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A Decision Support Tool for Indoor WLAN Modeling Using Optimization Techniques

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Abstract: Wireless Local Area Network (WLAN) is a technology that provides wireless broadband Internet access in indoor or outdoor environments. It is low cost, easy to use and widely deployed. However, there are many factors that affect its coverage due to the complex structure of indoor settings. For this reason, it is necessary to locate the Access Points (APs) in such a way as to provide the wireless network with the strongest and most consistent coverage. Since these factors directly affect WLAN performance, network specialists often encounter unexpected problems and tend to optimize network coverage by trial and error, taking measurements from access points after they're located. Several metrics such as antenna type, channels, wall structures, throughput can be used for WLAN optimization. Our decision support tool helps network specialists generate a network model by employing these metrics. Determining the coverage of APs in indoor settings is a nonlinear problem. Therefore, our tool is based on the heuristic approaches of the simulated annealing and genetic algorithm. Via this tool, the optimum number of APs to be placed in an indoor setting can be decided and the best AP placement for optimal network coverage can be easily obtained.

Keywords: WLAN Optimization, Genetic Algorithm, Simulated Annealing, AP Placement

Optimizasyon Teknikleri Kullanılarak Kapalı Alan WLAN Modelleme için Bir Karar Destek Aracı

Öz: : Kablosuz Yerel Ağ (WLAN), kapalı alan ve dış ortamlarda kablosuz yayın ile Internet erişimi sağlayan bir teknolojidir. Düşük maliyetli, kullanımı kolay ve yaygın olarak kullanılmaktadır. Bununla birlikte, kapalı alanların karmaşık yapısı nedeniyle kapsamını etkileyen birçok faktör vardır. Bu nedenle, Erişim Noktalarını (AP'ler) kablosuz ağa en güçlü ve en tutarlı kapsama alanını sağlayacak şekilde yerleştirmek gerekir. Bu faktörler WLAN performansını doğrudan etkilediğinden, ağ uzmanları genellikle beklenmedik sorunlarla karşılaşırlar ve bulunduktan sonra erişim noktalarından ölçümler alarak ağ kapsamını deneme yanılma yoluyla optimize etme eğilimindedirler. WLAN optimizasyonu için anten tipi, kanallar, duvar yapıları, verim gibi çeşitli metrikler kullanılabilir. Karar destek aracımız, ağ uzmanlarının bu metrikleri kullanarak bir ağ modeli oluşturmasına yardımcı olur. Kapalı alan ortamlarında AP'lerin kapsamının belirlenmesi doğrusal olmayan bir sorundur. Bu nedenle, yazılım aracımız tavlama ve genetik algoritmanın sezgisel yaklaşımlarına dayanmaktadır. Bu araç aracılığıyla, bir kapalı alana yerleştirilecek optimum AP sayısına karar verilebilir ve optimum ağ kapsama alanı için en iyi AP yerleşimi kolayca elde edilebilir.

Anahtar kelimeler: WLAN Optimizasyonu, Genetik Algoritma, Tavlama Benzetimi, AP Yerleştirme

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1. Introduction

Wireless networks have gained worldwide popularity with an increase in smartphone usage rates. Therefore, data traffic on cellular networks and wireless local area networks (WLANs) is increasing. For this reason, different data transmission techniques are developed in wireless network technologies [1]. There is a growing need for WLANs to be constructed, especially in indoor areas such as hospitals, airports, shopping centers, and arenas. In these areas, wireless access points provide communication abilities per the IEEE 802.11x standard, which enables access to data networks. In this standard ISM band, it uses the 2.4 GHz frequency band at IEEE 802.11b / g / n standards and the 5 GHz frequency bands at the IEEE 802.11ax standard. The IEEE 802.11ax workgroup has developed 256 QAM modulation techniques in the modulation and coding scheme (MCS) to increase the efficiency of the PHY and MAC layer [2]. They have developed the IEEE 802.11ac standard using the 5 GHz band. The main purpose in the development of this standard; It is to increase users' throughput requirements and to address more users. Especially indoor areas such as new generation classrooms, campuses, multi-storey buildings are the main target points. Performance analysis of this technology is measured by scenarios made in such areas. In these performance analyzes, APs broadcast radio frequencies (RFs) starting from the location where they are placed, via their pre-positioned antennas. However, RF waves do not provide adequate coverage, due to several factors. To increase the coverage of a WLAN, APs should be added in areas where the RF signal is currently insufficient.

The decision to place APs depends largely on a network specialist’s experience. The performance and coverage of a WLAN is often lower than expected due to the complex structure of indoor settings. However, in large indoor settings, even the most experienced network specialist struggles. There are too many factors to consider that affect the design of a WLAN such as channels, antenna types, numbers of users, wall structures, etc. that are found in any indoor setting. It would be a monumental and time-consuming task to manually design a WLAN that takes all these factors into account. Therefore, there is a need for a decision support tool that network specialists can use to simulate WLAN setups in both small and large indoor settings.

There are many commercial software tools available to support WLAN design. Most prominent are RingMaster from Trapeze Networks, AirMagnet Planner from AirMagnet and CIndoor from the GISAR Group at the University of Cantabria, Spain, Cisco Wireless Control System from Cisco, LanPlanner from Motorola, Red-Predict from Red-M [3]. Although these tools help the network specialists plan and evaluate WLAN design, they are not able to guarantee sufficient coverage for WLAN users. Another disadvantage of these tools is that they simply display the approximate coverage of the APs according to the AP locations that are manually added by the user. They are designed solely for reporting purposes and do not have a prescriptive function. Therefore, they are not set up to help a network specialist optimize a WLAN.

In the literature, there are several studies that aim to find the optimal locations and the minimal number of APs required. During the WLAN planning process, network administrators should consider AP locations and channel assignment problems when making decisions. The decisions should be made to obtain good network performance and optimal coverage. These problems can be solved by applying mathematical models [4, 5, 6] or heuristic models [7, 8, 9, 10, 11, 12]. The related studies presented above all aim at finding the AP coverage, the optimal locations of the APs and identifying path losses in indoor settings, which is a difficult problem.

In this study, we have employed the genetic algorithm method as in other similar studies. However, in contrast to the previous work, we consider the complexity of the structures such as wall type, door type, and window type that affect the signal strength and contribute to path loss. As a result,

the locations and optimum number of the APs were determined by finding the path loss value that will provide the best coverage in an indoor setting.

In this study, we have developed a tool for generating an indoor WLAN that can provide optimal coverage. This decision-making tool enables the installation of WLAN, which provides the best coverage according to IEEE 802.11x standards. This tool determines the optimum locations and numbers of APs for the closed area selected using path loss models and heuristic algorithms. Especially in large-scale indoor settings, our tool considers many factors (e.g., channel, antenna type, wall structures) that the network specialists may miss in WLAN design. This user-friendly software tool is designed to guide the network specialist through the decision-making process.

The remainder of this paper is organized as follows. In Section 2, we discuss studies that are related to WLAN development. In Section 3, we present our software architecture and we describe WLAN optimization using GA and SA. In Section 4, we present evaluation of our software tool and report our experimental results. Finally, in Section 5, we provide our concluding remarks.

2. Software Architecture

In this study, we developed a tool called the "AP Placement Decision Support Tool" for indoor WLAN modeling. Our software tool helps network specialists decide the optimal locations for APs by aiming to design indoor WLANs that have the best coverage. Figure 1 shows the architecture of the software tool. The users start using the tool by selecting the building plan of the indoor setting (1:500), which will be displayed in the GUI later. Design results, parameters, and data entries are stored in database. Additionally, the tool can produce easy-to-understand reports such as a WLAN map that shows the optimized coverage and portraying signal strength distribution. The architecture is composed of three layers. The first layer is where the system specialist interacts with the program, inputting the parameters that are necessary for AP placement and displaying the results accordingly. The second layer serves as a middleware.

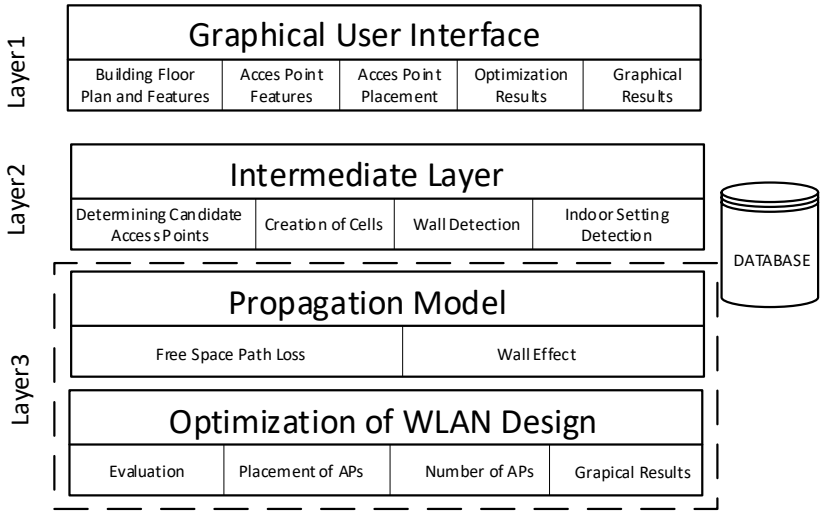


Figure 1. AP Placement Software Tool Architecture

In this layer, there are several operations such as determining the wall types that affect RF signal, creating cells, producing the coverage of indoor setting according to random AP placement, and building the plan using the features determined in Layer 1. In the third layer, the location and optimal number of APs are identified and the results are evaluated according to the objective function that will be used for WLAN design optimization. This function is created by applying WLAN propagation modeling.

2.1. WLAN Propagation Modeling

In the WLAN propagation modeling, the path loss is defined as the loss between the transmitting antenna and the receiving antenna and can be described as

$$P_L = P_{TX} - P_{RX} \quad (1)$$

In Equation 1, PL is the total power loss that is caused by the indoor channel effects, and the PTX and the PRX are the received signal power and transmitted signal power, respectively, in units of dBm. In an indoor setting, the signal strength attenuates until it reaches the receiver, based on wall type, wall thickness, the frequency, and the distance between transmitter and receiver [13]. There are many methods developed for radio propagation modeling due to the complex structure of indoor WLANs. The path loss between the receiver and the transmitter can be calculated using deterministic models such as Free Space Path Loss (FSPL) [14], the One Slope Model (OSM) [15] or empirical models [16]. Furthermore, the Motley Keenan Model [17] can be used to evaluate the effects of the walls on the attenuation of signal strength. In our study, we applied the FSPL model to construct the fitness function of the genetic algorithm and simulated annealing.

The FSPL model provides a measure of path loss as a function of transmitter - receiver separation when the transmitter and receiver are within the light-of-sight range in a free space environment[18].
The Equations 2 - 4 for FSPL is in term of dB;

$$P_L = 20\log(d) + 20\log(f) + 20\log\left(\frac{4\pi}{c}\right) \quad (2)$$

$$= 20\log(d) + 20\log(f) - 147.55 \quad (3)$$

$$= 20\log(d) + 20\log(f) - 27.55 \quad (4)$$

where f is the signal frequency (in hertz), d is the distance from the transmitter (in meters), c is the speed of light in a vacuum, 3×10^8 meters per second. In Equations 2 - 4, d is in meters and f is in megahertz, respectively. The FSPL model cannot be applied alone to find indoor path losses since the complex structure of the indoor space, along with the receiver and the transmitter antenna gains affect the path loss. Other factors that affect the FSPL should be considered as part of determining the signal that reaches the receiver. The link budget is an equation that calculates the value of the transmitter signal strength that reaches the receiver.

$$P_{RX} = P_{TX} + AntennaGains - P_L - BML \quad (5)$$

In Equation 5, PTX depicts the outgoing signal strength. The transmitter and the receiver antenna gains are added to the signal strength value since they increase the signal strength. PTX and antenna gain values are defined by ETSI (European Telecommunications Standards Institute). According to ETSI specifications, maximum transmission power of an AP can be 17dB and maximum antenna gain can be 3dB. Therefore, the maximum transmission power for APs from different manufacturers are limited to 20dB [19]. BML is the building material loss value.

Our tool considers the wall types, the frequency (number of channels) and the distance between the AP and the receiver while finding the signal strength that reaches the receiver. In particular; in indoor settings, any walls, wooden doors, metal or glass objects, and signals from other devices that interfere the WLAN signal are the main factors that affect it. Table 1 shows the impact of building materials on the RF signal strength.

Table 1. Impact of Building Materials on RF Signal Strength

Building Materials	Signal Loss (dB)
Plaster, Wooden Door, Tile, Block Wall, Unpainted Glass	2 – 4
Painted Glass, Metal, Brick Wall, Wire Grid, Marble	5 – 8
Bullet-Proof Glass, Concrete Wall, Ceramic, Paper	10 – 15
Silvered Glass, Metal	>15

In this study, we ignored the reflection, refraction, and scattering factors that also affect receiver signal power, simply to reduce the computational complexity.

2.2. WLAN Optimization

- Genetic Algorithm

Genetic Algorithm (GA) is a heuristic approach that models the transfer of genetic features of living things. The genetic algorithm, based on the principle of survival of the best, was first introduced by John Holland. It is generally used to provide the most optimum solutions to problems that are difficult to solve. In our previous study [20], we researched the AP placement problem and proved that the GA approach was successful. In this study, we based our optimization process on the GA and simulated annealing (SA) approaches. Figure 2 shows our GA-based optimization algorithm.

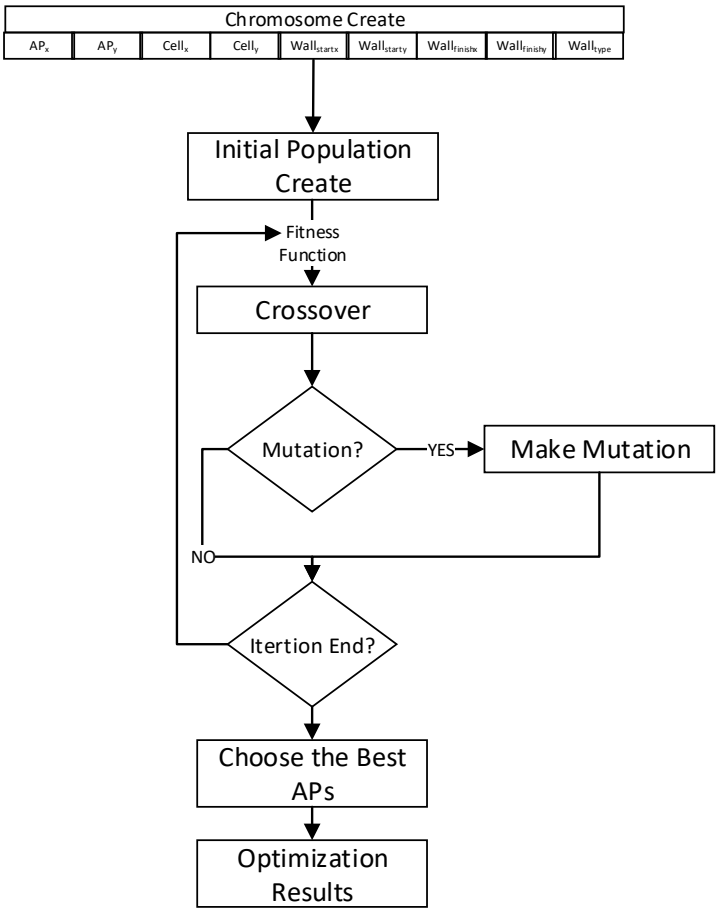


Figure 2. GA based Optimization Algorithm

In the GA process, the best child can be considered as the solution. The success of the GA depends on proper gene coding, choosing the right fitness function, crossover, and mutation operators [20]. The following provides a brief description of the main components used in the genetic algorithm. The building plan is divided into 1.2 m2 cells that represent receiver points before gene encoding.

Gene Encoding: In GA, the first step is to encode the genes of the chromosome. The gene is encoded by considering the factors that affect the RF signal, such as the AP coordinates (APx, APy), the receiver points in the indoor setting (Cellx, Celly), the wall types, (Walltype), the start and the end points of the walls (Wallstartx, Wallstarty, Wallfinishx, Wallfinishy) [21].

Initial Population: After the gene encoding process, different chromosome structures are constructed for the APs that are randomly placed on the building plan of the indoor setting, considering the fact that these APs will produce signal strength for the receiver points. Through this process, the initial population is generated by identifying the walls where the AP signal will pass through and defining the wall types.

The objective function (OF) that is shown in Equation 6 calculates the sum of the signal strength values. According to this function, more than one AP can be placed in cells and the maximum signal strength in the jth cell is chosen. Equation 7, the fitness value (F_i) is defined as the signal strength at each cell, divided by the OF value. The fitness value is produced for each chromosome in the initial population. This value is used to determine the good chromosomes in the population.

$$F = \sum_j^N max_j \left(P_{AP} - \left[\left(20\, log\, f + 20\, log \frac{d(AP_i, c_j)}{1000} \right) + \sum wall\ effect \right] \right) \tag{6}$$

$$F_i = \sum_j^N \frac{P_{AP} - \left[\left(20 \log f + 20\, log \frac{d(AP_i, c_j)}{1000} \right) + \sum wall\ effect \right]}{OF} \tag{7}$$

Equation 7, in order to determine $d(AP_i, c_j)$, that is, the distance between the AP and the cell, the Euclidean distance formula is used [22]. P_{AP} is the signal transmission strength of an AP. The coverage area of the AP is proportional to its transmission strength. The coverage area of the AP in the gap is associated with the frequency (f) and the distance $d(AP_i, c_j)$. FSPL value is normally calculated by considering the fact that there is no interference when the signal leaves from Access Point. However, different types of wall structures in indoor settings affect and reduce the signal strength. Therefore, when calculating the FSPL value, we considered several factors that are wall types, wall thickness and distance to walls. Since there may be many walls and the signal will reach the receiver from AP through these walls, total wall affect is added to FSPL calculation.

Selection: The selection of the most suitable chromosomes in the population is the process of choosing the chromosomes that will be transferred to the next population from the existing population. This process enables transferring the good chromosomes with the determined compatibility values to the next generation. The bad chromosomes, whose compatibility value is below the -80dB threshold value (for the elimination of bad chromosomes) will not be transferred to the next generation. Here, -80dB has been determined as the best threshold value according to our experimental trials. The simplest and most useful selection mechanism to gain this determination is Tournament Selection.

Crossover: A chromosome is transferred to the next generation by changing the original chromosome structure through crossover and mutation operators. In the current study, a single-point crossover was used between the chromosome pairs in the population to provide chromosome diversity in the next generation. In the single point crossover function, a random integer value

between 1 and the number of genes in the chromosome. crossover operation is used by combining the Parent1's and Parent2's genes that have numbers smaller than the determined values

Before Crossover	**222**	**230**	430	150	688	454	945	494	1	Parent1
	308	**124**	288	016	654	436	668	452	1	Parent2
After Crossover	**308**	**124**	430	016	688	454	945	494	1	Child1
	222	**230**	288	150	654	436	668	452	1	Child2

Figure 3. Crossover Process

In Figure 3, the crossover points are shown for two chromosomes that have been randomly selected and the new chromosomes after crossover. Two new individuals are produced after the crossover operation. The fitness value is recalculated for these chromosomes and applied to new chromosomes.

Mutation: The mutation operator was applied in the case that the chromosome diversity could not be provided in the next generation. This is achieved through the variation of the genes in the chromosomes in which diversity decreases. Here, the chromosomes were mutated at a rate of (Pm) 0.01 (1%). Figure 4 shows the gene that will perform the mutation for a randomly selected chromosome and the final state of the gene after the mutation.

Before Mutation	420	262	880	165	582	**481**	656	438	5
After Mutation	420	262	880	165	582	**486**	656	438	5

Figure 4. Mutation Process

- Simulated Annealing

Another approach that can be used to find the optimum locations of APs is the simulated annealing (SA) algorithm. SA is a heuristic technique used to approach the global optimum of a function. SA can approximate global optimization in a broad search area for an optimization problem. SA is a technique that is used for solving combinational problems and is based on the principle of cooling heated matter until it has crystallized [23]. In indoor settings, the AP and the building features that affect the signal strength form the multi-variable function [24]. The SA algorithm is best suited for these types of problems because of its structure. Our purpose is to minimize the multi-variable objective function that is shown in Equation 6. Thus, the path loss will be minimized and the signal strength and coverage will be maximized in the WLAN that is generated based on the architectural plan of the building. The pseudo-code of the SA is shown in Table 2.

The initial solution set of the problem consists of AP features, AP locations that are randomly placed, cell locations and features, wall locations, and features of the indoor setting. The objective function Equation 6 calculates the total signal strength that covers the obstacles between the APs and the cells. The first solution is not considered as a good solution since the number of APs that is entered in the software tool is random (S_{old}). The number of APs is revaluated to find a new solution (S_{new}) based on the previous number of APs, according to the value of s^k (between 0 and1) that is randomly generated in Equations 8 and 9.

Table 1. Pseudo-code of SA

```
t0=100; //Initial temperature
n=0;                    //iterationNumber
S = {APi0,Cellj0,Wallk0 };          //initial solution
Sold = Objective_Function(S);
Snew = Sold ;
do
while (n < iterationTotal)
Sn = {APij,Cellij,Wallij }              // new solution create
Snew = evaluate Objective Function(Sn);
if (Δ ≤ 0) then
Sold=Snew;
   else
            u=randomDouble(0,1);
  if (u<e^(-Δ/t0) ) then Sold=Snew;
   end if
   n = n + 1;
end while
t0=coolingStrategy(t0);
while (t0 > 0.1)
```

$$\mathrm{AP_{xnew}} = \mathrm{AP_{x0}} + (s^{\mathrm{k}}(\mathrm{AP_x} - \mathrm{AP_{x0}}) \tag{8}$$

$$AP_{ynew} = AP_{y0} + (s^{k}\left(AP_y - AP_{y0}\right) \tag{9}$$

Furthermore, the cost function is calculated according to the newly generated solution set (S_{new}). Delta (Δ) is calculated by taking the difference between the new solution (S_{new}) and the old solution (S_{old}). If Δ is smaller than zero, the new solution is accepted. However, if Δ is greater than zero, we look into the solution's probability of acceptance. Each step of the algorithm is checked by a specific iteration count at a specific t_0 temperature. When the temperature iteration is over, t_0 temperature is decreased according to the cooling strategy in Equation 10. Here, c_k is the cooling factor. In this study, ck value was obtained experimentally and its value was determined as 0.8. The minimum temperature value of 0.1, which terminates the algorithm, was obtained with experimental results.

$$\mathrm{t_0} = \mathrm{t_0} * \mathrm{e}^{-\sqrt{\mathrm{c_k}}} \tag{10}$$

As a result of the algorithm, the APs that provide the best signal strength to the cells in the indoor setting are chosen.

3. Discussion and Results

The decision support tool is composed of five modules: Building Features, Access Point Features, Optimization Features, Optimization Results and Graphical Results Module. The Building Features Module includes a user-friendly graphical interface where a 2D building plan (jpeg, png, bmp) is selected. The 1/100-scaled image of the building plan that can be used in the optimization process is produced using AutoCad software. The width and height values (in pixels) and the distance between two pixels are calculated. Users can save the settings for this optimization by giving it a name and then continuing on to the next step. The details related to this floor plan are shown in Figure 5.



Figure 5. Building Features Module

Additionally, the user enters wall structures in the environment. The building materials can be chosen from concrete wall, drywall, metallic obstacle, elevator, glass door, metallic rack, and wooden door. Drywall, brick wall, concrete wall, and metallic obstacle were selected as building materials. All these features are important for determining the complexity of the indoor environment. Additionally, different wall types can be painted in different colors so that the user can distinguish them. The tool provides users flexibility to delete wall structures that they have added, write notes on them, copy, and also print them. All features of wall structures can be seen simultaneously in the properties panel.

In the Access Point Features Module, a system specialist determines the features of APs and the APs which are randomly placed in the environment. Supported AP features are WLAN standard, antenna type, transmission rate, and antenna gain. In our study, we used Aruba Network AP-300 series as our AP model. 802.11b/g/n/ac was selected as the wireless standard and 2.4 GHz was selected as the frequency band. The transmission power of AP304 model is +23 dB; its antenna gain is 1,6 dBi in 5GHz [25]. After this step, the user randomly places the candidate APs on the indoor WLAN architectural drawing. Figure 6 shows 12 APs that were randomly placed by the user. Furthermore, the receiver's antenna gain has an effect on the fitness value Equation 6. In our experiment, we assumed that the receivers were generally mobile phones and the antenna gain of -1,5db was chosen.



Figure 6. Access Point Features Module

In the Optimization Features Module, the optimal locations for the APs are found according to the building features. Optionally, a user can enter a specific value for the number of generations or assign a random value. Furthermore, the crossover and the mutation rate values that are necessary for the genetic algorithm are determined. There is also an option to select the type of crossover method which can be one point, multipoint or uniform. For this study, the generation was random and the crossover method was one point. Additionally, the initial temperature, the temperature reduction factor, and the iteration count values are entered for the simulated annealing algorithm. After selecting the appropriate parameters, the optimization is started and the optimal locations for the APs are determined. Figure 7 shows the optimization process.

After the optimization process, a visual screen displays the optimal locations and the signal strengths of each point in the indoor space according to the locations of optimized APs. Figures 8 and 9 show the optimum locations for APs and the best coverage according to GA and SA, respectively.

In the Graphical Results Module, four different charts are created. Figure 10 depicts the signal strength distribution and the changes in the fitness function according to the results of GA and SA. Using these charts, users can analyze their WLAN setup and print it out. The developed software tool includes measures to prevent AP placement outside of the building plan.

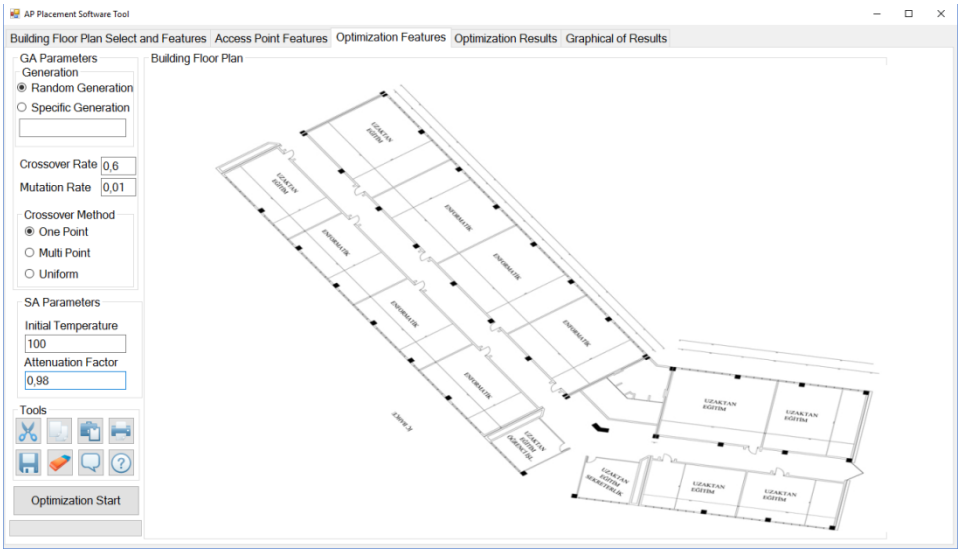


Figure 7. Optimization Module



Figure 8. Result of Genetic Algorithm

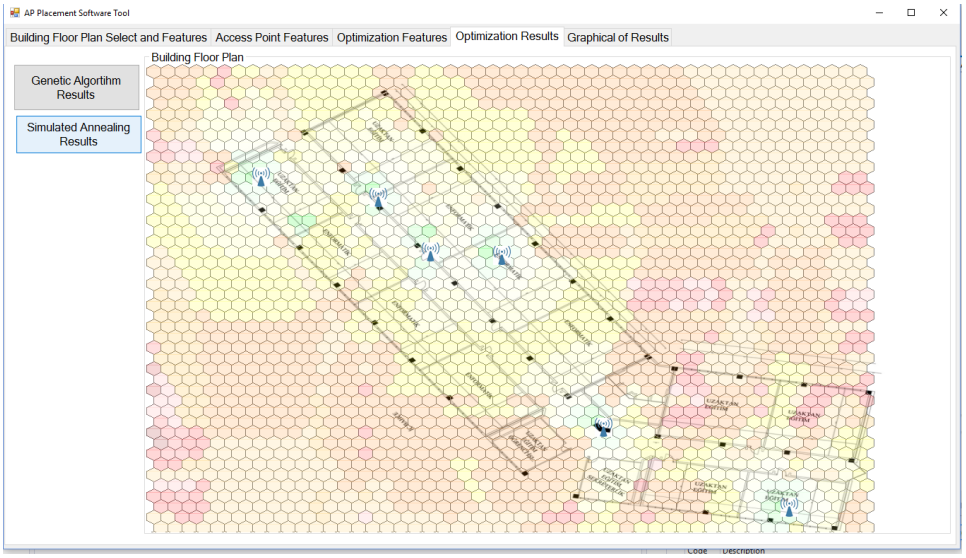


Figure 9. Result of Simulated Annealing

At the end of the optimization process, the optimal coverage is illustrated in full color. Additionally, the results are represented graphically. As presented in Figure 10, the SA approach performed better than the GA approach. In the charts titled "Fitness Change of Iteration" in Figure 10, it is seen that the most suitable placements are obtained according to the AP placements performed with GA and SA. In these graphs, the fitness values reached optimum results in both algorithms. According to these results, the most optimal AP placement is completed in about 300 iterations. In the charts titled "Link Budget" in Fig. 10, the graphs of signal strength distributions in cells covering 1.2 m^2 areas are shown on the floor plan of 1/500 scale. According to these figures, sufficient coverage is defined in GA and SA and indoor WLAN. However, APs placed with the SA method provide better signal strength in the cells. While GA can provide -50 dB signal strength in some cells, whereas SA has achieved a signal strength of -35 dB in the same cells.

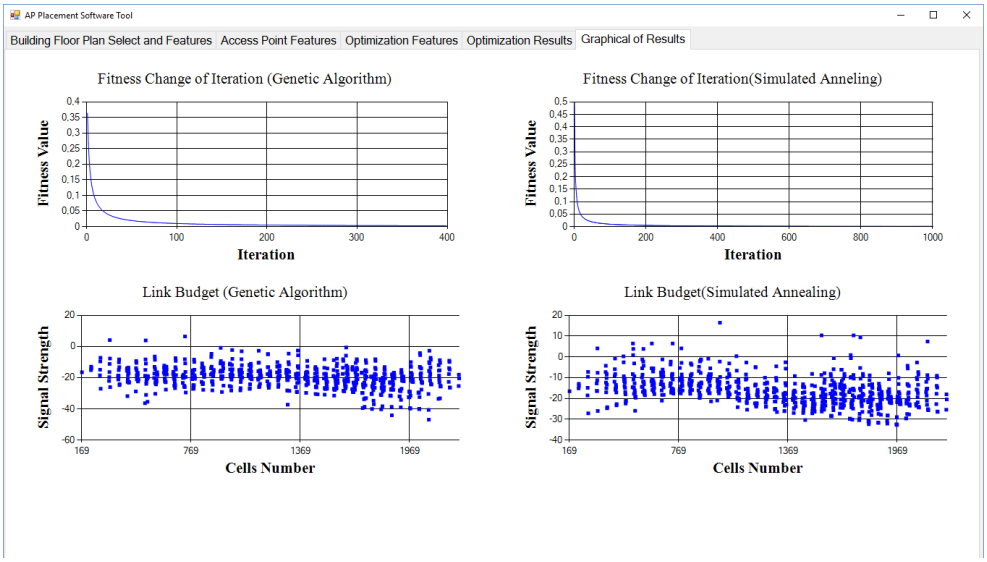


Figure 10. Graphical of Results Module

4. Conclusions

WLAN technology is widely used in communication sector and continues to evolve. Laptops, desktops, tablets, mobile phones are able to connect to WLAN with their onboard network card that supports 802.11 b/g/n/ac standard. Main reason behind this evolution is their low-cost deployment and easy installment features.

In installment process, one or more APs are deployed to provide wireless connectivity. A user can connect to the network if he/she is in the radio coverage area and the transmission power is in a stable condition. The radio coverage and the locations of APs are generally determined by traditional approaches such as trial and error. Therefore, WLAN performance completely depends on the experience of network administrator that causes terminals to communicate with APs inefficiently. Furthermore, AP signals cannot be measured in some areas of indoor setting.

In this study, unlike traditional approaches, we have designed and developed a decision support tool that will help system specialists set up a WLAN in indoor spaces such as shopping malls, airports, and arenas. The primary objective of this tool is to design a WLAN that will provide optimum signal strength at each point of the indoor setting. Any user walking around this area will be able to connect to the network with no interruptions. The developed software tool employs GA and SA methodology and provides an easy way to set up WLANs in indoor settings. It presents a robust solution to a complex mathematical challenge. Our evaluation showed that the software tool successfully identified the optimal locations and the number of APs by performing GA-based and SA-based optimizations. Our results showed that the SA method provided better performance.

As a future work, we hope to implement new features such as locating base stations in outdoor cellular networks. Furthermore, the developed tool can be applied to many different domains. In safety domain, it can be utilized to optimize the locations of forest watchtowers and fire monitoring systems for forests can be developed. Monitoring coverage of forest fires can be maximized and the construction costs can be minimized. In sensor networks domain, it can be used to find the optimal deployment of wireless sensors that will provide the best coverage and evaluate the results. In security domain, the area that will be observed and monitored can be optimized to track the movements and efficiently allocate resources and system performance.

As a future work, we hope to implement new features such as locating base stations in outdoor cellular networks. Furthermore, the developed tool can be applied to many different domains. In safety domain, it can be utilized to optimize the locations of forest watchtowers and fire monitoring systems for forests can be developed. Monitoring coverage of forest fires can be maximized, and the construction costs can be minimized. In sensor networks domain, it can be used to find the optimal deployment of wireless sensors that will provide the best coverage and evaluate the results. In security domain, the area that will be observed and monitored can be optimized to track the movements and efficiently allocate resources and system performance.

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