Proposed APs Distribution Optimization Algorithm: Indoor Coverage Solution

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Abstract. Recently, Wireless systems for indoor environments have become very important and popular. With increasing the need for mobile devices like laptops, tabs and smartphones, the optimization of WLAN coverage became very necessary to provide efficient communication with less cost. This optimization is verified by decreasing number of WiFi Access Point coverage. A multi objectives algorithm is proposed in this paper to optimize WiFi coverage in indoor environment using MatLab software. The proposed algorithm employs (BPSO) to determine the optimal number and locations for WiFi APs distribution based on predefined received power thresholds value. it has been found that the proposed algorithm is flexible using weighted multi- fitness functions. In addition, conducting site survey in real environment verifies the reliability of the proposed algorithm. Applying APD-CS algorithm in the adopted real environment increase the coverage by 64.6% and the average received power 7 dBm at Pth equal to-55 dBm.

Keywords. AP, BPSO, Coverage, WiFi, Indoor network.

1. Introduction

Wireless systems usage is increasing recently because of its important role in our life. This increase the need for indoor propagation models with high accuracy [1]. However, Wireless Local Area Networks (WLAN) structure required installing many WiFi access points (APs) to grantee all receivers receive high power at any point in the indoor environments [2]. In addition several factors impact signal propagation such building structure and the furniture present in the environment [3].Therefore the number of APs is often significantly will be more than required. As a result, the communication cost will increase with the number of APs. Moreover, some of the indoor environment areas will be uncovered in spite of installing many APs because of the unstudied network deployment [4]. APs positions must be studied carefully in order to cover full area and all receivers have high received power with less number of APs [5]. WLAN structure employs a radio signal to transfer data. Therefore the characteristics of indoor channel on the radio signal like diffraction, reflection, and scattering will have a high effect on the coverage area range of APs [6]. So APs positions in indoor environments required
to be studied and optimized [7]. Optimization of APs positions is a big challenge in a real environment for mathematical methods because of radio signal characteristics [8]. Recently, and for this complex problem many optimization algorithms which are inspired by the animal swarm intelligent have been adopted like Particle Swarm Intelligent (PSO).

Several techniques algorithms and frameworks have been developed due to many researchers' efforts to solve the coverage for the entire area of indoor environments with a minimum number of APs. In [2], PSO algorithm is used to set up a network of WiFi in a room. However, the result showed that with increasing the number of access points, coverage percentage increase. Simulated annealing method is used in [9] to deploy at least three APs and reduce the cost of APs installation and adjust their position to provide maximum coverage for the real environment by simulating it. While in [10], A New Global Optimization algorithm (AGOP) is used to produce full coverage for an indoor environment and calculate the path loss at the receivers with different receiver sensitivity thresholds and different transmission power. The results obtained indicate that the model described above can be used for finding the optimal number and placement of APs while covering all parts of design area. It is observed that the dimension of the building, number of users and their locations and the value of transmitted power and receive threshold has an effect on the number and placement of APs needed to cover an area. The authors in [11] used PSO based Adaptive Neural Fuzzy Inference System (ANFIS) to predicating WiFi signal strength in a corridor. Many factors that affect in received signal and path loss were investigated, such as distance and radio signal characteristics. According to the results, it is clear that signal strength decreases with increasing the distance between transmitter and receiver. In addition, the authors found that the PSO trained ANFIS has high accuracy to the model prediction of signal propagation. The Genetic Algorithm based GenoPlacement framework is used in [12] to optimize APs position in a building floor. The results obtained clarified that this algorithm can deal with indoor environments including many obstacles such as glass, brick walls, and concrete. In addition, it verified the goal in minimizing APs number and decreasing the cost. In [13] the Genetic Algorithm was used to design a network and test its coverage in the outdoor area. The authors improve the ability of the algorithm to create network planning with a tradeoff between capacity, coverage and cost. The authors in [14] employed PSO algorithm to minimize the number of Radio Frequency IDentification (RFID) readers in RFID network and their positions in order to maximize coverage area based on simulation. It was found that PSO can be applied to this type of applications with suitable fitness function. All the above-mentioned researches employed single fitness function.

To this end, the work is organized as follows: Section 2 describes the general expects about signal strength and adopted algorithm, section 3 script designing of proposed algorithm while the forth section discusses this work results. Finally, the conclusion will be illustrated in section five.

2. Theoretical Background
The main aim of WLAN is to support connectivity in term of coverage over all desired areas. Network planning is not an easy process. It requires scheduling and studying the factors that effect on the signal strength, then calculating the cost for determining the number of required APs and their positions. Sometimes, network planner based on traditional manual method to predict the best APs number and positions, and then followed by site survey to modify and configure the network parameters [15]. They may be performing site survey for many times after the initial deployment till finds the typical positions. For indoor environment and because of the building structure and the present of furniture, this method in planning considers time and efforts consuming. Therefore, optimization algorithm is needed to solve the access point distribution problem to reduce the cost and time. Network planner usually employed network planning software in order to analyze and assesse the proposed network performance before the network installation in reality.

This work is performed via two stages. First, Wireless InSite software is based to simulate the WiFi network performance. Wireless InSite software employed Ray Tracing (RT) method as the propagation model to predict the behavior of signal propagation in the adopted scene. By analyzing the network performance, a data base in terms of received power was constructed and fed the next stage. In the
second stage, the proposed APs Distribution Optimization Algorithm for Coverage Solution (APD-CS) is implemented which based on multi objectives Binary Particle Swarm Optimization (BPSO) to optimize the number of Aps. Accordingly, the concept of both RT and BPSO will be explained through next sections.

2.1. Ray Tracing (RT)

RT method is used to simulate and predict the behavior of radio signal through its propagation in complex environments. The main function of the RT method is to define the beam signal path transmitted from a sending antenna towards the receiver. This method takes into consideration all of the multipath phonemes such as; diffraction, reflection, and scattering [16-17].

The received power \( P_r \) represents the accumulated power of all paths taken into account the phase. It can be calculated by equation (1)[18]:

\[
P_r = \sum_{i=1}^{N_p} P_i
\]

\( P_i \) is the time averaged power in watts of the ith path, \( N_p \) is the number of paths. \( P_i \) is given by equation (2)[18]:

\[
P_i = \frac{\lambda^2 \beta}{8\pi \eta_0} \left| E_{\theta,i} g_{\theta}(\theta_i, \phi_i) + E_{\phi,i} g_{\phi}(\theta_i, \phi_i) \right|^2
\]

where \( \eta_0 \) is the impedance of free space at 377 \( \Omega \), \( E_{\theta,i} \) and \( E_{\phi,i} \) are components of the electric field for each path at received point, \( \theta_i \) and \( \phi_i \) give Direction Of Arrival (DOA), the quantity \( \beta \) is an overlap of the waveform, \( g_{\theta}(\theta_i, \phi_i) \) is the DOA waveform, and \( \lambda \) is of the waveform.

2.2. Binary Particle Swarm Optimization (BPSO)

Particle Swarm Optimization (PSO) algorithm is one of the optimization algorithms. It has been exposed in 1995 by James Kennedy and Russel Ebhart. It is inspired form birds and fish behaviors to lead bird or fish group toward the most suitable regions [19-21].

Each particle attracted to the locations where the food is there. Each one of them has its best location according to its previous experience. Moreover, each one modify its position the algorithm rounds towards the optimal solution. The optimization solution is the location of the organism with the highest fitness value. In the BPSO, the velocity of the particle is modified to be between 0 and 1, and hence limits the position values also between 0 and 1. Figure (1) explain the BPSO steps.

At each round, the particle updates the velocity and position according to pbest and gbest. The velocity can be calculated by:

\[
v_i(t + 1) = \omega v_i + c_1 \times a_1 \times \left( pbest(t) - x_i(t) \right) + c_2 \times a_2 \times \left( gbest(t) - x_i(t) \right)
\]

\[
x_i(t + 1) = x_i(t) + v_i(t + 1)
\]

Where \( v_i \) is the velocity of the ith particle, \( x_i \) is the initial position of the ith particle, gbest is the global best position for all the particles and pbest is the best position for the ith particle. \( \omega \) applies weighting to initial velocity, \( a_1 \) and \( a_2 \), are random numbers between 0 and 1, \( c_1 \) and \( c_2 \) determine the pull of the particle to pbest and gbest respectively, and \( t \) indicates the round number for which this velocity is applied. In order to convert current position to 0 and 1, equations (5) and (6) are employing [22-25]

\[
sigmoid(v_i(t)) = \frac{1}{1 + e^{-v_i(t)}}
\]

\[
x_i(t) = \begin{cases} 1, & \text{rand < sigmoid(v}_i(t)) \\ 0, & \text{otherwise} \end{cases}
\]

3. APs Distribution Optimization Algorithm (APD-CS) Design

Each indoor environment requires a specific deployment which convenes with its architecture. This imposes the network engineering planner to select carefully the Aps number and their positions keeping into account the factors govern the network performance which in most cases contradict (e.g. cost,
coverage, interference, limits of power exposure...etc.). From this concept, each internet service provider (ISP) may introduce different network planning based on the customers' goals.

In this work, APD-CS algorithm is proposed for improving the WiFi network performance, where it could optimize APs deployment and reduces network installing costs. Because of APD-CS ability to be applied in any indoor environment with any environmental conditions by changing the weight of related conditions parameters. Therefore, its flexibility can receive great interest to any network engineering planner who desires to install a new WiFi indoor network in either office or home environments. It allows meeting a certain throughput requirement with less APs number.

APD-CS algorithm is employed to design a wireless network with optimal APs numbers and locations based on a suitable fitness function which is solved by BPSO.

The APD-CS algorithm entity is a set of all possible candidate locations of APs (M). A set of N users materialized as a grid of test points (TPs) deployed all over the platform with (2m) spacing between them. Each nth TP is identified by a received power vector from all candidate transmitters:

\[ P_{r_1} = [\alpha_1 P_{r_{1,1}}, \alpha_2 P_{r_{1,2}}, \ldots, \alpha_m P_{r_{1,m}}, \ldots, \alpha_M P_{r_{1,M}}] \]

where:

\[ \alpha_m = \begin{cases} 0 & \forall AP_m \in \text{inactivated set} \\ 1 & \forall AP_m \in \text{activated set} \end{cases} \]

At each optimization step, a set of active and inactive APs is predefined in such a way that:

\[ \sum_i AP_i^{active} + \sum_j AP_j^{inactive} = M \] (8)

where \( AP_i^{active} \) and \( AP_j^{inactive} \) are the ith and jth AP in the active and inactive set respectively.

Equation (7) guarantees that received power by the nth TP from the deactivated jth AP will be zero. At each optimization step, each TP will be represented by a vector of received power including zeros for inactive APs. Moreover, the maximum received power will be determined and depended to identify the APs affiliation.

A multi-objective functions is performed at each step, which consists of two cost functions \( f_1 \) and \( f_2 \) to select the optimized set of APs based on different customer's requirements as explained by Equations (9-13). These two functions are considered to be trade-off between increasing coverage and reducing the cost.

Coverage area is materialized by the number of TPs which are considered covered (\( PT_n^{cov} \) if the maximum power received equals to or greater than a predefined threshold (\( P_{r_n}^{th} \)) as represented by equations (10) and (12). On the other side, the cost is determined by the number of APs to be installed as explained by equation (11):

\[ \text{Cost} \ f_3 = \ w_1 \ f_1 - \ w_2 \ f_2 \] (9)

\[ f_1 = \max \ \frac{\sum PT_n^{cov}}{\sum PT_n} \] (10)

\[ f_2 = \min \ \frac{\sum AP_m^{active}}{\sum AP_m} \] (11)

s.t. \( PT_n = PT_n^{cov} \) if \( \max(Pr_n) \geq P_{r_n}^{th} \) (12)

\[ \sum_m AP_m \geq 3 \] (13)

As above mentioned, increasing the number of covered TP counter act minimizing the number of APs. Hence, \( w_1 \) and \( w_2 \) represent the weight of each condition and can be used to balance both requirements, which add flexibility to the proposed algorithm. Equation (13) guarantees that the number of APs will be no less than already installed APs in the adopted scene. Also, both number of active APs and covered TPs are being normalized by dividing them by the total number of APs and TPs.

The pseudo-code for APD-CS algorithm is:

Begin
Input APD-CS parameters.
Initialize BPSO parameters (\( u_1, u_2, c_1, \) and \( c_2)\).
Initialize \( V_i \).
Initialize APi, with random binary values.
Repeat the following steps until the stopping condition is met to get the best optimization Set counter (Rx)
if \( Pr_n \geq P_{th} \)
Rx=Rx+1 (equation (12))

End if

Calculate $f_1$ using equation (10)

if sum $AP_i \geq 3$ (equation (13))

Calculate $f_2$ using equation (11)

End if

Calculate $f_3$ using equation (9)

If $p_{best} > f_3$

$p_{best} = f_3$, $G_{best} = \min p_{best}$.

End if

Update $v_i$ and $x_i$.

Convert $x_i$ to binary value.

End loop of step 4 and determine the best $Aps$ positions.

4. APs Distribution Optimization Algorithm (APD-CS) Implementation

4.1. Case Study Network Environment

A real indoor environment which is the second floor of "departments building" at "Electric Engineering Technical College" has been adopted to optimize its network by simulation using wireless InSite software using 3D ray-tracing method and then apply BPSO algorithm to perform optimization in MatLab software.

The area of the floor is (25m*41m) with high 3.2m. The floor involves four lab rooms each one has dimensions 17m length and 7.5m width. In addition, the floor includes four office rooms with dimensions (3.5m*7m) and three corridors (30m by 3m) for each one. Three APs are already installed at the floor in randomized manner and are operated at 2.4 GHz These APs are represented as blue points before the optimization in Figure 1; the first one is located in a computer lab, the second one located in the office room and the last one is located in the corridor. The TPs are deployed in the floor as a grid consists of 252 receivers to cover the entire environment.

![Figure 1. APs locations.](image)

4.2. APD-CS Algorithm Simulation Results and Discussion

The real indoor environment has been simulated to determine received power at each point in the floor in order to implement the proposed APD-CS algorithm. In this work, various $Pth$ are assumed to analyze the network performance, and these values are identified also by the metric Quality of Service (QoS) as illustrated in the first column. For each $Pth$ different cases are proposed to reflects the effect of changing $w_1$ and $w_2$, where $w_1$ and $w_2$ represent the priority of $f_1$ and $f_2$ respectively. The results from the analyses are illustrated in table (1). The results show that, decreasing $Pth$ required more APs for the same coverage which in turns increasing the network cost. For this reason, $w_1$ and $w_2$ are employed to balance both constraints (coverage and cost). As an example, by eliminating $w_1$ in Case 1, $f_3$ will be equal to $f_2$ which led to decrease the number of APs to the minimum (3). At the contrary, eliminating $w_2$ in Case 1, indicates that $f_3=f_1$which led to select the first solution provides the maximum coverage despite the number of APs. Case 3 to case 5 represents other percentage ratio of $w_1$ and $w_2$ between zero and one.
Accordingly, the proposed algorithm gives the flexibility via \( w_1 \) and \( w_2 \) after predefining \( P_{th} \) according to each ISP requirements and then the BPSO is performed to verify the optimization.

### Table (1). APD-CS algorithm results.

| QoS       | Pth(dBm) | case  | \( w_1 \) | \( w_2 \) | No. of Rx covered | No. of Tx | Cost ($) | Coverage ratio |
|-----------|----------|-------|-----------|-----------|------------------|-----------|----------|----------------|
| excellent | -40      | Case1 | 0         | 1         | 24               | 3         | 158      | 9.5%           |
|           |          | Case2 | 1         | 0         | 189              | 52        | 2,379    | 75%            |
|           |          | Case3 | 0.5       | 0.5       | 169              | 23        | 1,073    | 67.06%         |
|           |          | Case4 | 0.3       | 0.7       | 115              | 11        | 524      | 45.6%          |
|           |          | Case5 | 0.7       | 0.3       | 183              | 31        | 1,439    | 72.6%          |
|           |          | Case1 | 0         | 1         | 28               | 3         | 158      | 11.11%         |
|           |          | Case2 | 1         | 0         | 189              | 56        | 2,562    | 75%            |
|           |          | Case3 | 0.5       | 0.5       | 168              | 23        | 1,073    | 66.6%         |
|           |          | Case4 | 0.3       | 0.7       | 108              | 10        | 499      | 42.8%          |
|           |          | Case5 | 0.7       | 0.3       | 183              | 31        | 1,439    | 72.61%        |
| Very good | -45      | Case1 | 0         | 1         | 108              | 3         | 158      | 42.8%          |
|           |          | Case2 | 1         | 0         | 250              | 40        | 1,830    | 99.2%          |
|           |          | Case3 | 0.5       | 0.5       | 245              | 7         | 341      | 97.2%          |
|           |          | Case4 | 0.3       | 0.7       | 238              | 6         | 316      | 94.4%          |
|           |          | Case5 | 0.7       | 0.3       | 250              | 9         | 474      | 99.2%          |
|           |          | Case1 | 0         | 1         | 196              | 3         | 158      | 77.7%          |
|           |          | Case2 | 1         | 0         | 250              | 40        | 1,830    | 99.2%          |
| good      | -50      | Case3 | 0.5       | 0.5       | 248              | 5         | 296      | 98.4%          |
|           |          | Case4 | 0.3       | 0.7       | 246              | 4         | 183      | 97.6%          |
|           |          | Case5 | 0.7       | 0.3       | 250              | 6         | 316      | 99.2%          |
|           |          | Case1 | 0         | 1         | 244              | 3         | 158      | 96.8%          |
|           |          | Case2 | 1         | 0         | 251              | 40        | 1,830    | 99.6%          |
| Fair      | -55      | Case3 | 0.5       | 0.5       | 247              | 4         | 183      | 98%           |
|           |          | Case4 | 0.3       | 0.7       | 246              | 3         | 158      | 97.6%          |
|           |          | Case5 | 0.7       | 0.3       | 250              | 4         | 183      | 99.2%          |
| poor      | -60      | Case3 | 0.5       | 0.5       | 247              | 4         | 183      | 98%           |
|           |          | Case4 | 0.3       | 0.7       | 246              | 3         | 158      | 97.6%          |
|           |          | Case5 | 0.7       | 0.3       | 250              | 4         | 183      | 99.2%          |

As mentioned early, the cost has a high effect on the network planning in terms of cable cost, devices cost and the throughput cost. However, the network engineering planner is limited with a specific cost. Reducing the cost led to minimizing the APs number thus reducing the coverage. The network cost can be determined by its’ structure, which includes a Nano station device, APs, cables, and hubs if necessary. The hub is required to connect four APs to gather for better connection and long-distance. Each four APs shared with one Nano station, one hub and cables to connect between them. The cost of each of mentioned devices is desterilized as: 20$ for AP, 5$ for cable, 75$ for nano station, and 8$ for hub.

Each TPs in the grid receive alternate signal strength from multiple active APs as shown in Figure (2). The number of these active APs has been selected to verify an average received power equal to \( P_{th} \) and the null locations in the figure represents inactive APs since each TP does not receive any signal from these APs. Case 3 has been chosen to be the example at each \( P_{th} \).
Figure 2. Signal strength at each TP.

Figure (3) depicts the CDF for the maximum received power by each TP. The results show that, maximum coverage ratio can always achieved at higher cost represented by large number of APS. With other words, the with increasing w1 the TP that receive received power higher than Pth will be increased. Also, it can be noticed that as Pth increase, the probability of required optimal coverage become far apart and hard to obtain, which requires an accurate planning that verifies only via optimization.

Figure 3. Number of maximum receivers: (a) at Pth= -40 (b) Pth= -50 (c) Pth= -60 at all cases.

In this work, the range of signal strength transmitted from each active AP to all TPs has been investigated as represent in Figure (4) for the selected Pth values. The x-axis represents the number of selected APs to be active form a set of 77 candidate APs. It has been noticed that, the numbers of selected APs increase as Pth decrease due to the high signal quality requirement to meet the algorithm conditions.

Also, despite reducing the active APs as the Pth decrease but, the activated selected set will cover the rage of Pth with 67%, 95% and 98% for Pth equals to -40dBm, -50dBm and -60dBm respectively. These results verified that proposed APD-CS algorithm can be depended for cost effective network design. The received power of these APs to all TPs can be also analyzed via Figure (4).
4.3. APD-CS Algorithm Experimental Results and Discussion

In order to verify the reliability of proposed APD-CS algorithm case 4 at $P_{th} = -55$ has been chosen to be applied in the real indoor environment. A comparison is test conducted by measuring signal strength before and after implementing APD-CS algorithm using NetSpot software. Figure (5-a) shows the wireless network of the adopted environment before BPSO optimization. The figure exhibits that many areas don't have signal or receive weak signal strength. It can be known as dead zones. That's show the weakness of the network coverage area and the installing APs are not enough to cover the area or their position doesn't help to achieve high coverage area. After APD-CS algorithm, four APs are chosen and their positions are determined as shown in figure (5-b). The dead zones are minified and the coverage area became larger than the previous network. Comparing the results before and after optimization show that 63.6% coverage ratio has been gained over 34% coverage ratio before the optimization for the same $P_{th}$.

Average signal power in the adopted environment has been found as shown in figure (6). After optimization the coverage area obviously increased to -53 dBm after applying APD-CS algorithm.

Figure 5. Indoor network (a) before optimization (b) after optimization.

Figure 6. Comparison between average signal power after and before optimization.
5. Conclusion
In this paper, 3D ray tracing simulation is used to study coverage area of installing a network in a real indoor environment by Wireless Insite software. After that, it has been optimized using proposed multi-objective APD-CS algorithm based on BPSO and implemented using MatLab software. Multiple cases are studies by changing the weights of two counteract fitness functions (coverage and cost). At specific Pth, one case has been adopted to compare network performance in terms of coverage area before and after APD-CS optimization. The first investigation in this work is that APD-CS algorithm is flexible and effective in any environment and for any level of network quality. The second investigation is reliability, where applying APD-CS algorithm in the adopted real environment, the coverage ratio increased form 34% to 97.6% and the average received power increased from -60 dBm to -53 dBm at Pth equal to-55 dBm.

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