Deployment of Large-Scale WLANs

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***Abstract*– This paper analyzes the deployment issues for large-scale WLANs and presents our latest results on indoor propagation modeling and network planning. Proper network planning is necessary for large WLAN installations in order to achieve adequate coverage, and it relies heavily on the propagation model. We used the dominant path method to predict the propagation loss for each possible reception point in an indoor environment. Based on this propagation model, we further examined different combinatorial optimization methods to obtain close to optimal positioning of the WLAN access points and compare their cost effectives to the simple installation methods. The optimization algorithms evaluate an objective function that aims to maximize both the coverage area and the overall signal quality over a discrete search space. We propose a combination of two algorithms, Genetic Algorithms or Simulated Annealing, for the initial set of base stations positions, followed by Pattern Search algorithm, for the final accurate positions.**

***Keywords* – WLAN, radio propagation modeling, network planning and optimization, simulated annealing, genetic algorithms**

1. INTRODUCTION

Wireless LANs are already widespread in home and office environments, providing best-effort services at high-data rates while supporting limited user mobility. The increase of the density of the Access Points (AP) in a given indoor environment stimulates the need of their proper deployment to achieve adequate coverage. The traditional approach to cellular network deployment relies on advanced coverage and capacity planning to achieve optimal infrastructure with minimal number of base stations while sustaining a given quality of service. The WLANs, however, are designed to provide low-cost connectivity and are usually deployed in an ad-hoc fashion. Advanced coverage planning is regarded as too complex and too costly for WLANs, hence we investigate ways to reduce complexity and improve WLAN performance by different types of network planning [1].

While deploying WLANs for a small home network might be easy, deploying them for a large enterprise is a non-trivial task. The overall complexity of the network planning problem further depends on the number of AP sites to be optimized and the frequency at which the network operates. By increasing the frequency, the achievable cell size shrinks; hence, more APs are required to cover the same area.

The simplest way to install a WLAN is to skip propagation analysis and install a few APs in the areas where coverage is required and easy access to a wired backbone infrastructure is available. It does not require a specific radio network planning, so this method is most likely to be employed by the end users themselves. Although simple, this deployment method may result in a wireless network with coverage gaps in some areas.

A second approach is to divide the service area (i.e., the part of a building in which wireless access should be provided) into K equally sized rectangles, where K is the number of available APs, and install APs in the center of each rectangle. In such a *grid installation*, the AP sites are uniformly distributed within the service area, thus reducing the probability of coverage gaps.

The *coverage optimization* is the most complex method, as it involves the use of propagation analysis and optimization algorithms for determining the optimal AP positions that provide adequate coverage with a minimum infrastructure density. Coverage optimization can reduce the number of required APs, but the potential cost saving can be limited due to the relatively low costs of WLAN equipment, thus necessitating a careful cost trade-of.

The remainder of this article is organized as follows. We first discuss the specific problems involved in the deployment of WLANs and preset three common deployment approaches. In Section 2 we give a review of commonly used propagation models and present the used ones. Comparison of the user deployment model to coverage optimization method is given in third section. Section 4 presents the used objective function, review a number of optimization algorithms for objective minimization, and selects the most suitable algorithm. We then conclude the article.

2. RF PROPAGATION MODELING

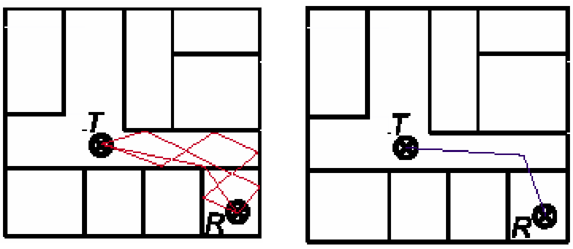
The radio propagation modeling is the most complicated aspect of any wireless network planning. The indoor radio channel differs from the cellular mobile radio channel in two aspects: the distances are much smaller, and the variability of the environment is much larger for much smaller range of transmitter-receiver distances. The propagation within buildings is strongly influenced by specific features such as layout of buildings and construction materials.

The problem of RF propagation modeling is to devise a model that can predict the signal coverage of an AP placed at a certain location. The classic statistically based model is the Hata-Okumura model [2], which determines the mean path loss $L_p(d)$ as according to

$$L_p(d) = L_p(d_0) + 10 \cdot n \cdot \log(d / d_0) + X_\sigma \qquad (dB) \quad (1)$$

where d is the distance between transmitter and receiver, and n is the path-loss exponent indicating the rate at which path loss increases with distance. The X_σ is a log-normally distributed random variable describing the shadowing phenomenon. $L_p(d_0)$ is the reference path loss at a given distance d_0. All three parameters are site and distance dependent, and their choices for given environment can best be determined by measurements. To determine the actual path-loss, transmitter and receiver antenna gains must be subtracted from (1).

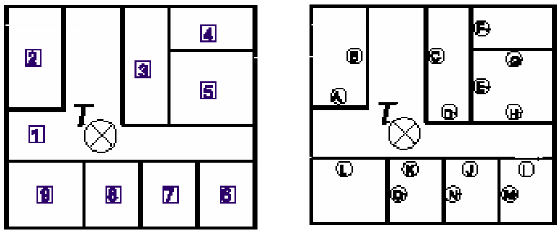
In this paper, we present our approach for prediction of the mean path loss in an indoor channel. We used the so-called *dominant path approach* for this purpose [3]. As shown in Fig. 1a, different rays may reach the receiver passing the same sequence of rooms and penetrating the same walls. The contributions of those rays which offer the same number of interactions to the over–all field strength are very similar (and grouped together to form the dominant path, Fig.1b), while the other rays with more interactions can be neglected because of their higher attenuation.



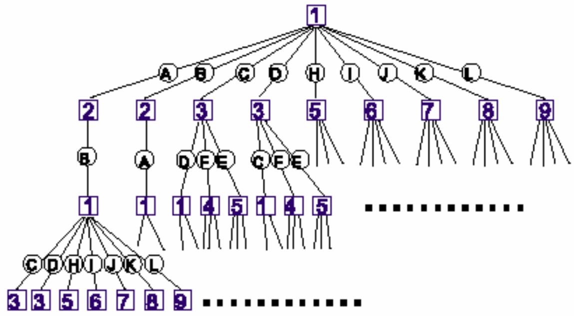
(a) Posible rays (b) Dominant path

Fig. 1. Representation of the multipath by a single dominant path

For determination of the dominant paths in a given indoor environment, information about the room locations is necessary. The determination of the rooms includes an analysis of the neighboring rooms, so that the walls coupling to each pair of rooms must also be considered. The information about the neighboring rooms is used to compute the room structure of the indoor environment in form of a tree. For the room from Fig. 1, the tree formation, based on the wall couplings, is depicted in Fig.2.



(a) Room numbers and coupling of walls



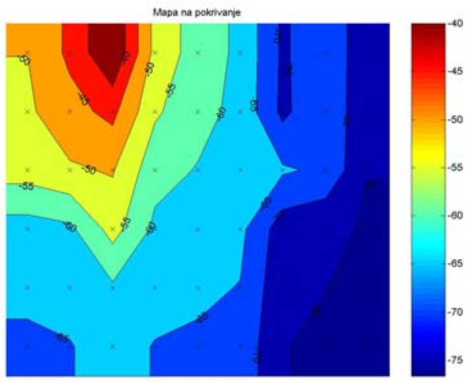
(b) Tree structure of rooms

Fig.2. Determination of the dominant paths

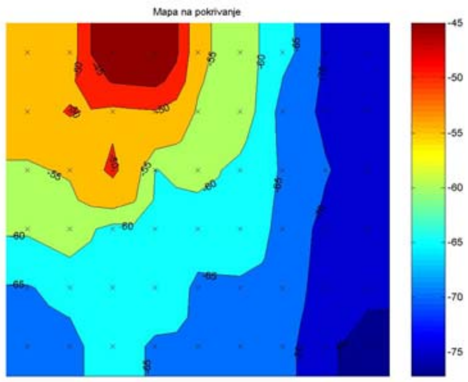
The root of the tree corresponds to the room in which the transmitter is located (Fig.2a). The first layer of the tree contains all neighboring rooms and if there is more than one coupling wall between the room of the transmitter and the neighboring rooms, the neighboring room is placed in the first layer as many times as there are coupling walls between the two rooms. All further layers are determined in a similar way. We used the well-known Dijkstra algorithm to determine the shortest path between the transmitter (i.e. the tree root) and the potential receiver in any room (i.e. the node).

We applied the dominant path approach to predict the mean received signal strength within the premises of the Institute of Telecommunication at the Faculty of Electrical Engineering in Skopje. The prediction results are compared to the field measurements at the same location realized by using our own RF site survey tool. Both the RF site survey tool and the measurement methodology are presented in Section 3. The prediction and the measurements are realized at potential receiver locations placed in the virtual rectangle grid over the given floor layout (9 x 6 matrix in this case).

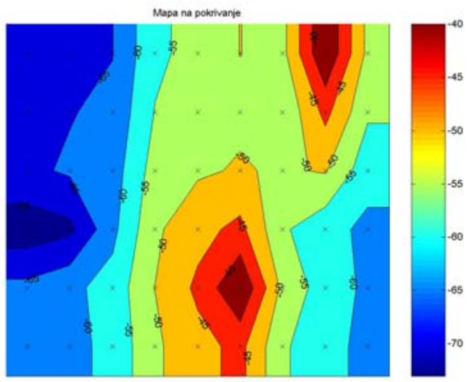
Fig.3 depicts the coverage maps for two AP deployment scenarios at the Institute of Telecommunications: the single AP placed at location 3 (Figs. 3a and 3b for prediction and measurement, respectively), and the two APs placed at locations 8 and 42 (Figs. 3c and 3d for prediction and measurement, respectively). The colorbar by each figure represents the colors mapping to the received signal's mean power in dBm for 5dBm transmitter's output power and omnidirectional transmit and receive antennas.



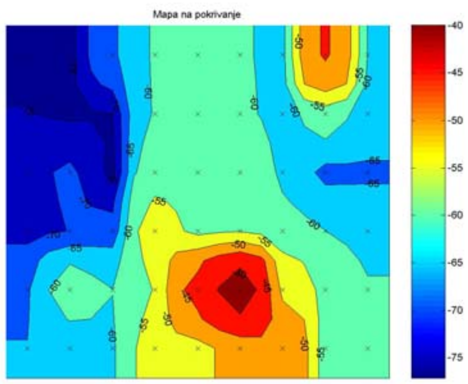
(a) Prediction for AP location 3



(b) Measurements for AP location 3



(c) Prediction for AP locations 8 and 42



(d) Measurements for AP locations 8 and 42

Fig.3. Comparison of dominant path prediction model with the field measurements

The dark red regions, where the mean power level reaches its peak, pinpoint the actual AP locations. The dark blue regions represent regions of very low mean power, where the wireless clients operate near theirs receiver sensitivity threshold. The threshold differs among client adapters from different vendors. Exceeding this threshold means automatic reduction of the bit rate due to low signal quality from 11 Mbit/s to 5.5, 2 or 1 Mbit/s in the case of the IEEE 802.11b WLAN.

Fig.3 demonstrates the accuracy of the dominant path prediction method for the signal strength (<5%).

3. RF SITE SURVEY

The RF site survey is one of the most painstaking steps in the deployment process. The purpose of this step is to ensure that the preliminary deployment plan indeed provides the required coverage. The RF site survey involves measuring network performance at representative locations, such as the received signal's mean power. The RF site survey tool (Fig.4.), developed at the Institute of Telecommunications, generates signal strength coverage maps (Fig.3) as according to the well-defined measurement methodology. The required measurement hardware is found in any IEEE 802.11b client adapter. The wireless adapter has a measurement module of its own for controlling the link quality using Beacon frames from the AP.

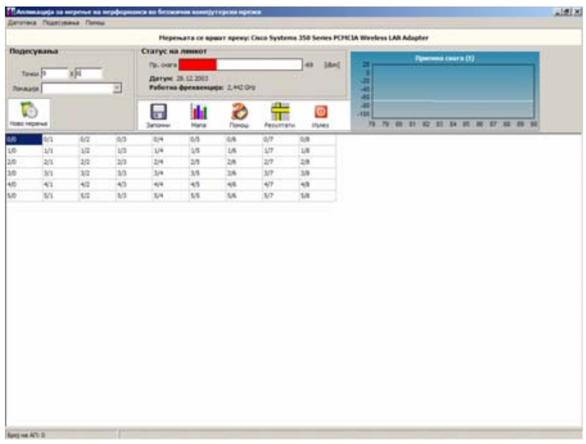


Fig. 4. GUI of the RF site survey tool

Based on the properties of indoor radio channels at 2.4 GHz for IEEE 802.11b WLANs, the measurement scenario depends on the predicted RMS delay spread Δ for small office/home office (SOHO) and large-office environments. The mean path loss at each location in a SOHO (a large-office) environment is determined from 30 (40) power samples gathered at equidistant points along a 20λ circular or linear track by calculating the linear average of the series. Note that λ is the carrier wavelength at 2.4 GHz, so $20\lambda = 2.5$ m. The equidistant points are positioned at $0.5\lambda = 6.25$ cm spacing.

The choice for 30 measurements for SOHO environments is made under assumption that RMS delay spread is Δ = 0.22 ns (so B·Δ = 0.5), which assures the 95% confidence limits of the measurements as about ±1dB. The choice for 40 measurements for large-office environments is made under assumption that RMS delay spread is Δ = 0.45 ns (so B·Δ = 1), which assures the 95% confidence limits of the measurements as about ± 0.7dB.

4. OPTIMIZATION ALGORITHMS AND OBJECTIVE FUNCTION

The base station coverage optimization requires finding a minimal set of locations for placing base stations such that all the receiver locations are covered. A location is said to be covered if the power received by it from its corresponding base station is greater than certain threshold.

User deployment approaches that completely avoid any numerical optimization can often provide sufficient coverage in case for dense networks with relatively large cell overlap, such as in typical home or office environments. In outdoor environments or indoor networks at higher frequencies user deployment cannot guarantee good coverage, grid installation could be used.

For environments with difficult propagation characteristics coverage optimization is required. According [4] numerical coverage optimization should be used for sparse networks. In contrast, dense networks typically achieve almost the same performance with much more cost-efficient user deployment.

An issue with numerical coverage optimization is that the optimization functions for the problem are several times non-differentiable and even discontinuous. Since standard numerical optimization techniques cannot be applied, we reverted to using heuristic techniques such as direct search methods, simulated annealing, or genetic algorithms.

4.1.1. Objective Function

Coverage optimization typically comprises two objectives: improving the average signal quality in the entire service area and minimizing the area with poor signal quality. The former objective involves placing the APs such that the average signal quality is maximized. The latter involves placing APs such that the lowest signal quality within the service area is maximized, thus reducing the probability of area outage. The two objectives do not necessarily have the same set of optimal AP locations; hence, a suitable trade-off must be found. We use an approach proposed in [5], a combination of a minisum and a minimax objective function.

Maximization of the average signal quality is achieved by evaluating and minimizing the average path loss f_1, expressed by:

$$f_1 = \frac{1}{M}\sum_{i=1}^{M}(g_i^k + \mu \max\{0, g_i^k - g_{i,\max}\}) \quad (1)$$

over the entire service area. Here, M is the total number of measurement points in the service area, and g_i^k is the path loss from AP k in the i-th measurement point. Each point is assigned to K APs and the minimum path loss is chosen, i.e.,

$$g_i^k = \min_{k=1,\dots,k}\{g_i^j\} \quad \forall i = 1,\dots M \quad (2)$$

Where K is the total number of APs. The term $g_{i,max}$ defines the maximum tolerable path loss in measurement point i. If the threshold g_{max} is exceeded, a penalty term of $\mu(g_i^k - g_{i,\max})$ is added, where μ is the penalty factor.

In order to lessen the worst case path loss second part of objective function is introduced to minimize the contribution of measurement points with maximal path loss:

$$f_2 = \max_i(g_i^k + \mu\{0, g_i^k - g_{i,\max}\}) \quad (3)$$

The final form of the objective function (OF), given in equation (4), is a combination of equations 1 and 3 controlled by balancing parameter ψ.

$$OF = \psi f_1 + (1-\psi) f_2 \quad (4)$$

For the simulations we took the recommendation in [5] and set ψ to a value within the range of [0.5, 1], i.e. we used ψ=0.6 that slightly emphasize the first term of the OF. Furthermore, in the simulations $g_{i,max}$ is set to the value g_{max}=100dB.

The optimal location for single AP can be obtained by evaluating equation (4) for all possible AP locations and choosing the one that achieves the minimum OF. Since the number of OF evaluations increases linearly with the number of possible AP sites N, the global optimal solution couldn't be obtained by exhaustive search.

The problem of selecting K out of N possible sites is a combinatorial problem of order:

$$O\left(\frac{N!}{K!(N-K)!}\right) \quad (5)$$

thus limiting exhaustive search algorithms to cases where K and N are very small.

Unfortunately, there is no known polynomial time algorithm that can provide an exact solution to the above problem for realistic values of K and N. Therefore heuristic-based optimization algorithms are used.

4.2. Optimization Algorithms

For our test bed environment we used four types of heuristic-based algorithms: *pruning*, *simulated annealing*, *genetic algorithms* and *pattern search*.

4.2.1. Pruning Algorithm (PA)

Pruning is greedy algorithm based on removal of AP with worst OF in iteration. In the initialization each AP is iteratively removed, the OF is re-evaluated without the removed AP, and the removed AP is reseeded. This proceeds until the algorithm has calculated the OF for every possible AP removal. The AP whose removal achieved the lowest OF is then permanently removed, and the algorithm repeats for the remaining *N-1* APs. The algorithm repeats same steps until there are only *K* APs left.

In the simulations the algorithm was useful for problems where N≤500, and for such cases it could be used for providing good starting solution to other heuristic search algorithms used for refining the local optimum (e.g. pattern search).

4.2.2. Genetic Algorithms (GA)

The genetic algorithm is a method for solving optimization problems that is based on natural selection, the process that drives biological evolution. The genetic algorithm repeatedly modifies a population of individual solutions. At each step, the genetic algorithm selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution.

The genetic algorithm uses three main mechanisms for creating the next generation from the current population: selection, crossover and mutation.

In our simulations the genetic algorithm starts with a random set of *K* AP, or it takes the input from previously ran SA or PA algorithms. We used GA algorithm’s parameters as shown in table 1.

Table 1. GA parameters

Population Size	10
Generations	200
Fitness Scaling	proportional
Selection function	roulette
Reproduction	Elite Count=2 CrossoverFraction=0.75
Crossover	Single point
Mutation	Uniform MutationRate=0.8

4.2.3. Simulated Annealing (SA)

Simulated annealing is a random search algorithm that gradually decreases the degree of randomness until it converges to a local optimum.

The algorithm starts by evaluating the OF for an initial set S_0 of AP positions that are then randomly altered, resulting in a new set, S_1. If the new AP positions result in an improvement (i.e., OF(S_1)<OF(S_0)), S_1 is accepted as the new solution. Otherwise, if OF(S_1)≥OF(S_0), S_1 is accepted with probability:

$$P_a(T) = \min\left(1, e^{-\gamma \frac{OF(S_1)/OF(S_0)-1}{(T/T_0)^2}}\right) \quad (6)$$

where γ is attenuation coefficient and T the system temperature (*To* is the starting temperature).

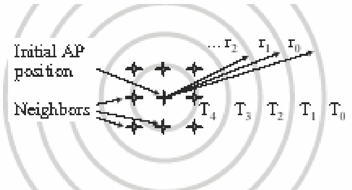


Fig. 1. Cooling strategy for simulated annealing

T is a measure of the intensity of the random alterations to the AP positions. To improve convergence, SA uses a cooling strategy (Fig. 1), where the randomness is reduced as the algorithm progresses. The cooling strategy used for the AP placement problem permits, during its initial phase random changes to the AP positions with a large radius r_0. As the temperature is gradually lowered, the circle becomes smaller, and hence the number of available neighbors decreases. We’ve used five temperature levels as recommended in [5]. The acceptance probability $P_a(T)$ should prevent the algorithm from becoming trapped in a local optimum. It needs to be carefully tuned by adjusting γ to encourage convergence while permitting sufficient inertia to eventually escape a local optimum. In the simulations we used γ=100 and acceptance probability in range [0,0.1]. The convergence properties of SA depend on the initial solution S0, which can be obtained either randomly or as input from previous ran of an optimization algorithm (e.g. PA or GA). We ran SA for a fixed number of iterations at each of the five temperature levels. In the simulations we found that SA is equally useful as algorithm for finding good global optimum as algorithm for finding good local optimum. In combination with PS it regularly converged toward global i.e. local optimum. For trivial environment it converges straight to local optimum without using a PS for refining the results.

4.2.4. Pattern Search

Pattern search algorithms represent a special class of direct search algorithms. Direct search is a method for solving optimization problems that does not require any information about the gradient of the objective function. As opposed to more traditional optimization methods that use information about the gradient or higher derivatives to search for an optimal point, a direct search algorithm searches a set of points around the current point, looking for one where the value of the objective function is lower than the value at the current point. A pattern search algorithm computes a sequence of points that get closer and closer to the optimal point. At each step, the algorithm searches a set of points, called a mesh, around the current point i.e. the point computed at the previous step. If the algorithm finds a point in the mesh that improves the objective function at the current point, the new point becomes the current point at the next step of the algorithm.

4.2.5. Optimization results

In the simulations we used chain of two optimization algorithms:

- Genetic algorithm in combination with pattern search (GA+PS),
- Simulated annealing in combination with patter Search (SA+PS).

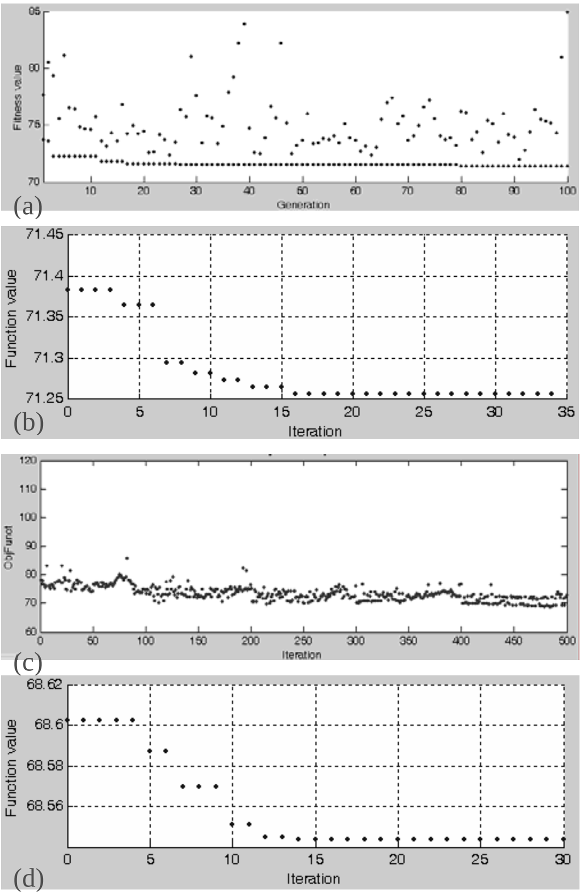


Fig.2 Convergence of the algorithms in office environment.

The GA+PS chain has lesser computational complexity but not always converge to the optimum. SA+PS chain has greater computational complexity but for evaluated office environments it always converged to the global optimum. Standard deviation of the results for OF was zero i.e. the consecutive runs of SA+PS for same office environments gave same values for the objective function and same positions for the chosen *K* APs. Fig.2 depicts time execution plots of the two mentioned chains of optimization algorithms. On plots (a) and (b) we could examine the convergence of the GA+PS and on plots (c) and (d) the convergence of SA+PS algorithms. We deduce that former combination gave suboptimal results compared to the latter combination which is optimal. The plots are for office environment with size $25 \times 16 m^2$, 10 rooms divided by 10cm thick gypsum walls and 1m grid size.

5. Conclusion

This paper presents the various network planning issues for large-scale WLAN deployment: *propagation modeling*, *RF site survey* and *coverage optimization algorithms*. We utilized the dominant path method for indoor channel's signal strength prediction and applied it on two separate deployment scenarios on our office floor. Comparison with the measurements from the RF site survey verifies the accuracy of the prediction model. The prediction coverage maps for each possible AP location in the virtual layout grid are the input variables to the optimization algorithms. The optimization objective function aims both maximize the average signal strength and minimize the area with poor signal quality in the entire service area over a discrete search space. We explored and tested several optimization algorithms over a well-known objective function. The least computational effort and the most accurate results are obtained by the combination of two algorithms that are initiated in sequence. The Genetic Algorithms or Simulated Annealing is used to determine the initial solution set and the Pattern Search algorithm to determine the final accurate AP positions.

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