Mono- and Multiobjective Formulations for the Indoor Wireless LAN Planning Problem

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Abstract

Wireless LANs experienced great success in the past five years. This technology has been quickly adopted in private and public areas to provide a convenient networking access. The fast pace of development has often induced an uncoordinated deployment strategy where WLAN planning tools have been barely used. This article highlights the difficulty of planning such wireless networks for indoor environments. The first issue the WLAN planning problem has to face is to accurately describe the quality of a network, based on realistic propagation predictions. The second issue is to implement a search strategy that provides efficient deployment strategies.

This article is introduced by a description of previously proposed planning strategies. Their study opens out onto a problem formulation that accounts for coverage, interference level and quality of service (in terms of data throughput per user). This formulation is then introduced as either a mono-objective or a multiobjective optimization problem. In the first case, we propose to solve the mono-objective problem

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with a Tabu search metaheuristic minimizing a weighted sum of the planning criteria. Then, we compare the outcome of this strategy to the results of our previously proposed multiobjective Tabu search strategy. We highlight the fact that efficient solutions are obtained quickly with the mono-objective approach if an appropriate set of weighting coefficients of the evaluation function is chosen. The main issue of mono-objective search is to determine these coefficients. It is a delicate task that often needs several runs of the algorithm. Multiobjective search is an interesting alternative heuristic as it directly provides a set of planning solutions that represent several trade-offs between the objectives. Our multiobjective heuristic looks for a set of non-dominated solutions expected to converge to the Pareto front of the problem and selects the most significant ones for the end user. Both QoS-oriented planning methods are illustrated on a realistic environment representing a building floor of about 12600m^2. Results show the assets of both approaches but mainly emphasize the benefit of the multiobjective search strategy that offers several alternative solutions to the radio engineer.

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Index Terms

Wireless networks planning, Tabu optimization, Multiobjective optimization, 802.11

I. INTRODUCTION

The wireless LAN (WLAN) planning problem is closely related to the widely-studied cellular network planning problem. The main matter is to find a configuration of the access points (APs) that guarantees a given quality of service (QoS) as for instance coverage, low interference level or minimum available throughput. Several variables can be taken into account for planning: the number of APs, their location, their transmission power or the type of their antenna. Albeit lots of WLAN APs' placements are done by radio engineers everyday, when the number of APs increases, the simple use of coverage constraints does not provide efficient large-scale interference-free networks. It becomes then critical to develop automatic planning techniques based on realistic radio wave propagation predictions.

In the last decade, indoor WLAN planning mainly focused on coverage and cell-overlapping optimization [1], [2]. More recent works [3], [4], [5] were devoted to more sophisticated criteria aiming at ensuring a level of quality of service (QoS) for connected users. The QoS may be considered from different points of view where either the bandwidth per user or the network capacity is chosen to be relevant. The related issues are then twofold: $i)$ the efficient formulation of such a QoS criterion for the WLAN planning problem and $ii)$ the evaluation of this criterion. In [3], [4], [5], [6], it is assumed that the available aggregate bandwidth of an access point is fixed, albeit stochastic performance evaluation of 802.11 shows different results. Indeed in [7], [8], the available bandwidth of an AP is shown to be decreasing when the number of connected users increases. Defining a realistic QoS oriented criterion must take this feature of the medium access control (MAC) protocol into account. In this article we use a criterion based on a performance evaluation model of the MAC protocol that estimates the aggregate throughput of an access point based on the mobile users distribution [9]. This model behaves as a real but isolated 802.11 network cell and therefore interference between APs are not taken into account. To compensate for this issue, the QoS criterion is combined with an interference mitigation criterion. This objective favors the selection of solutions minimizing the number of adjacent cells. It reduces drastically the occurrence of remaining interference after channel assignment has been performed. Of course, both criteria are balanced by a coverage criterion that focuses on coverage provision.

The wireless planning problem can clearly be identified as a multiobjective optimization problem where coverage, interference mitigation and QoS need to be concurrently optimized. In this case, the quality of the WLAN network relies on the optimization of several antagonistic criteria and the optimal solution is the result of a fixed trade-off between them. There are two algorithmic ways of handling such problems. The first one applies common mono-objective optimization algorithms to an evaluation function gathering all the criteria. The second one relies on a multiobjective (MO) search strategy and looks for a set of Pareto-optimal solutions, each solution representing a different trade-off between the criteria involved.

Most of the works have applied a mono-objective solving heuristic. In [10], [11], [12], the optimization criteria are gathered into a unique evaluation function by defining a weighted sum of the criteria. In this case, continuous derivative-based [10] and direct search [12] algorithms have been implemented but these approaches suffer from a lack of efficiency due to the non-convex shape of the evaluation function. The planning problem can also be defined as an integer linear program where one criterion becomes the main objective and the other ones are translated into constraints. In [3], Lee et al. propose to use a mathematical programming optimizer to find the optimal solutions of their integer linear program. Such programs are complex to solve what makes planning of large environments untractable within the time frame available for the conception of WLANs that can't exceed one or two days. To overcome this issue, combinatorial metaheuristics have been implemented to solve such integer linear programs [13], [2], [14]. In this case the solutions' optimality is not guaranteed anymore but they at least provide a good solution for large environments and are less sensible to the shape of the evaluation function. Constraint programming heuristics have also been proposed in [6], [15]. All these works only offer a single planning solution. If this solution doesn't suit the radio engineer, the search has to be started all over again with different initial settings.

The use of a multiobjective optimization algorithm as proposed in [4], [16] has the main advantage of providing in a single search launch a set of Pareto optimal solutions, each one of them representing a different trade-off between the criteria. Based on such results, it is possible to select a relevant subset of planning solutions to be shown to the radio-engineer. The main asset of an MO approach is to account for the engineer's experience in the final roll-out choice.

In this article, we propose to solve the planning problem by optimizing concurrently coverage, interference and throughput with two mono- and multiobjective approaches. First, a Tabu metaheuristic is applied to a unique evaluation function defined as a weighted sum of the planning criteria. This work highlights the delicate choice of the weighting coefficients as there is no direct relationship between the values of these coefficients and an expected trade-off in the planning criteria. To overcome this issue, we have proposed in [16] to tackle the problem with a multiobjective approach introducing a multiobjective Tabu metaheuristic. This multiobjective algorithm is herein detailed again but with a more technical insight and a first convergence analysis. This multiobjective approach first looks for a set of non-dominated planning solutions, each one of them reflecting a peculiar trade-off between the planning objectives. To reduce the size of this set, N_{opt} solutions are selected to provide different realistic roll-out scenarii to the radio engineer. The comparison of both mono- and multiobjective approaches are based on a realistic case-study that exploits an Indoor propagation engine called WILDE which is described in [18].

The formulation of the planning criteria is provided in section II. Section III presents the implementation aspects by focusing on the propagation simulator and both mono- and multiobjective Tabu heuristics. Results and conclusions are respectively given in sections IV and V.

II. The WLAN planning criteria

An automatic WLAN planning process is based on a mathematical description of one or several objectives. The main objective is to provide radio coverage everywhere offering to the mobile user a full connectivity. A complementary objective concerns the efficiency of the network, which mainly relies on the interference level between cells. Additionally, it is relevant to use a user-oriented objective to increase the level of service in terms of throughput.

In section II-A, a generic formulation based on a penalty function is proposed for any criterion. The related coverage penalty function is then described in section II-B, the non-interfering one in section II-C and the QoS one in section II-D.

A. A generic combinatorial formulation

Let be defined a discrete set of M candidate AP locations in a building floor. Variables of the planning problem are the number N of APs to plan, their locations, their transmission powers and their directions of emission if the antennas are directional. We use a discrete formulation where a solution S of the problem is defined as a vector of M items $S = (s_1, \ldots, s_i, \ldots, s_M)$. Each item represents a candidate AP location. It stores the transmission power p_i and direction of emission d_i if the candidate AP location is part of the solution S. An item is defined by:

$$s_i = \begin{cases} (p_i, d_i) & \text{if an AP is placed at the } i^{th} \text{ candidate location,} \\ 0, & \text{otherwise.} \end{cases} \quad (1)$$

Transmission power $p_i \in \mathcal{P} = \{P_1, \ldots, P_{N_P}\}$ and direction of emission $d_i \in \mathcal{D} = \{D_1, \ldots, D_{N_D}\}$ belong to two discrete sets of values. Given a directive antenna, each d_i represents a possible orientation of the main lobe of the radiation pattern. In the results presented in section IV, an omnidirectional antenna is used and thus d_i is fixed.

For each candidate location, a 2D coverage map is computed with the propagation simulator described in section III-A. A coverage map is defined as a set of mean received signal powers associated with rectangular areas defined by their top left hand corner $p = (x, y)$ and dimension $s = (s_x, s_y)$ in pixels. For the sake of clarity, these areas are numbered from 1 to L, and referred to as the blocks B_l. The mean received signal power in dBm (logarithmic scale) from an AP numbered k on the block B_l is referred to as F_l^k.

For each criterion, a specific utility value U_l is assigned to each block B_l. This utility value is derived from the power values F_l^k and depends on the kind of evaluation performed. For instance, for the coverage criterion, this value represents the maximum received power value.

A penalty function

$$\mathtt{fp} \ : \ B_l \mapsto \mathtt{fp}(U_l) = \mathtt{fp}_l \quad (2)$$

estimates the quality of B_l regarding the value of U_l. The shape assigned to fp when utility is maximized (respectively minimized) is presented in Fig.1-(a) (respectively Fig.1-(b)). In Fig.1-

(a), Block B_l is not penalized if its utility value is higher than a threshold value S_{max}. A maximum penalty of Δ is applied when U_l is smaller than another threshold S_{min}. The penalty is linear between both thresholds. The fact that this function is bounded helps reducing the influence of too bad or too good blocks on the final evaluation criterion, and thereby avoid border effects in the optimization process.

Each optimization criterion is a quadratic weighted sum of the values of $\mathtt{fp}_l$ accounted for each block B_l:

$$f = \sqrt{\sum_{B_l, l \in \{1,\dots,L\}} \mu_l . \mathtt{fp}_l^2} \tag{3}$$

μ_l is a weighting coefficient representative of the importance of B_l. It is here defined as the ratio between the surface area of B_l and the total surface area to cover. L is the number of blocks representing the whole environment. We defined a quadratic formulation to both minimize the average and the variance of the penalties.

B. Coverage Criterion

For the coverage criterion, the utility U_l is defined as the received signal power of the best server AP on B_l denoted F_l^{BS}. This value will be penalized according to the function depicted in Fig.1-(a). The thresholds are $S_{min} = S_{low}$ and $S_{max} = S_{high}$ standing for the minimum signal powers that ensure respectively the lower and the higher transmission rates. The maximum penalty Δ is set to $\Delta = \mid S_{high} - S_{low} \mid$ as the threshold values are give in decibels. We get the following penalty function:

$$\mathtt{fp}_{cov}(F_l^{BS}) = \begin{cases} 0 & \text{for} \quad F_l^{BS} > S_{high}, \\ \mid S_{high} - F_l^{BS} \mid & \text{for} \quad S_{high} \geq F_l^{BS} > S_{low}, \\ \mid S_{high} - S_{low} \mid & \text{for} \quad F_l^{BS} \leq S_{low}, \end{cases} \tag{4}$$

Adapting this criterion to any technology is done by choosing accordingly S_{low} and S_{high}. Table I summarizes the threshold values we advocate for IEEE 802.11 networks.

C. Interference Mitigation Criterion

In a CSMA/CA based network the radio medium is shared between terminals (APs and mobiles) by a carrier detection process. Thus, two neighboring cells having different but overlapping frequency channels cannot share efficiently the medium because the carrier sense mechanism doesn't work. With 802.11b equipments, there are few strictly non-overlapping channels (3 or 4) and the frequency assignment problem (FAP) becomes intractable manually when the size of the APs' neighborhood increases. At a first glance, this issue calls for including the FAP into the optimization process. To that end, either a FAP algorithm is run for each solution evaluation or the channel number is added as a variable into the combinatorial optimization problem [14]. As both approaches lead to a wide increase of the computational time, we rather propose a two-step approach keeping the FAP out of the planning task. But to get a robust two-step approach that still mitigates interference, we introduce an interference criterion in the planning process. This criterion maintains a low number of adjacent cells, resulting in a WLAN configuration that facilitates the *a posteriori* FAP resolution.

The interference mitigation criterion is based on the following penalty function. At B_l, received signal powers F_l^k, $k = 1, \dots, N$, exceeding the noise level $\mathcal{N}$, are ordered from the strongest to the weakest:

$$F_l^{BS} \geq F_l^{BS_1} \geq \dots \geq F_l^{BS_k} \geq F_l^{BS_{k+1}} \geq \dots \geq \mathcal{N} \tag{5}$$

To control the interference level and to make the *a posteriori* FAP easier, it is needed to maintain a low number of adjacent cells. For this purpose, only h signals are kept valid on each block. Received signals are divided into 3 sets: the best server signal F_l^{BS} $(k = 0)$, adjacent signals $(1 \leq k \leq h)$ and interfering signals $(k > h)$. We consider that interference created by the h adjacent signals will be mitigated through proper channel allocation. The choice of the value of h is critical and reflects a trade-off between handover and FAP requirements.

Our goal is to mitigate the strongest interfering signal F_l^{h+1} by maintaining its power level under noise level $\mathcal{N}$. The utility is defined as $U_l = F_l^{h+1}$ expressed in decibels. The penalty function is represented on Fig.1-(b) and defined as:

$$\texttt{fp}_I(F_l^{h+1}) = \begin{cases} 0 & \text{for} \quad F_l^{h+1} < \mathcal{N}, \\ \mid S_{high} - F_l^{h+1} \mid & \text{for} \quad \mathcal{N} \leq F_l^{h+1} < S_{high}, \\ \mid S_{high} - \mathcal{N} \mid & \text{for} \quad F_l^{h+1} \geq S_{high}, \end{cases} \tag{6}$$

The minimum threshold is $S_{min} = \mathcal{N}$, the maximum threshold is $S_{max} = S_{high}$ and the maximum penalty is $\Delta = \mid S_{high} - \mathcal{N} \mid$.

This formulation has been adapted from [19] initially proposed for GSM networks planning. In our simulations, the noise level is fixed to $\mathcal{N} = -98$ dBm and the number of adjacent signals is set to $h = 1$. This small value of h has been chosen for 802.11b networks because of the few number of independent channels. Here, h represents the number of adjacent cells seen at a specific receiver location but absolutely not the number of cells neighboring an AP. It may be furthermore possible to add a connectivity criterion as proposed in [19] to obtain more regular cell shapes. We disregarded such an approach because of the induced higher computational load.

D. QoS Criterion

In this section, a QoS-based criterion implementing a *per-user throughput* utility value is proposed. Previous works introducing such a constraint considered that all the nodes are transmitting with a unique data rate, that they perfectly share the available bandwidth and that each AP offers a constant total bandwidth [3], [4], [5]. However, $802.11b$ users share the bandwidth at 4 different data rates (1, 2, 5.5 or $11 Mbits/s$). Our contribution aims at introducing a more realistic sharing model between the users.

A uniform distribution of users is considered by defining a user's density over the whole environment. Based on this density and the coverage maps of all the APs, we determine the number of users assigned to each AP. These users are then divided into classes of service groups based on the data rate $r = \{1, 2, 5.5, 11\}$ $Mbits/s$ they are working at. The group of users attached to an AP number k and transmits with data rate r is made up of N_r^k users sharing an aggregate throughput D_r^k. For each AP and service area, D_r^k is assumed equitably distributed between the associated N_r^k users. Knowing the location of one block B_l and its best server power level F_l^{BS}, the service area it belongs to is known. The realistic throughput estimation d_l of a single user in block B_l is estimated by the throughput a user gets in the same service area. It is given by:

$$d_l = D_r^k / N_r^k \tag{7}$$

The key point of this approach holds in the estimation of the aggregate throughput D_r^k for each group. This estimation is obtained thanks to a stochastic performance evaluation model described in [9] and based on a Markov chain modeling of the IEEE 802.11b MAC protocol [7], [8]. The bi-dimensional discrete-time Markov chain represents in this work the backoff stage of a given wireless station at slot time t and the backoff time counter for this station. This chain provides the probability that one station transmits at data rate 1, 2, 5.5 or 11 Mbit/s, the channel occupation efficiency for each type of nodes and the duration for which the channel is occupied by either successful or unsuccessful transmissions leading to retransmission. The aggregated throughput D_r^k in the QoS criterion is derived from these values. In this model, it is assumed that there is no interference left between the cells. This makes sense because the interference criterion already aims at mitigating interference. Even if some interference remains after channel assignment, this assumption provides at least an upper-bound on the achievable per-user throughput.

Finally, once the throughput per user d_l has been determined, we define a criterion that favors solutions with d_l higher than a limit D_l^* for each block B_l. The corresponding QoS penalty function is given by:

$$\mathtt{fp}_{QoS}((d_l)_{dB}) = \max((D_l^*)_{dB} - (d_l)_{dB}, 0) \tag{8}$$

where the throughput values are computed in decibels for $d_{bits/s} \geq 1$ ($d_{dB} = 10 \cdot \log(d_{bits/s})$) to get the same order of magnitude for the QoS criterion than for the two other ones. When $d_{bits/s} < 1$, we assign $d_{dB} = 0$. Here, the utility value is $(d_l)_{dB}$ and the penalty function is depicted in Fig. 1-(a). The maximum penalty $\Delta = D_l^*$ is obtained when $d_{bits/s} < 1$ bits/s. The minimum threshold is $S_{min} = 0$ and the maximum threshold is $S_{max} = (D_l^*)_{dB}$.

III. Implementation

A. Propagation Simulations

In order to get realistic planning objectives, an accurate propagation simulation tool WILDE (Wireless LAN Design) is used [17]. It implements the Multi-Resolution Fourier Domain ParFlow (MR-FDPF) model in 2 dimensions [18]. This propagation model is based on a finite element frequency domain modeling. This kind of approach is known to be very realistic but in turn computational-load consuming. The originality of our approach described in [18] was to gather all the computational load into a pre-processing phase, exploiting a multi-resolution formalism and providing a pre-computed multi-resolution (MR) tree. This phase neither depends on the

APs' characteristics (position, emission power...) nor on their number but it accounts for the propagation features of the materials in the building (refraction index and permittivity). The next phase, i.e., the propagation phase, exploits the MR tree and therefore exhibits a very low computational load (less than 1s. for $100m \times 100m$ environments) to compute the coverage of each AP candidate. This time is comparable to the time needed with a standard multi-wall model (MWM). But while these standard approaches compute the received power from the main path only, WILDE exploits all paths, including all reflected and diffracted rays. The first advantage of the MR-FDPF model is that multiple reflection and diffraction effects of radio waves are completely rendered. The second one is that the multi-resolution concept allows to compute the mean power over homogeneous blocks instead of computing the mean power in each pixel, further reducing the coverage computational time. In this approach, the environment is divided into homogeneous regions, the blocks, and the received power F_l^k from AP numbered k is estimated over each block B_l defined by its top left hand corner $p = (x, y)$ and its size $s = (s_x, s_y)$. This model has been experimentally assessed for Indoor environments, leading to a mean square error of about $5dB$ [17].

B. *Mono-objective Tabu planning algorithm*

To achieve simultaneously several objectives, the WLAN planning problem may be formulated as a sum of complementary objectives. The planning process aiming to minimize a single aggregate evaluation function f is thus defined as:

$$f = \alpha_1 \ . \ f_{cov} + \alpha_2 \ . \ f_I + \alpha_3 \ . \ f_{QoS} \tag{9}$$

where f_{cov}, f_I and f_{QoS} stand respectively for the coverage, interference mitigation and QoS criterion.

Each solution follows the definition of equation 1 and is evaluated using the cost function of equation (9). Finding the optimal solution is a difficult optimization problem from the practical point of view as the size of the solution space grows exponentially (Card$(\mathcal{S}) = \sum_{n=1}^{M} \binom{M}{n}$) and a single solution evaluation lasts several milliseconds. This calls for the use of a metaheuristic. To that end, a Tabu approach [21] has been implemented. Tabu algorithms perform successive local search within the neighborhood $V(S)$ of the current solution S. The best solution in this neighborhood is chosen as the new current solution. To avoid local convergence and cycling problems, a memory called the Tabu list stores the choices made in the last T iterations. If the best solution found in $V(S)$ belongs to the Tabu list, the move is forbidden and the best non-Tabu solution is selected. This algorithm has been implemented with the following features:

a) A neighbor solution: is obtained either by

- moving a selected AP to a different position,
- adding an AP,
- removing a selected AP,
- changing the transmission power of a selected AP,
- changing the direction of emission of a selected AP.

The cardinality of $V(S)$, the neighborhood of S, is $\texttt{Card}(V(S)) = N((M-N)+(N_D-1)+(N_P-1))+M$. If transmission power and direction of emission is not chosen as a variable of the problem, the two last moves are ignored in the algorithm.

b) The Tabu list: stores the last solutions that have been selected to prevent reverse moves. This list can be referred to as the short-term memory that enables the algorithm to escape from local minima and prevents cyclic search. In this implementation, once a new current solution has been chosen, the former one becomes Tabu and is stored in the Tabu list. A solution of the neighborhood belonging to the Tabu list cannot be selected in the next search iteration. When an AP is either added or removed from the current solution, a fake solution is stored in the Tabu list to prevent cyclic add-and-remove steps. In this case, the fake solution stored in the Tabu list either represents the addition or the removal of an AP. This ensures that the search works with the same number of selected APs for at least the duration of the Tabu list.

This short term memory has a length T that is chosen randomly at each iteration between two user-defined parameters T_{min} and T_{max}. When T is reduced, the oldest moves, which exceed the new length of the list, become feasible.

c) Termination criteria: The algorithm stops when one of the following termination conditions is satisfied

- the number of iterations has reached the maximum number of iterations NI_{max},
- the number of successive iterations without improvement of the cost function has reached a specified number NWI_{max},
- the cost function returned value is equal to zero.

d) The parameter values: have been chosen empirically after several tests as it is recommended in [22]. We set $T_{min} = M/5$ and $T_{max} = M/2$ with M the number of candidate AP locations. In the same way, we set $NI_{max} = 1000$ and $NWI_{max} = 200$.

C. Multiobjective Tabu planning algorithm

1) Multiobjective optimization: Each constraint defined in section II measures the quality of one feature of the network. Getting the solution that has the best possible rating for each criterion is barely possible, especially when the optimization criteria have an antagonistic influence on the variables. For instance, networks made up of a high number of APs have good coverage and throughput performance but suffer from high interference levels. A good planning solution is the result of a trade-off between the constraints involved in the search. Joint optimization of antagonistic objectives is the definition of a multiobjective search problem.

Each multiobjective problem has a set of Pareto-optimal solutions defined as the set of non-dominated solutions. This set of non-dominated solutions is called the *theoretical Pareto front*. For a multiobjective problem minimizing n objective functions $f_{i,i\in[1,n]}$, a solution $\mathbf{x}$ dominates a solution $\mathbf{y}$ if and only if:

$$\forall i \in [1,n] : f_i(\mathbf{x}) \leq f_i(\mathbf{y}) \qquad \wedge \qquad \exists j \in [1,n] : f_j(\mathbf{x}) < f_j(\mathbf{y}) \tag{10}$$

Each non-dominated solution represents a different optimal trade-off between the objectives. For such solutions, it is not possible to improve one criterion without worsening another one. Figure 2 illustrates dominance by representing solutions for a generic two objectives minimization problem. The x- and y-axis respectively stand for the values of two arbitrary functions f_1 and f_2. The solutions depicted with crosses belong to the set of Pareto-optimal solutions. These solutions are not dominated as there is no other solution that is better for both criteria.

The solutions of an MO problem can be sorted according to their *Pareto rank*. A solution's rank is defined by the number of solutions by which it is dominated in the set. The solutions of the theoretical Pareto front have a rank $r = 0$.

A multiobjective search algorithm looks for the theoretical Pareto front of the problem, referred to as $\mathcal{F}_T$ in this paper. The algorithm obtains at each iteration an estimate of the theoretical Pareto front, referred to as the practical Pareto front $\mathcal{F}_P$. Search succeeds when $\mathcal{F}_P = \mathcal{F}_T$.

Once the MO search has been performed, depending on the application, it may be useful to select a subset of Pareto optimal solutions. The proposed multiobjective approach presented in the next subsection is composed of two steps. First, a Tabu-based MO search is performed to retrieve $\mathcal{F}_P$. Secondly, a dedicated selection heuristic is proposed to retrieve significant solutions to design the WLAN.

2) A multiobjective WLAN planning heuristic: The MO algorithm looks for the number, the location, the power and the direction of emission of the APs, too. Its aim is to minimize concurrently the three defined criteria: f_{cov}, f_I and f_{QoS}. This algorithm is derived from the previously presented Tabu metaheuristic. At each iteration, it aims at improving the quality of the current search front. This front consists of the set of solutions that dominate the other ones found during the search in the objective function space. The pseudo-code of our multiobjective heuristic is the following:

1) For each solution $\vec{S}_c^k$ of current front $\mathcal{F}_c(i)$:
   - $a)$ Computation of the neighborhood $V(\vec{S}_c^k)$ of $\vec{S}_c^k$;
   - $b)$ Selection of the set $\mathcal{P}_R(V(\vec{S}_c^k))$ of solutions of Pareto rank $R \leq R_{max}$ from $V(\vec{S}_c^k)$;
   - $c)$ Addition of $\mathcal{P}_R(V(\vec{S}_c^k))$ in the optimal front $\mathcal{F}_P$;
   - $d)$ Random selection of a solution of $\mathcal{P}_R(V(\vec{S}_c^k))$ and addition of it in $\mathcal{F}_c(i+1)$;
2) Removal of the solutions with rank $R > 0$ from $\mathcal{F}_P$;
3) Update of the Tabu list for each solution.

In this algorithm, the current search front $\mathcal{F}_c(i)$ of iteration i is made up of K solutions. For each solution, the neighbor solutions are created with the same rules than in the mono-objective Tabu heuristic. Then, the solutions whose Pareto rank R is smaller than R_{max} are selected and added to the estimated optimal front $\mathcal{F}_P$. The new current search front $\mathcal{F}_c(i+1)$ is created by adding for each solution a randomly selected solution of $\mathcal{P}_R(V(\vec{S}_c^k))$. Once these steps have been performed, it is necessary to remove the dominated solutions from the estimated optimal front $\mathcal{F}_P$. The K Tabu lists are then updated with the solutions of the former current front $\mathcal{F}_c(i)$. The duration of this Tabu list is then randomly chosen at each iteration within an interval $[T_{min}, T_{max}]$.

The algorithm is stopped after a fixed number N_I of iterations. The random selection of the new search front introduces diversity in the search process. To increase diversity, the solutions of the initial search front have all a different number of APs. Solution 1 of the search front presents N_{min} APs and the last solution of the front is made of $(N_{min}+K)$ APs. Position of each selected AP is chosen randomly. Here, we set $N_{min}=3$.

3) Selection of optimal solutions on the Pareto front: At the end of the search, $\mathcal{F}_P$ counts numerous solutions. It is necessary to select a number N_{opt} of solutions figuring significant and different trade-offs between the objectives. The selection is based on two elements:

- dissimilarity of the criteria trade-offs obtained,
- dissimilarity of the selected solutions,

The dissimilarity in the criteria trade-offs is evaluated by the analysis of coverage, interference and QoS criteria, too. The solutions of $\mathcal{F}_P$ are divided into N_{sh} sets representing different trade-offs between the three criteria. These sets referred to as the sharing sets, are obtained thanks to a sharing function $Sh(\vec{S})$ defined by Srinivas and Deb in the N.S.G.A. algorithm [23]. This function assigns a weight $m_i=\sum_{j=1}^{F} Sh(d(i,j))$ to a solution number i depending on its neighborhood density within a ball of radius σ_{share}. F is the number of solutions in $\mathcal{F}_P$ and $d(i,j)$ the distance in the criteria space between solution i and j. The sharing function $Sh(d(i,j))$ is given by:

$$Sh(d(i,j))=\begin{cases} 1-\left(\frac{d(i,j)}{\sigma_{share}}\right)^2 & \text{if } d(i,j)<\sigma_{share} \\ 0 & \text{otherwise} \end{cases} \tag{11}$$

Neighbor solutions are the ones that belong to the same sphere of radius σ_{sh}. Each sharing set represents a family of solutions expressing the same order of trade-offs between the criteria.

When these sharing sets have been determined, the dissimilarity of the solutions is evaluated. For each sharing set, an average geometrical distance (in the physical space) between the solutions is computed. The D most different solutions are then selected in each set.

The quality of the remaining $D.N_{sh}$ solutions is then evaluated more precisely. First, an optimal channel assignment is computed thanks to a Tabu FAP heuristic described in [20]. A variant of our QoS criterion, f^{I}_{QoS}, is computed knowing the exact interference distribution now defined. This criterion also follows the expression of Eq.(8) and uses the same model to estimate the throughput $(d_l)_{dB}$. The difference holds in the computation of the input values of the performance evaluation model which needs the number of users per AP working at the different transmission rates r. The rate on a block B_l is here based on a real SINR estimation after FAP instead of a simple SNR value. The best solution regarding this new criterion is selected in each sharing set and the N_{opt} most different solutions among them are finally selected. These N_{opt} final solutions are proposed to the radio engineer for further analysis and a manual final selection.

4) Convergence of the multiobjective approach: Two test environments, called $Env1$ and $Env2$, have been used to assess the convergence properties of the proposed multiobjective heuristic. They differ by the number of candidate AP locations as we have $M = 115$ for $Env1$ and $M = 155$ for $Env2$, located in a rectangular building floor of about $2100m^2$. For being able to compute the theoretical Pareto front, the search space size is limited by fixing the number of antennas to plan to $N = 3$. The only variable is the location of the APs. Size of the search spaces for $Env1$ and $Env2$ are respectively $\binom{115}{3} = 246905$ and $\binom{155}{3} = 608685$. Only coverage and interference criteria are optimized (with h=0).

For each environment, the theoretical Pareto front $\mathcal{F}_T$ is computed with an exhaustive search. We also performed 20 runs of the proposed MO heuristic with $N_I = 50$ iterations, $R_{max} = 2$ and $K = 10$. The practical Pareto fronts $\mathcal{F}_P$ obtained are compared to $\mathcal{F}_T$ based on the following performance metrics:

- **The error ratio** that measures the non-convergence of a search method to $\mathcal{F}_T$. It is given by:
$$E = \frac{\sum_{i=1}^{n} e_i}{n} \tag{12}$$
where $e_i = 0$ if solution i belongs to $\mathcal{F}_T$ and $e_i = 1$ elsewise, and n the number of solutions of the practical Pareto front $\mathcal{F}_P$.
- **The generational distance** that measures the distance between a set of n solutions and the theoretical Pareto front. It is defined by:
$$G = \frac{(\sum_{i=1}^{n} d_i^p)^{1/p}}{n} \tag{13}$$
where d_i is the smallest distance betweeen a solution and $\mathcal{F}_T$. Here, we use $p = 2$.

The smaller both metrics are, the closer the solutions of $\mathcal{F}_P$ are from $\mathcal{F}_T$. These metrics have been calculated for the practical Pareto fronts obtained every 10 iterations for each one of the 20 runs. The average and standard deviation values for both metrics over the 20 runs are given in Figure 3 for $Env1$ and $Env2$. The optimal Pareto Front for $Env1$ and $Env2$ are respectively composed of 24 and 31 solutions.

For both environments, the average error ratio and generational distances become small after 50 iterations. After 30 iterations, convergence slows down as most of the solutions of the practical Pareto front are optimal. When $E = 0.1$, only about 2 solutions of $\mathcal{F}_P$ don't belong to $\mathcal{F}_T$ for $Env1$ and about 3 solutions for $Env2$. The same error ratio is obtained for both environments, but the average distance to $\mathcal{F}_T$ for $Env2$ is smaller although it is the problem instance with the biggest search space. For the WLAN planning problem, we consider that such convergence properties are sufficient. We plan in future work to compare the performance of this Tabu-based MO search to other multiobjective approaches on benchmarks test functions.

IV. Results

A. Test environment

The test environment shown in figure 4 is the ground floor of a 12600 m^2 building. The M candidate positions ($M = 256$) have been chosen at the center of some selected blocks associated with the multi-resolution structure of the WILDE propagation simulator. A block in this multi-resolution structure is selected if and only if it is made of air (homogeneous block) and if its surface area S is bounded by $10m^2 < S < 80m^2$. The lower and upper bounds have been chosen respectively to limit the density of potential APs locations and to provide several locations within big rooms, as for instance in halls or patios. Larger homogeneous blocks are further divided while smaller blocks are disregarded. As selected blocks are only made of air, it makes sense to assume that the radio coverage of a candidate AP placed in the center of a block is representative of the coverage of any AP's location in the same block.

Receiving test points are also selected thanks to the multi-resolution structure of WILDE. A set of $L = 499$ blocks are selected in the same way, the constraint on their surface area being: $10m^2 < S < 40m^2$. The distribution of these blocks is depicted in Fig.4-(b).

The $M = 256$ coverage maps of 2.5dBi omnidirectional antennas with an emission power of 13 dBm are computed prior the search in about 6 minutes on a PC with a 2.4GHz Pentium IV CPU and 1Gb of RAM. These coverage maps are stored and used by the mono- or multi-objective planning algorithm to compute the values of the optimization criteria.

In the problem instance used here, the emission power of the APs is fixed at 13 dBm and antennas are assumed omnidirectional. A distribution of 200 users supposed to transmit simultaneously is defined for the QoS criterion. The probability of having a user in each pixel is uniform and is computed as the ratio between the number of users and the number of pixels. Minimum throughput is fixed to $D_l^* = 256$ Kbits/s for f_{QoS}. An 802.11b network is considered and the threshold values of Table I are used for the coverage criterion. Noise level for the interference mitigation criterion is set to $\mathcal{N} = -98$dBm and the number of adjacent channels to $h = 1$.

B. Mono-objective planning results

Three test scenarios have been defined to evaluate the mono-objective search:

1) $f = 0.5 f_{cov} + 0.5 f_I$,
2) $f = 1/8 f_{cov} + 1/8 f_I + 3/4 f_{QoS}$ with a minimum throughput per user of $D_l^* = 256$Kbits/s,
3) $f = 1/8 f_{cov} + 1/8 f_I + 3/4 f_{QoS}$ with $D_l^* = 512$Kbits/s.

Table II shows the values of the evaluation criteria for each of the three solutions found and the number of access points N planned. For the first test, f_{QoS} has been computed for $D_l^* = 256$Kbits/s and a distribution of 200 users. The two last columns of this table provide the search time T and the number of solutions N_s tested before convergence. It can be inferred from this table that the average time for planning such an environment is only of a couple of minutes. The more criteria are added or the more APs are needed, the longer the computation lasts.

The quality of the solutions can be evaluated by the figures of merit presented in Tab. III. For each solution, the following data is available:

- the percentage p_{cov} of surface area covered with $F_l^{BS} \geq S_{low}$,
- the percentage p_O of surface area where the interference constraint is fulfilled ($F_l^2 \leq \mathcal{N}$),
- the percentage p_I of surface area where there is no interference left after channel assignment.
- the percentage p_{QoS} of surface area where the QoS constraint is fulfilled ($d_l \geq D_l^*$).
- the mean throughput per user value T_m.

Note that computing p_I requires a channel allocation. The FAP algorithm we have used is also based on a Tabu metaheuristic and is detailed in [20].

For test 1, P_{QoS} is given for $D_l^* = 256$Kbits/s. The basic coverage and non-interfering criteria allow by themselves to achieve the requested per-user throughput on 23% of the surface area.

The use of the QoS criterion helps in providing the targeted QoS on a larger surface area (61%). This improvement is the best one obtained without drastically increasing interference level by adding more APs for the given weighting coefficients. Besides, the higher the minimal per-user throughput is, the higher the number of APs and the smaller the service areas are, as presented on Fig. (5). The number of APs is the result of a trade-off between the QoS and the non-interfering criteria as they both try to respectively increase and decrease the number of APs.

In test 3, it is the throughput constraint that is favored during the search. The strict overlapping constraint is only fulfilled for 18% of the environment but the FAP algorithm was still able to completely avoid interference. On figure (5), the APs of test 3 are placed by pairs due to the acceptance of $h = 1$ interferer. By this way, it is possible to increase the throughput without affecting the link quality. The weakness of this approach is that these pairs of APs create cells that are parceled out. Such cells present more bounds and thereby increase the occurrence of channel changes for the user. We think that it would be worth introducing a connectivity criterion as already proposed in [19] for cellular networks.

Increasing throughput without degrading f_I may be achieved by introducing variable transmitting powers in the planning process. This feature would lead to smaller service areas, as required by high QoS constraints.

A delicate task is to choose the weighting coefficients of the aggregated evaluation function to get the desired trade-off between both QoS and interference criteria. There is no linear relation between the values of these coefficients and the observed trade-off. Gradient and order of magnitude of the criteria also influence the search, which makes the setting of the coefficients more difficult. For the instances presented, the weighting coefficients have been chosen empirically, after several launches. Next section presents the results obtained with a Multiobjective technique that avoids this prior choice of the weighting coefficients.

C. Multiobjective planning results

The multi-objective Tabu search presented in section III-C has been implemented with a search front $\mathcal{F}_c(i)$ of $K = 15$ solutions and a Tabu list duration $T \in [M/5\ ,\ M/2]$. This interval has been chosen empirically. A final set of $N_{opt} = 15$ solutions is selected and the size of the sharing radius is of $\sigma_{sh} = 0.5/\sqrt[3]{N_{opt}} = 0.20$ in the normalized distance space. The planning algorithm looks for both the number N and the locations of the APs. The multiobjective search is stopped after 300 iterations.

The results obtained with this multiobjective approach are summarized in Tab.IV and depicted on Fig.6. This figure represents the practical Pareto front composed of 148 solutions in the function space. The $N_{opt} = 15$ selected solutions have been highlighted on this front. For each one of them, the following figures are available in Tab.IV:

- the number N of APs,
- the values of the criteria $f_{cov},\ f_I,\ f_{QoS}$ and f^I_{QoS},
- the percentage p_{cov} of covered area,
- the percentage p_I of surface area where there is no interference left after channel assignment,
- the average throughput per user T_m.

These results show that the solutions selected present several trade-offs between the criteria. Most of the solutions of the Pareto front have good coverage properties. The main trade-off occurs between the interference and QoS criterion. With the available set of solutions, the end user of the planning tool is able to choose a solution that either guarantees high throughput with numerous APs or reduces the network cost with a still good transmission quality. In the first case, solution number 7 seems a good proposition with a deployment of 9 APs and in the second case, solution 3 looks competitive with only 6 deployed APs.

The distribution of the APs that belong to each of the 15 solutions is presented in Fig.7. The first solutions have a homogeneous AP distribution where interference remains low after frequency assignment and the service areas are regularly distributed. Each one of them figures another trade-off in terms of coverage, interference and QoS.

The last solutions composed of more than 12 APs show a concentration of the APs in some parts of the building. Their interference criterion varies from 10.5 to 12.4 and their QoS criterion is below 0.6. Such solutions meet the throughput and the coverage criteria but to the price of a high interference criterion. With that many APs, the variable of position does not influence the search anymore. When the number of APs is high, once all the selected APs provide coverage, changing their position does not modify f_I and f_{QoS} as interference is near its maximum level and throughput is already guaranteed. Of course, such solutions are not realistic as having both optimal QoS with high interference is not possible. To avoid such results, channel allocation for realistic QoS and interference estimation should be added in the search process but at the expense of a much higher computational load. Anyway, the first solutions provide interesting trade-offs.

When targeting a network with more APs and higher throughput, the target throughput has to be increased to $512 Kbits/s$, as shown in the mono-objective optimization results (cf. Test 3 in section IV-B).

For this problem instance, search has been stopped after 300 iterations to get a set of 148 solutions in the practical Pareto Front. Each search iteration lasts about 5 minutes and evaluates an average of about 40000 solutions in the neighborhood of the current search front. It is important to find an appropriate stopping criterion to reduce the overall computational time. A stopping criterion measuring the difference between the successive Pareto front might be applied. If this practical Pareto front does not improve enough during a fixed amount of iterations, convergence may have been achieved for most of the solutions.

V. Conclusion

This paper describes an automatic QoS-oriented planning process for wireless LANs. A global formulation for WLAN planning criteria based on a penalty function has first been proposed. Coverage, interference and average throughput per user goals have then been defined thanks to accurate propagation predictions. The WLAN planning optimization problem has been solved with a mono-objective Tabu heuristic and a multiobjective Tabu heuristic. This paper has highlighted the advantage of a multiobjective approach which provides several alternative solutions to the radio engineer in a single optimization step. In terms of computational time, the mono-objective search performs far better than the multiobjective approach but the tuning of the mono-objective evaluation function parameters takes several launches to get the desired trade-off. Planning results showed that the multiobjective search is promising. Future work will focus on reducing the multiobjective search duration. The most interesting way concerns the introduction of strong dependencies between the solutions of the search front for each local Tabu search. A proper stopping criterion also needs to be defined to decide wether convergence has occurred or not.

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VI. Vitae

Katia Jaffrès-Runser received her MSc. (2002) and PhD. (2005) from the INSA university in Lyon, France. During her PhD, she was a member of the CITI laboratory and of the ARES project team of INRIA. She mainly focused on wireless LANs optimization and Indoor prediction propagation. In 2006, she joined the Stevens Institute of Technology in Hoboken, NJ, USA as a post-doctoral researcher where she's working with Pr. Comaniciu on wireless ad hoc and sensor networks optimization. She received a 3-year Marie-Curie fellowship from EU to pursue her work in 2007 in both Stevens I.T. and INSA Lyon.

Jean-Marie Gorce received the Dipl. Ing. (M.Sc.) degree in electrical engineering from the National Institute of Applied Sciences (INSA), Lyon, France, in 1993. He completed his PhD thesis in 1998 on parametric feature extraction from radio-frequency ultrasound signals. After a postdoctoral year at Bracco Research, Geneva, Switzerland, he joined the telecommunications department at INSA Lyon as an associate professor. He is head of the radio modeling axis of CITI Laboratory, and is involved in the ARES project of INRIA Rhone-Alpes, France. His main research field concerns wireless networks focusing on realistic modeling, wireless system optimization, and performance assessment, considering as well architecture-based and ad hoc networks.

Stéphane Ubéda has a Ph.D. in computer sciences from the Ecole Normale Supérieure de Lyon (1993), France. He was an associate professor at the Swiss Federal Institute of Technology until 1994. He joined Jean-Monnet Univeristy (Saint-Etienne) as an associate professor until 2000 and became a full professor at INSA in the Telecommunications Department. He is head of CITI Laboratory. His main interest concerns distributed algorithms and protocol evaluations.

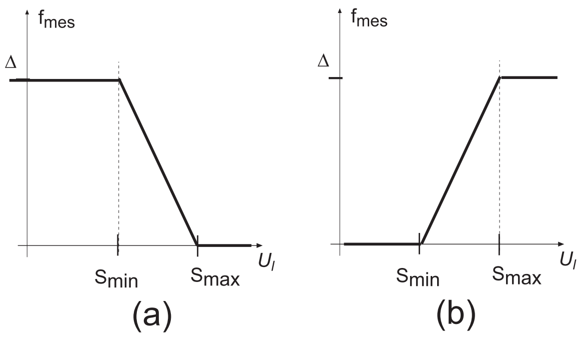


Fig. 1. Fig.1 . Penalty function `fp` when the utility value is (a) maximized and (b) minimized. The x-axis represents the utility value obtained for a block B_l.

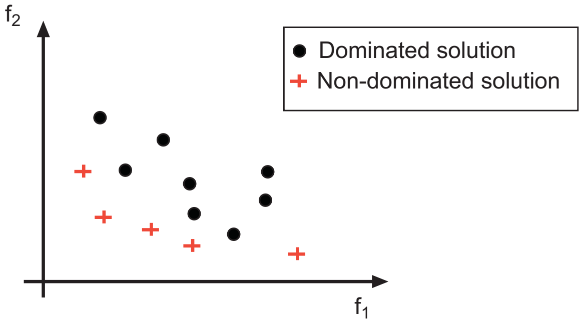


Fig. 2. Non-dominated and dominated solutions for a 2-function minimization problem. The evaluations of the solutions obtained for both given functions f_1 and f_2 are represented in the according function space.

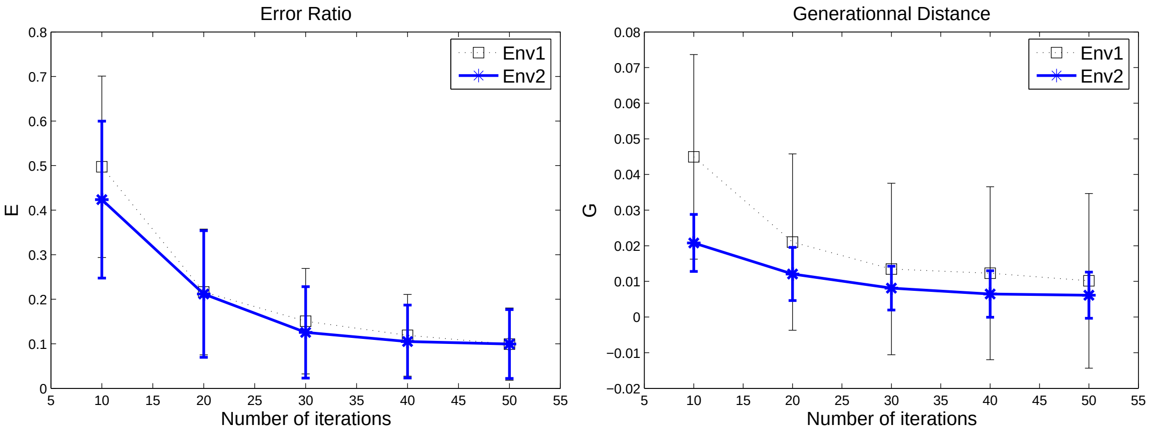
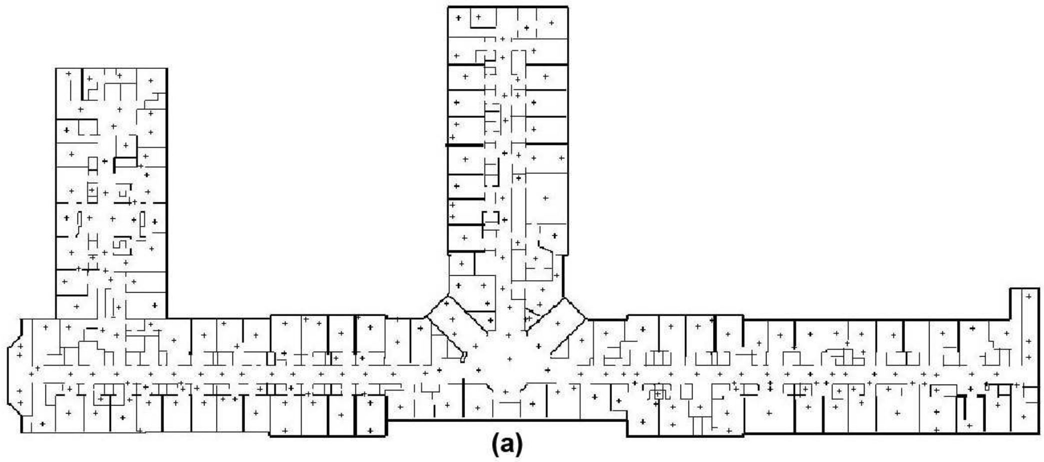
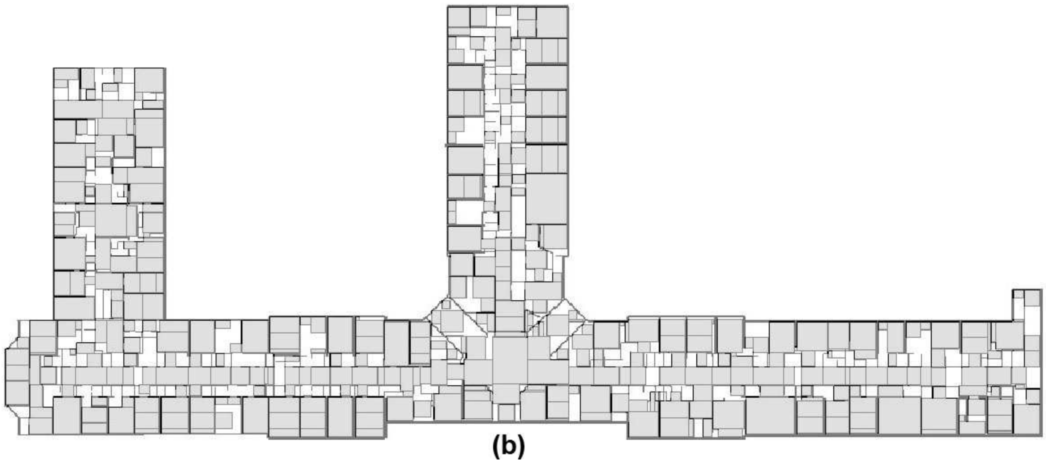


Fig. 3. Error ratio and Generational distance statistics obtained for environments $Env1$ and $Env2$. The average and standard deviation values are computed after 20 runs of the MO Tabu heuristic with the practical Pareto fronts obtained every 10 search iterations.



(a)



(b)

Fig. 4. Test environment of $12600\ m^2$: (a) Distribution of the $M = 256$ candidate AP locations. (b) Distribution of the $L = 499$ areas to cover.

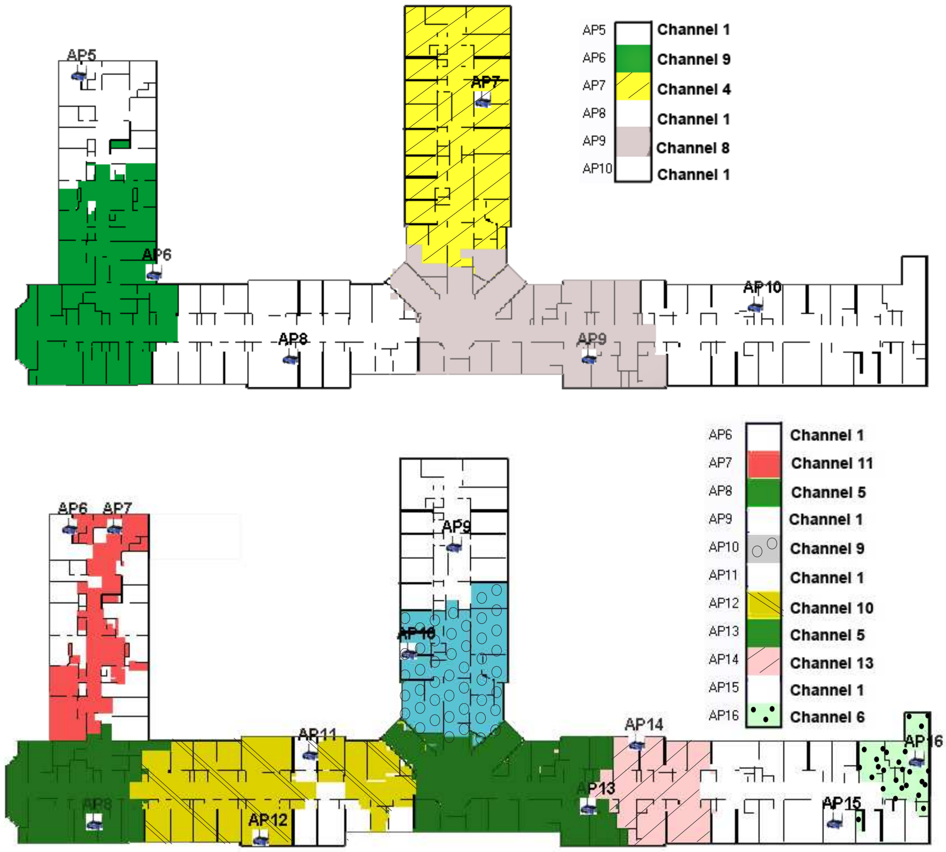


Fig. 5. Service areas and channel allocation for the solutions obtained with test 2 (top) and test 3 (bottom)

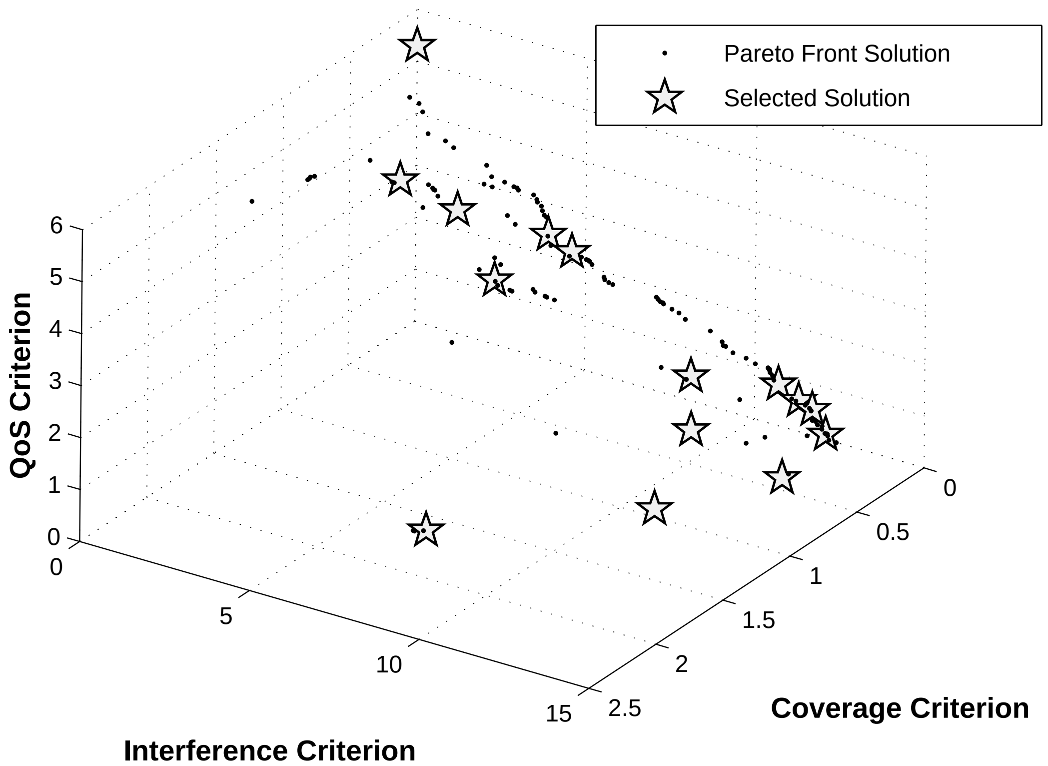


Fig. 6. Practical Pareto front after the MO search and the 15 solutions selected solutions.

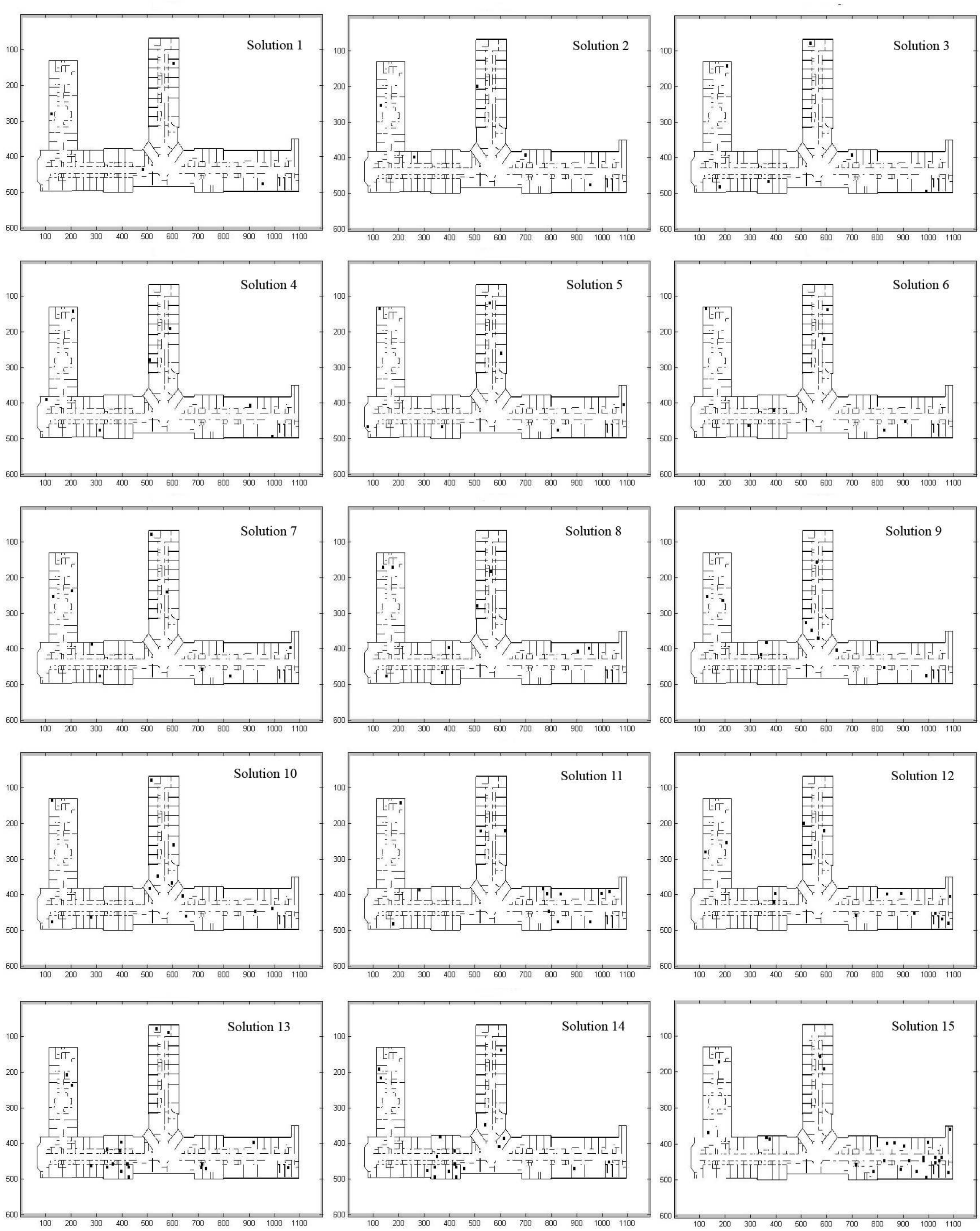


Fig. 7. The 15 solutions selected after multiobjective optimization.

TABLE I

EXAMPLE OF THRESHOLD VALUES FOR IEEE 802.11 COVERAGE. THESE VALUES CAN SLIGHTLY VARY ACCORDING TO THE TRANSMISSION MATERIAL IN USE.

Network	S_{low}	S_{high}
802.11a	-85dBm (6 Mbits/s)	-67dBm (54 Mbits/s)
802.11b	-90dBm (1 Mbits/s)	-86dBm (11 Mbits/s)
802.11g	-90dBm (1 Mbits/s)	-67dBm (54 Mbits/s)

TABLE II

PLANNING RESULTS: EVALUATION FUNCTIONS AND SEARCH TIME.

Test	N	f_{cov}	f_I	f_{QoS}	T	N_s
1	5	0.15	0.0	1.53	440s	54081
2	6	0.10	3.08	0.02	400s	11487
3	11	0.0	12.03	0.07	620s	47828

TABLE III

PLANNING RESULTS: PERFORMANCE OF THE SOLUTIONS

Test	P_{cov}	P_O	P_I	P_{QoS}	T_m
1	100 %	100 %	100 %	23 %	256 Kbits/s
2	99.5 %	70 %	100 %	61 %	300 Kbits/s
3	100 %	18 %	100 %	89 %	597 Kbits/s

TABLE IV

PLANNING RESULTS: THE $K = 15$ SELECTED SOLUTIONS.

Solution	N	f_{cov}	f_I	f_{QoS}	f_{QoS}^I	p_{cov}	p_I	T_m
1	4	0.0	0.0	5.3	5.3	100 %	100%	92 Kbits/s
2	5	0.4	1.1	3.6	3.6	98.5%	100%	116 Kbits/s
3	6	0.3	2.4	3.1	3.1	98 %	100%	141 Kbits/s
4	7	0.4	3.9	2.2	2.6	99 %	98%	164 Kbits/s
5	7	0.0	3.9	2.4	2.4	100%	98%	170 Kbits/s
6	7	0.0	4.6	2.2	2.4	100%	96%	164 Kbits/s
7	9	2.2	9.0	1.4	1.5	97 %	96%	214 Kbits/s
8	9	0.3	9.3	1.2	1.6	98.5%	98%	218 Kbits/s
9	11	1.1	11.4	0.4	1.3	98 %	84%	241 Kbits/s
10	12	0.0	11.3	0.6	1.3	100 %	77%	232 Kbits/s
11	13	0.6	10.5	0.9	1.7	98 %	69%	212 Kbits/s
12	13	0.0	10.7	0.8	2.1	100 %	76%	307Kbits/s
13	19	0.4	12.4	0.0	0.8	99%	53%	354 Kbits/s
14	19	0.0	12.1	0.1	1.0	100 %	77 %	392 Kbits/s
15	25	0.0	11.7	0.5	1.4	100%	66%	557 Kbits/s