by maximizing SIR, as demonstrated in Figure (16). The best fitness function reached the best value of -78.5483 at iteration 697484. The SIR at zone1, zone 2, zone3 and zone4 equal 1.00334, 1.02551, 1.05186, and 1.03846, respectively which are less than the SIR threshold which means that the interreference between the APs across each zone is minimum.

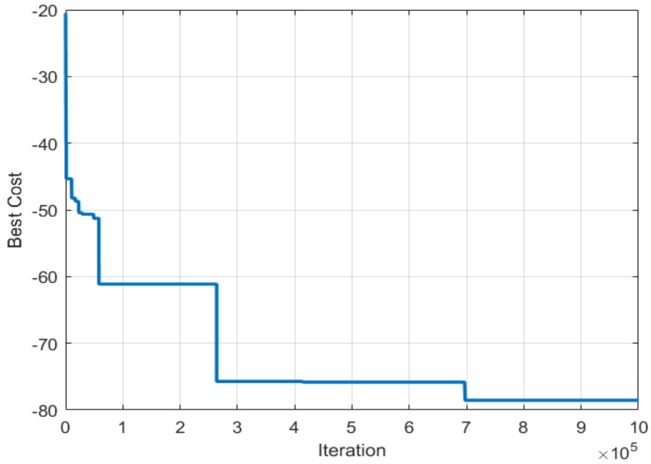


Figure 16: fitness function of the APs locations optimization stage.

APs locations in the optimized network are determined by PSO at all zones which is shown in Figure (17). The APs distributed in locations at a height of 2m above the ground on the floor. These locations covered a wider area and made each RP receive high RSSI with less interference between APs.

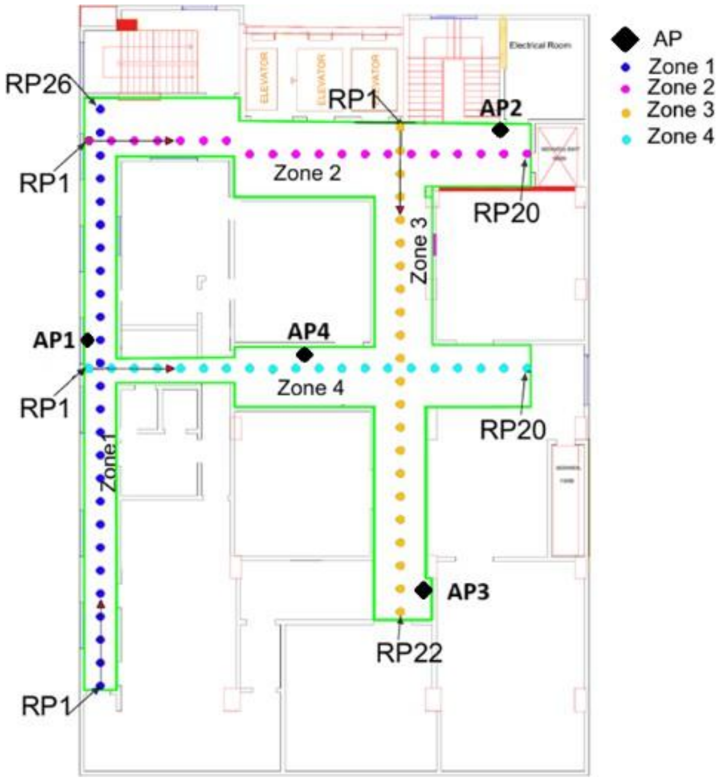
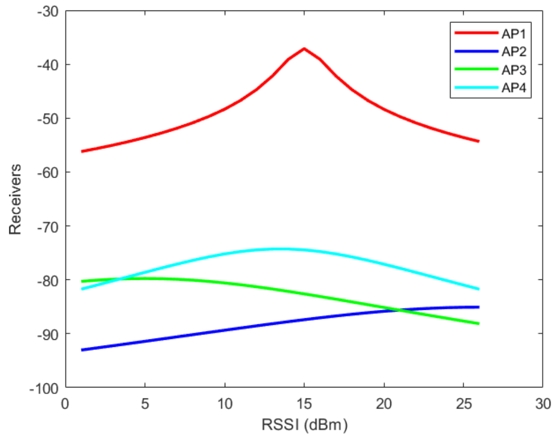


Figure 17: optimized Network.

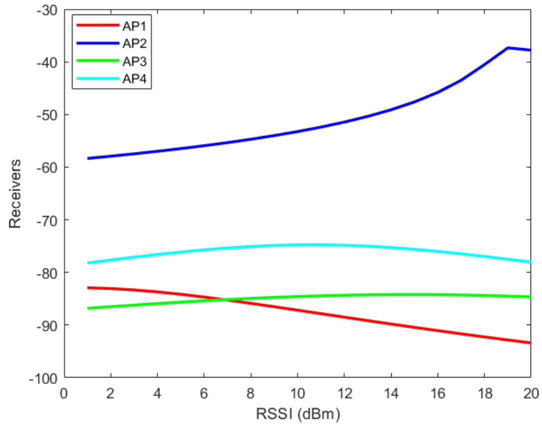
DOI: 10.46121/pspc.53.2.26

Power System Protection and Control
ISSN:1674-3415

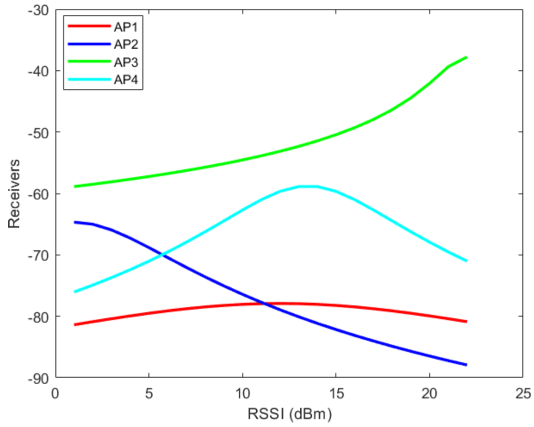
The RSSI and PL of the optimum network at each RP in all zones are show in Figures (18) and (19) respectively. At zone 1, RPs (1-5) primarily receive the RSSI from the AP4 then RPs (6-17) covered by AP1, while the remaining RPs signals receive from both AP4 and AP2. In Zone 2, AP2 provides full coverage for the entire zone. RPs from (1-7) receive RSSI from AP3, RPs (8 -17) are covered by AP4, and RPs(18-22) receive RSSI from AP3 at zone 3. The last zone, zone 4, AP4 propagates to all RPs in the zone.



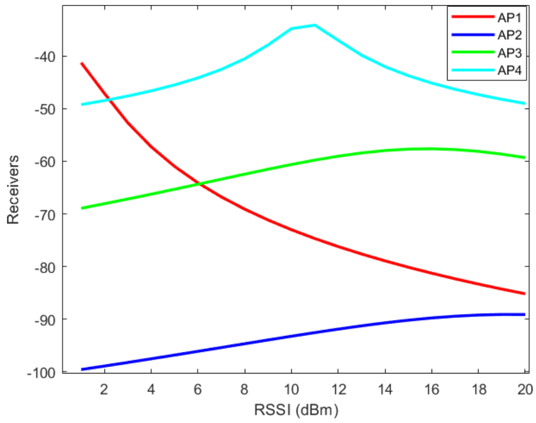
(a)



(b)

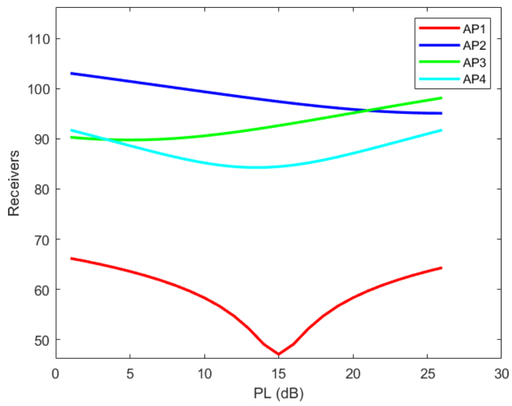


(c)

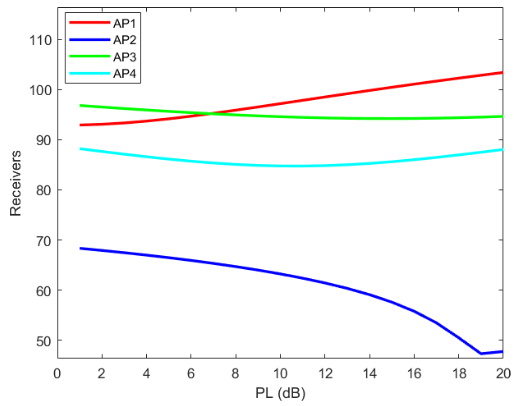


(d)

Figure 18: Optimized RSSI Distribution Across Receivers in: (a) zone1 (b) zone2 (c) zone3 (d) zone4



(a)



(b)

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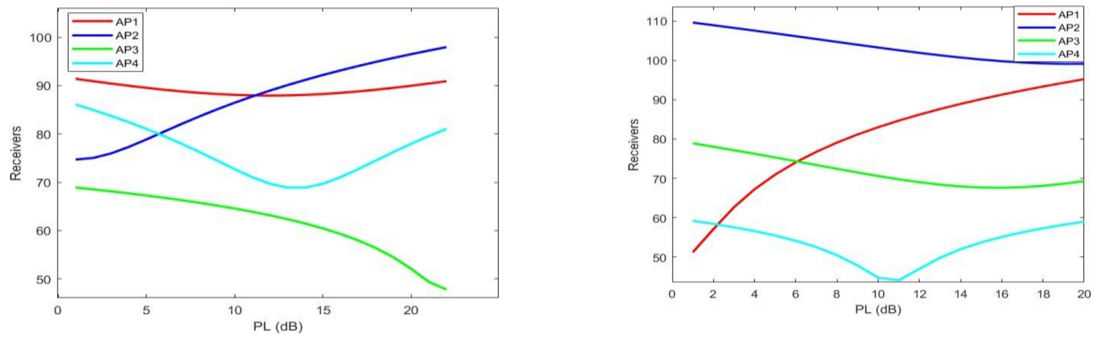
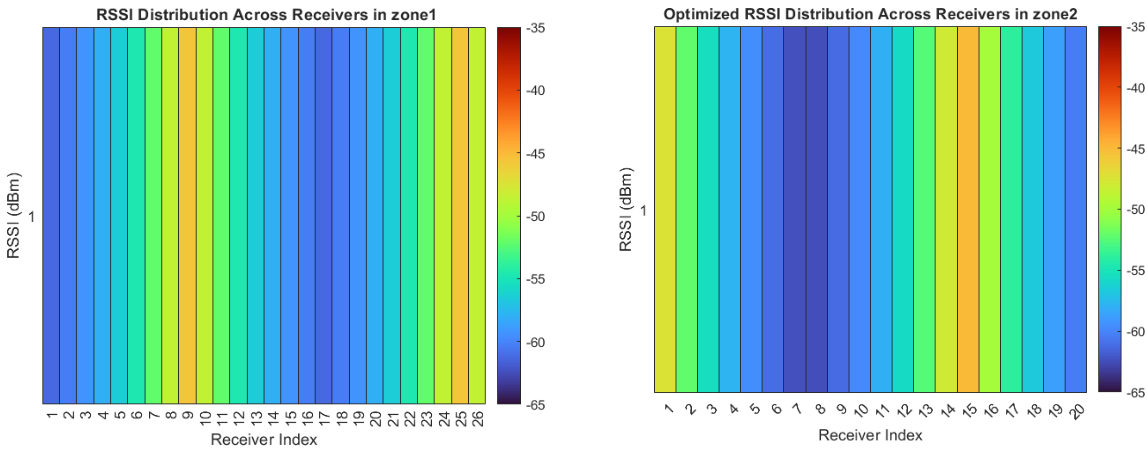


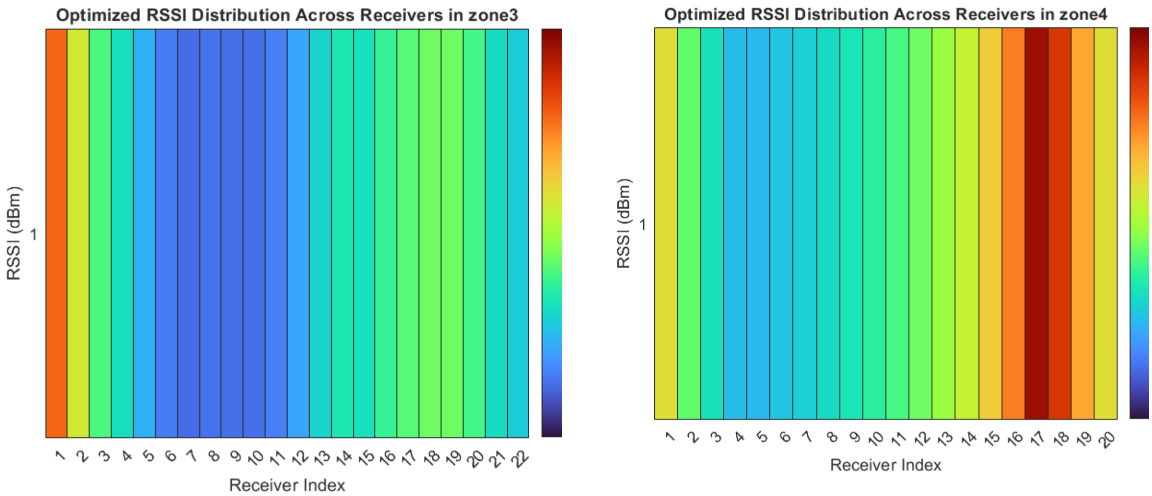
(c) (d)

Figure 19: PL of optimized Network

The heatmap for all zones optimization illustrates the RSSI distribution after and before optimization cross each RP with red to cyan gradient in Figure (20) and Figure (21It demonstrates how RSSI values fluctuate with the red parts showing stronger signals and the cyan area showing lower signals.. For the visualization, it is evident that all RPs cross each zone and receive RSSI values above the predefined RSSI threshold. The comparison between RSSI distribution in the installed network and the optimized network demonstrates that all PRs at all zones get good RSS.



(a) (b)



(c) (d)

Figure 20: : heatmap of RSSI for installed network in : (a) zone 1, (b) zone 2, (c) zone 3, (d) zone 4.

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Power System Protection and Control
ISSN:1674-3415

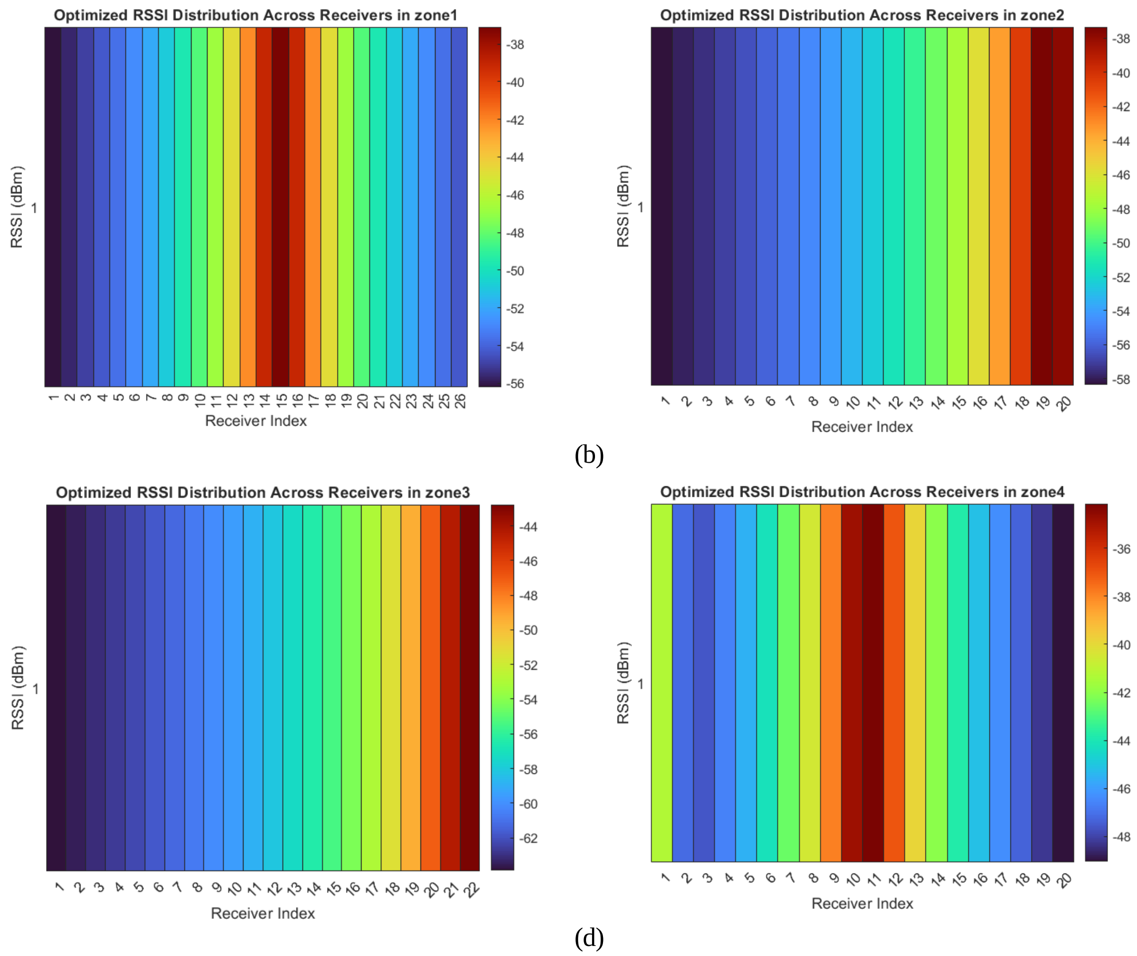
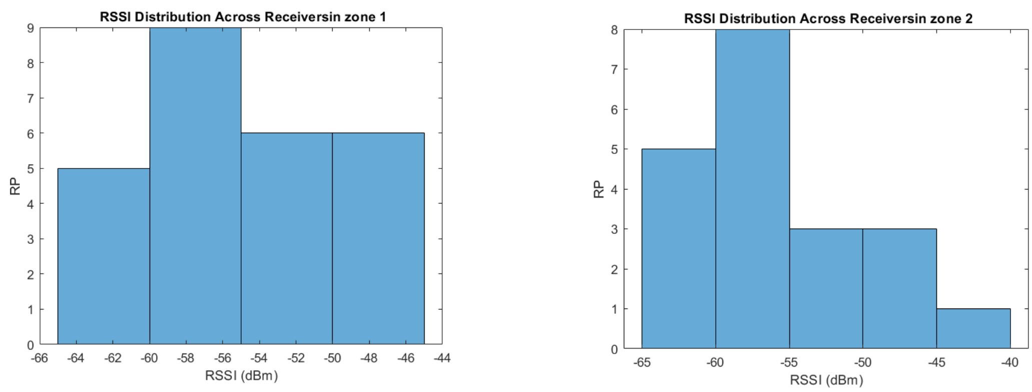


Figure 21: heatmap of RSSI for optimized network in : (a) zone 1, (b) zone 2, (c) zone 3, (d) zone 4.

The histogram of RSSI for both installed and optimized networks as shown in figures (22) and (23), illustrate the RSSI range across all RPs:

- zone 1: in installed network the range of RSSI, ranged between -45 dBm to -65 dBm while in optimized network, it improved to a range of -35 dBm to -60 dBm.
- zone 2: the RSSI for the installed network varied between -40 dBm to -65 dBm, while for the optimized network, it ranged from -30 dBm to -60 dBm.
- zone 3: the installed network exhibited an RSSI range -40 dBm to -65 dBm whereas the optimized network showed an improved range of -35 dBm to -55 dBm.
- zone 4: in contrast to other zones, the installed network had an RSSI range of -30 dBm to -60 dBm while optimized network showed a range of -30 dBm to -50 dBm.



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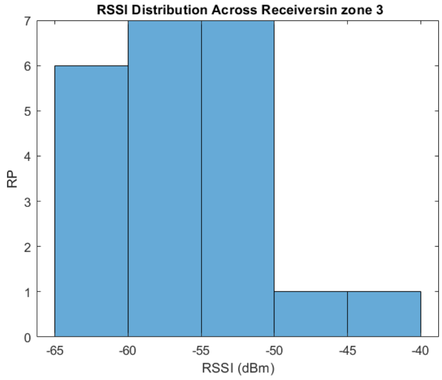
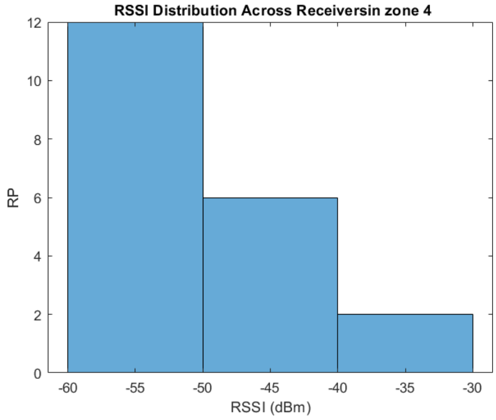
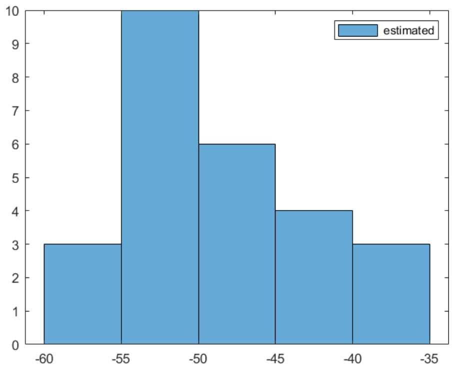
(a) (b)

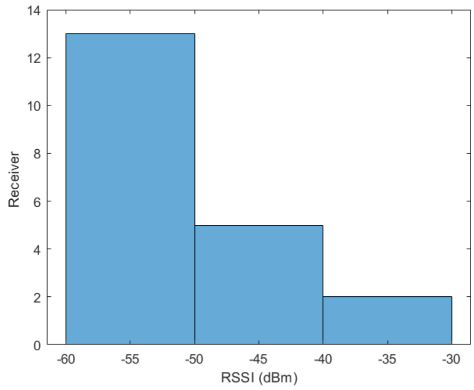




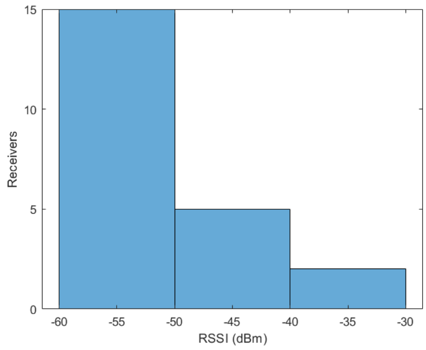
(c) (d)

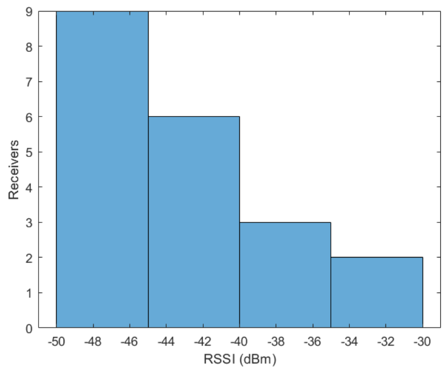
Figure 22: histogram of RSSI for installed network in : (a) zone 1, (b) zone 2, (c) zone 3, (d) zone 4.





(a) (b)





(c) (d)

Figure 23: histogram of RSSI for optimized network in : (a) zone 1, (b) zone 2, (c) zone 3, (d) zone 4.

The SIR at RPs in all zones are illustrated in figure (24), its clearly show that not only PSO enhanced coverage across all zones but also reduce coverage gaps and interference in dead zones. Additionally, Enhancement at zone 4 is the highest among the rest zones.

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Power System Protection and Control
ISSN:1674-3415

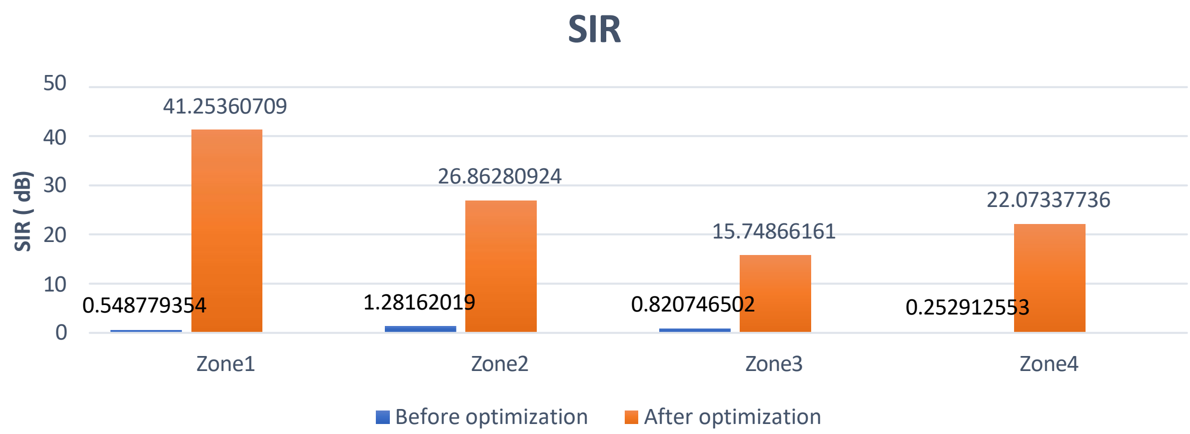

Figure 24: SIR before and after applied PSO for all zones.

The proposed multi-stage optimization framework for Wi-Fi APs demonstrates significant improvements in indoor wireless network performance compared to installed network. Through addressing the issue of signal coverage, interference, and PL issues in intricate indoor environments, this investigation offers an effective strategy for AP placement optimization in smart healthcare applications and other contexts. The combination of PL model optimization, empirical data collecting, and PSO-assisted AP placement optimization demonstrates how well the strategy works to provide great coverage and low interference. The results obtained demonstrate that the optimized PL model improves prediction accuracy for signal propagation by considerably lowering MSE between empirical and theoretical PL values. By guaranteeing that all RPs get strong signal strength over the predetermined threshold (-60 dBm) while minimizing interference, the optimal AP location further improves network performance. The suggested approach effectively strikes a compromise between coverage and interference reduction, as demonstrated by SIR values for each zone. The SIR is optimized from 0.5488 dB, 1.2816 dB , 0.8207 dB ,and 0.2529 dB to 41.2536 dB, 17.4920 dB, 10.6807 dB and 13.8691 dB, for zone1, zone2, zone3 and zone4, respectively. According to SIR results the optimized network is successful interference mitigation. Moreover, from Figure (3), its clear that SIR is much higher after optimization ×(75.17, 20.96,191.19, and 87.28) times for zone1,2,3,and 4, respectively ,than before optimization pointing to PSO performance to mitigate the weak spots across the zones.

The significance of taking into account both LoS and NLoS situations in interior spaces is also emphasized in the study. The PSO-derived optimized PL parameters for each zone give a more accurate representation of signal propagation in the actual environment, which is essential for creating dependable wireless networks. Visual representations of the RSSI distribution's heatmaps and histograms before and after optimization show how well the suggested technique works to increase signal strength and coverage. The study has limitations to a particular indoor environment (a hospital building) with regulated configuration, notwithstanding its beneficial results. Due to variations in construction materials, layout, and sources of interference, the suggested solution may not function as well in other situations, such as offices, retail centres, or industrial settings. Furthermore, the study is based on static conditions, which could not accurately represent the dynamic nature of situations in reality where signal propagation might be impacted by human movement and other variables.

CONCLUSION AND FUTURE WORK

This study presents a novel indoor placement model based multistage process. The proposed model uses PSO to novel a PL model for four zones and use this model to optimize a WiFi placement model considering LoS and NLoS scenarios. In PL parameters optimization stage, MSE have been calculated between measurement PL and theoretical PL to evaluate the reliability of measurement data. The RSME optimized by select the best PL parameters which is achieved 0.28dB, 0.23 dB, 0.53 dB, 0.2dB at zone 1 zone 2, zone 3, and zone 4, respectively. At APs location stage, the optimum distribution of AP reduced the interference and covered all RPs across zones with -60dBm. The SIR of the optimized network illustrates that the distribution of APs results low interference between them. The effectiveness of optimized process makes the optimized network more suitable for applications requiring precise indoor positioning and robust connectivity for future work.

REFERENCES:

1. Bakar, K.B.A., et al., A review on the immediate advancement of the Internet of Things in wireless telecommunications. IEEE Access, 2023. 11: p. 21020-21048.
2. Raman, R., et al. Enhancing Wi-Fi Signal Performance via Strategic Access Point Placement using Genetic Algorithm Approach. in 2024 Second International Conference on Data Science and Information System (ICDSIS). 2024. IEEE.
3. Yang, Y., et al., Positioning using wireless networks: Applications, recent progress and future challenges. arXiv preprint arXiv:2403.11417, 2024.
4. Steenkiste, P., Introduction to Wireless Networking and Its Impact on Applications. 2023: Springer.
5. Mahmud, S.A., et al., Co-existence of Heterogeneous Wireless Networks in 2.4 GHz and 5 GHz Spectrum. 2024, Idaho National Laboratory (INL), Idaho Falls, ID (United States).
6. Shwan, A., Indoor Multi-Different-Wall Path Loss Prediction Model Using Adaptive Neuro-Fuzzy Inference System. Jordan journal of electrical engineering, 2024. 11(1): p. 1-1.
7. Wang, Z., et al. Analysis and Optimization of FI Path Loss Model in 39GHz Indoor Line-of-Sight Scenario Based on MMSE. in 2024 International Conference on Microwave and Millimeter Wave Technology (ICMMT). 2024. IEEE.
8. Tun, P.T.Z., Path loss prediction by using RSSI values. Int J All Res Writ, 2018. 1(7): p. 1-6.
9. Grabowsky, D.P., J.M. Conrad, and A.F. Browne. Limited log-distance path loss model path loss exponent estimation using deep deterministic policy gradient. in SoutheastCon 2021. 2021. IEEE.
10. Assayag, Y., et al., Adaptive path loss model for ble indoor positioning system. IEEE Internet of Things Journal, 2023. 10(14): p. 12898-12907.
11. Lubis, N.D. and N.L. Marpaung, Optimizing WiFi Signal Quality Through Access Point Placement Using Genetic Algorithm Method. Indonesian Journal of Artificial Intelligence and Data Mining. 6(2): p. 262-269.
12. Alathari, B., et al. An Optimization for Access Point Placement in Indoor Communication. in International Conference on Computational Science and Technology. 2022. Springer.
13. Akram, M.R., et al. Proposed APs Distribution Optimization Algorithm: Indoor Coverage Solution. in Journal of Physics: Conference Series. 2021. IOP Publishing.
14. Erunkulu, O.O., et al., Cellular communications coverage prediction techniques: A survey and comparison. IEEE Access, 2020. 8: p. 113052-113077.
15. Kurt, S. and B. Tavli, Path-Loss Modeling for Wireless Sensor Networks: A review of models and comparative evaluations. IEEE Antennas and Propagation Magazine, 2017. 59(1): p. 18-37.
16. Gulia, R., Path loss model for 2.4 GHz indoor wireless networks with application to drones. 2020: Rochester Institute of Technology.
17. Freitas, D., L.G. Lopes, and F. Morgado-Dias, Particle swarm optimisation: a historical review up to the current developments. Entropy, 2020. 22(3): p. 362.
18. Rappaport, T.S., K. Blankenship, and H. Xu, Propagation and radio system design issues in mobile radio systems for the glomo project. Virginia Polytechnic Institute and State University, 1997.