QoS constrained wireless LAN optimization within a multiobjective framework

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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 in 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 several alternative solutions. By this way, the radio engineer can choose the most promising one among them based on his experience and maybe some additional constraints.

A description of already proposed planning strategies is given and opens out onto a new multiobjective planning formulation. This formulation evaluates coverage, interference level and quality of service (in terms of data throughput per user) to measure the quality of a planning solution. A Tabu multiobjective algorithm is then implemented to search for the optimal set of non-dominated planning solutions and a final selection process extracts the most significant solutions for the end user. This multiobjective QoS-oriented method is illustrated on a practical example that shows the performance of looking for several solutions, each one of them expressing other trade-offs between the planning objectives.

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I. Introduction

In the last decade, wireless LANs experienced great success as lots of networks have been deployed in companies or private areas either as hot spots for public access or as private networks. These networks provide the seed for developing new mobility-related applications such as Voice over IP for WiFi networks. Efficiency of such high-level services is strongly correlated to the transmission quality. First small WiFi networks were efficiently deployed with simple rules of thumb (e.g. site surveys, quick installations, on-site network tuning). Now, the growth of these networks impacts the IEEE802.11 WLAN standard that suffers from a lack of radio resource to face very large scale roll-out scenarii. For quick roll-outs, it is often preferred to overestimate the number of APs to avoid lack of coverage and to increase throughput. This choice strongly impacts the complexity of the channel allocation problem and provide high interference levels, worsening final network performance. Bad performance originates from three main reasons: lack of radio coverage (i.e. low Signal to Noise Ration (SNR)), inter-cell interference (i.e. low Signal to Interference and Noise Ratio (SINR)) and high number of users sharing the same channel resources. WLAN planning thus aims at contending with all of these issues by looking for the network configuration that minimizes one or more evaluation criteria.

Automatic planning solutions proposed for about ten years rely on two main features: the optimization algorithm and the propagation prediction model. Main efforts have been done for cellular networks planning problem, which strongly differs from WLAN planning as described in this paper.

Herein, three sets of primary criteria dealing with coverage, interference limitation and QoS provisioning are suitably defined for the WLAN planning problem. Because optimizing a global cost function combining all the criteria is delicate to handle, a multiobjective formalism is herein proposed. A problem is said multiobjective if a global cost function can only be defined as a trade-off between 2 or more criteria. It is exactly the concern WLAN planning is facing: on the one hand the number of APs and their power has to be high to achieve better coverage and throughput, and on the other hand, they have to remain low to reduce interference. The best configuration is obviously a trade-off between both objectives. In this framework, an implementation of a multiobjective Tabu search is proposed.

II. WLAN PLANNING OBJECTIVES

A. Overview

Network planning looks for a network configuration that provides an optimal quality of service to face the rapid growth in size of upcoming WLANs and the increased need for new QoS-oriented applications. The main variables are:

- the number N of transmitters,
- the set of potential transmitter locations,
- the transmission powers,
- the antenna type, azimuth and tilt.

This problem is closely related to the well-known cellular network planning problem. However, both planning problems differ in many points. The number N of chosen transmitters is important for both networks to mitigate data loss due to interference. But for cellular systems, the available set of base stations locations is limited due to environmental constraints, what makes the choice of transmission power and antenna parameters critical [1]. On the opposite, transmission power for WLAN access points is often fixed with a roughly omnidirectional radiation pattern. In this case, the foremost variable is the AP location that strongly impacts the WLAN QoS due to the density of obstacles. The environment also differs as Indoor propagation is difficult to handle. Lastly, concerning the QoS evaluation, WiFi planning faces the same problem than cellular systems in predicting the QoS in IP-based systems. To sum up, WiFi planning is a 'smaller problem' (less variables) but needs accurate propagation and traffic modeling.

First works on WLAN planning handled position and power as continuous variables [2], [3], often with a fixed number of APs chosen prior the search. Recent works [4], [5] determine the number N and locations of APs based on a combinatorial formulation of the problem. Such formulation helps to plan bigger environments by reducing the size of the search space. In this case, a set of candidate locations are selected before the search and the algorithm looks for the best subset of locations among all candidate ones.

The basic service a WLAN has to offer is access provision. It relies on satisfying both coverage and interference criteria. In the literature, first WLAN planning methods only deal with coverage [6]. Interference criteria minimizing the overlapping between cells are added to avoid a joined channel allocation [5]. Indeed, getting more accurate interference estimation implies performing a channel assignment for each solution resulting in more computational load [4], [7]. The NP-complete frequency assignment problem (FAP) of a finite set of frequencies aims at minimizing overall network interference. To ensure enough throughput for the users, new efforts have been devoted to the definition of bandwidth sharing criteria [4], [5], [7]. Based on these statements, we propose a generic formulation to gather all criteria in a multicriteria framework afterwards.

B. A generic combinatorial formulation

Let us consider both discrete sets:

i) $RI = \{RI_1, \dots RI_l \dots RI_L\}$, the set of the L regions of interest (RI) for which a radio access is expected. Each RI represents for instance a room.

ii) $AP = \{AP_1, \dots AP_m \dots AP_M\}$, the set of the M candidate AP positions. Locations may be chosen on a regular grid or account for the geometry of the environment.

In our case, RI and AP sets are obtained automatically with the wireless propagation simulator (cf. section V-A and Fig.3). The wireless prediction tool computes the mean power received F_l^m from each candidate AP_m on each region of interest RI_l.

Let be defined a generic measure of the service provided by the network for each region. This utility value U_l is assigned to each RI_l knowing the subset of N active APs, $(N < M)$. For instance, the strongest received signal power F_l^m on RI_l may be defined as the utility value for a coverage criterion.

Let be defined a penalty function $U_l \mapsto \mathtt{fp}_l = \mathtt{fp}(U_l)$ that estimates the quality of RI_l regarding the value of utility U_l. The aim of this function is to measure the asset of a region regarding a global optimization objectif. The shape assigned to $\mathtt{fp}$ for a minimization problem is presented in Fig.1. Here, a maximum penalty of Δ is considered when U_l is smaller than a threshold S_{min} and a null penalty when U_l is higher than S_{max}. The penalty function is linear or at least continuously decreasing between both thresholds. The fact that this function is bounded helps reducing the influence of too bad or too good small regions and thereby avoid border effects in the optimization process.

Let be defined a global optimization criterion as a weighted quadratic sum of the values of $\mathtt{fp}_l$:

$$f = \sqrt{\sum_{l \in [1..L]} \mu_l . \mathtt{fp}_l^2} \tag{1}$$

μ_l is a scaling coefficient representing the relevance of RI_l. Here, we use the ratio between the surface area of RI_l and the total surface are. This criterion both minimizes the mean and the standard deviation of the penalty function.

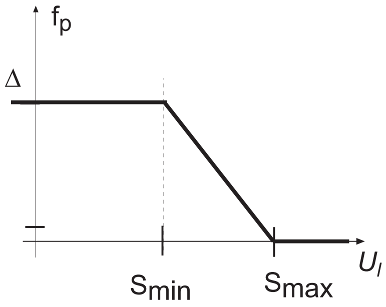

Fig. 1. Penalty function `fp` applied to a region of interest knowing its utility value U_l. Maximal penalty Δ is applied when U_l is smaller than S_{min} and no penalty exists when U_l is higher than S_{max}. The penalty is linear between both thresholds.

C. *WLAN planning criteria*

1) Coverage: A region of interest is covered if and only if the best signal to noise ratio $SNR_l = \max_k (F_l^m - N_l)$ allows efficient demodulation of the signal, N_l standing for the noise power. The coverage criterion is commonly based on measuring the satisfaction of the constraint $F_l^m \geq S + N_l$ in the building, S being the lowest received power permitting demodulation.

A hard criterion only based on coverage is used in [5] where a solution is said valid if all the RIs are covered. Smoother criteria have also been proposed: i) maximization of the covered surface area [3], ii) joint minimization of the average and the worst attenuation for all the RIs [2]. The latter criterion does not guaranty coverage for the whole environment as penalization is not bounded. Threshold based criteria have also been proposed [3], [8] where RIs are penalized according to a given function when a coverage constraint is not fulfilled.

The coverage penalization function used in our approach is threshold based, following the generic formulation previously introduced in Eq.(1). The utility value associated with each RI_l is the strongest received power and is referred to as the Best Server signal $F_l^{BS} = \max_{m \in (1,..,M)} F_l^m$. Threshold S_{min} is the receiver sensitivity needed to achieve the lowest data rate and S_{max} the sensitivity that ensures the highest data rate. The maximum penalization Δ equals $(S_{max} - S_{min})$. This coverage criterion aims at providing each mobile user with the best possible coverage.

Adapting this criterion to any technology is done by choosing accordingly S_{min} and S_{max}. For instance, for an IEEE802.11b network, our proposal is to set S_{min} and S_{max} respectively to the receiver sensitivity of a 1 $Mbits/s$ transmission and an 11 $Mbits/s$ transmission. Table II-C.1 summarizes the threshold values we advocate for IEEE802.11 networks.

Network	S_{min}	S_{max}
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 I

EXAMPLE OF THRESHOLD VALUES FOR IEEE 802.11 COVERAGE. THESE VALUES CAN SLIGHTLY VARY WITH THE TRANSMISSION MATERIAL USED.

2) Interference: Optimizing the previous coverage criterion alone can only be achieved with a fixed number N of APs having fixed transmission power P. If N and P are ideally chosen, this minimization may lead to a good solution. If either P or N are relaxed, this criterion leads to solutions overestimating either P or N, or both. An additional interference criterion is therefore introduced to compensate for it.

As already mentioned, interference can be controlled either by using an exact interference estimation or simply by exploiting adjacent cells overlapping [2]. The former needs to solve the channel allocation problem (FAP) within the planning stage [4], [7], while the later allows to make it afterwards. Reducing overlapping is an appealing method to avoid the computational cost of channel allocation. Main matter is to define overlapping. A definition has been proposed in the context of cellular systems planning in [9]. The powers received above noise power N_l by all the APs on RI_l are ordered from the strongest to the weakest:

$$F_l^{BS} \geq F_l^1 \geq \cdots \geq F_l^h \geq F_l^{h+1} \geq \cdots \geq N_l \tag{2}$$

The strongest signal is the Best Server signal F_l^{BS}, the h following ones are considered necessary for handover while the remaining ones are interferer.

To provide few interference on each RI, a penalty function based on the generic formulation of II-B is defined to get the strongest interferer F_l^{h+1} below the noise power N_l:

$$\mathtt{fp}_I(F_l^{h+1}) = \max(F_l^{h+1} - N_l, 0) \tag{3}$$

This formulation takes out the first h interferers because: i) they are originate from adjacent cells and ii) the a-posteriori FAP algorithm is expected to provide proper channel assignments for them. By this way, these h signals will use other frequencies preventing them from jamming the best server communication.

This penalty function balances the coverage criterion by:

1) minimizing the number of APs,

2) reducing the transmission power,
3) moving APs away from each other.

For WiFi based applications, experimental tests have shown that h should be kept low because of the lack of non-overlapping channels in IEEE 802.11a/b/g.

3) Quality of service: QoS refers to the final quality of service offered to the users. In a general scope, such a QoS may be defined as the average effective throughput per user, either for downlink and/or uplink communications [4], [5]. In this paper, we also focus on the average effective throughput per user.

The criterion proposed penalizes the RIs when the effective throughput T_l does not meet a target throughput per user ${T_l}^*$. The penalization function is given by:

$$\texttt{fp}_{QoS}(d_l) = \max({T_l}^* - T_l, 0) \tag{4}$$

The main matter is to get a correct estimate of T_l. As APs and users are interfering with each other, a global study of the WLAN has to be done to infer it. First of all, let us consider the case of an isolated AP and its connected users. Contrary to most wireless systems that dedicate a separated radio resource for uplink and downlink flows, IEEE802.11 flows share the same channel. Moreover, it is highlighted in [10] that the access fairness provided by the IEEE 802.11 CSMA/CA MAC protocol leads to a long term AP throughput that is a function of the transmission rate the users get from the AP. Besides, transmission rate is a function of the link quality in terms of SNR. Therefore, estimating the average effective throughput of an AP is done by: 1) selecting the RIs covered by the AP, 2) calculating its transmission rates R_l for each RI based on SNR_l, 3) finding the effective bandwidth of the AP based on the transmission rates of all the users present in the area.

This last step depends on the distribution of traffic flows. When having downlink traffic, it is the AP that chooses the best packet scheduling for each communication. One can assume that a basic access provides fair throughput distribution between the users. If there is only uplink traffic, the CSMA/CA protocol regulates the access and has to be evaluated. In this case, there are packet losses due to collisions and the whole back-off process of the IEEE802.11 MAC protocol has to be modeled as proposed in [11]. When there is a mix between uplink and downlink flows, access is still regulated by the same protocol but the AP has to share its bandwidth like other users.

The performance evaluation model of [11] provides a fine estimation of the effective uplink throughput per user, under the assumption that the medium is neither shared nor interfered by adjacent cells. But in the general case, multiple cells are deployed and the mean throughput of each cell decreases due to interference.

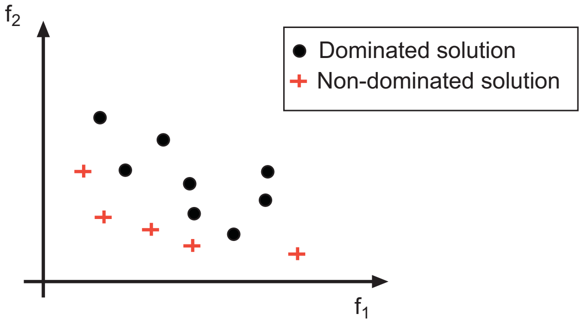

Fig. 2. Non-dominated and dominated solutions for a 2-function minimization problem.

During the planning stage, interference and QoS criteria are considered separately. The QoS criterion thus deals with the maximal achievable throughput for each cell. This throughput is achieved only if a FAP algorithm succeeds in annihilating co-channel and inter-channel interference. It is claimed herein that the association of a throughput per cell and an interference reduction criteria provides solutions reflecting a trade-off between throughput maximization and interference avoidance.

The chosen penalization function expresses the difference ${T_l}^* - T_l$ in decibels to improve readability of the penalty and for consistency with the other criteria. Hence, a difference of 3dB shows a loss of half of the bandwidth per user on the RI. For $T_l = 0$, the maximum penalization of $\delta = ({T_l}^*)_{dB}$ is applied. Average throughput per user is computed thanks the model of Lu and Valois [11] knowing the distribution of users in the building.

III. Multiobjective minimization

A. *Multiobjective search*

Each criterion defined in the previous section tackles the quality of one utility of the network. Getting the solution that has the best possible rating for each criterion is not obvious, especially when the criteria optimized have an antagonistic influence on the variables. For instance, networks composed 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 criteria involved in the search. Joint optimization of antagonistic criteria is the definition of a multiobjective search problem.

Each multiobjective problem has a set of Pareto-optimal solutions. Each solution represents a different optimal trade-off between the objectives and is said 'non-dominated' as it is not possible to improve one criterion without worsening another one. Figure 2 illustrates dominance by representing solutions for a 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 non-dominated Pareto-optimal solutions. These solutions are the solutions of Pareto rank $r = 1$. Solutions of Pareto rank r are obtained by removing the solutions of rank $r - 1$ and selecting the non-dominated solutions.

The aim of multiobjective search is first to find the solutions of the Pareto front (possibly extended to any rank r) and then to select the solutions that provide the most appealing compromises in this set by accounting for other deployment constraints.

B. Multiobjective problem resolution

As stated above, the wireless network planning problem faces simultaneously several optimization objectives. There are two ways of resolving such problems [12]:

1) First, each objective function can be weighted according to its importance. The problem can then be expressed as a unique evaluation function by adding all the weighted criteria. Standard mono-objective optimization heuristics can be applied [2], [3], [6] providing a unique trade-off between the criteria.
2) The second choice looks directly for the solutions of the optimal Pareto front and a-posteriori selects the most appropriate ones thanks to complementary constraints as already implemented for cellular planning [1].

With a mono-objective heuristic, the weighting coefficient of each objective function has to be defined. Finding the optimal values that correspond to a desired trade-off is tricky and often needs several optimization launches. On the opposite, multiobjective heuristics provide a set of optimal Pareto solutions in one launch. The best solution can be selected a posteriori to meet all the network roll-out requirements.

C. Multiobjective minimization

Multiobjective optimization algorithms either store the non-dominated solutions encountered during a mono-objective search process or look for the optimal Pareto front by trying to improve iteratively the quality of a set of solutions called the search front [12]. The main matter is to get the best representation of the optimal Pareto front by getting solutions distributed all over the problem trade-off surface. The search front based approach revealed to be the most successful. An iteration of such heuristic is composed of three main steps:

1) Search front expansion,
2) Update of the optimal Pareto front,

3) Selection of the new search front.

IV. Implementation

A. Tabu metaheuristic

Our search algorithm is derived from a *Tabu search* metaheuristic firstly suggested by F.Glover [13]. Tabu search corresponds to a local search algorithm whose main feature is its ability to store information about the choices done at previous iterations. The basic idea is to partially explore the search space of all feasible solutions by a sequence of moves. At each iteration, the move carried out is the most promising one among those available. The optimum solution is updated only if the solution found is better than the current optimum. A list of moves already done, called the Tabu list, is stored to prevent the search from cycling round on the same set of solutions.

B. Multiobjective Tabu

The multicriteria algorithm, derived from Tabu search, looks for the number, the location and the transmission power of the APs. Each variable is discrete and its values are selected in a previously computed set. The AP locations are here chosen among M candidate locations. A solution S is expressed as a vector of M items, each item $s(m)$ storing the transmission power $p_e(m)$ of the candidate access point AP_m at location number m if and only if this AP belongs to the solution. If AP_m does not belong to S, $s(m) = 0$.

The aim of the algorithm is to concurrently minimize the three previously defined criteria: f_{cov}, f_I and f_{QoS}. At each iteration, the quality of a current search front is improved if possible.

In our algorithm, the current search front $\mathcal{F}_c(i)$ at iteration i and made of K solutions is expanded by computing a set of neighboring solutions. A neighbor solution is obtained by either moving one candidate AP from position m to m', adding an AP, removing an AP or by changing the transmission power of one of the selected AP. The neighborhood of a solution is composed of all its non Tabu solutions. The set of neighboring solutions of the front is the union of the neighborhoods of the K solutions of the front.

The non-dominated solutions of this neighborhood are selected and the optimal front $\mathcal{F}_P$ is updated with these new solutions. The new search front $\mathcal{F}_c(i+1)$ is chosen randomly in the set of all the non-dominated solutions of Pareto rank r smaller than a fixed value R_{max}. The solutions of the optimal front $\mathcal{F}_P$ are the solutions of Pareto rank $r = 1$. When the solutions of rank $r \leq R$ are removed, the remaining set of non-dominated solutions is composed of solutions of Pareto rank $r = R + 1$.

Each new solution $\vec{S}_c^k$ is selected in the neighborhood of the old solution number k which is stored in a Tabu list. The duration of this Tabu list is randomly chosen at each iteration within an interval $[T_{min}, T_{max}]$. The algorithm describing an iteration i is the following:

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

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.

C. 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:

1) dissimilarity of the criteria trade-offs obtained,
2) dissimilarity of the selected solutions,

The dissimilarity in the criteria trade-offs is evaluated by the analysis of coverage, interference and QoS criteria, too. First, the solutions are selected based on a maximal admissible cost for each criterion. The remaining solutions 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 the use of a sharing function $Sh(\vec{S})$. This function assigns to each solution a weight proportional to the density of solutions in its neighborhood. This function has been presented in the N.S.G.A. algorithm (*cf.* [12] for further description). This sharing function is computed knowing the distance between solutions in the evaluation function space. 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 $D \cdot N_{sh}$ solutions are then evaluated more precisely. First, an optimal channel assignment is computed thanks a Tabu FAP heuristic described in [14]. A variant of our QoS criterion, f^{I}_{QoS}, is computed knowing the exact interference distribution now defined. This criterion follows the same expression of Eq.(4) and uses the same model to estimate the throughput T_l. The only difference holds in the computation of the transmission rate R_l that is now based on a real SINR estimation after FAP. Knowing the frequency assigned to each AP, the real interference powers I_l are evaluated, providing exact SINR values, $SINR_l = F_l^{BS}/(I_l + N_l)$; the transmission rate is then deduced. In each sharing set, the best solution regarding this new criterion is considered and the N_{opt} most different solutions among them are finally presented to the radio engineer for a final manual selection.

V. Illustrative example

A. Propagation prediction

The estimation of realistic planning criteria relies on accurate propagation simulations. The prediction tool presented in [15] implements the Multi-Resolution Fourier Domain ParFlow (MR-FDPF) model [16]. This propagation model is based on a finite element frequency domain modeling. Its originality stems from the pre-processing phase, exploiting a multi-resolution formalism and providing a pre-computed multi-resolution (MR) tree. This phase doesn't depend on the APs' characteristics (position, emission power...). The next phase, i.e. the propagation phase, exhibits a very low computational load (less than 1s. for $100m \times 100m$ environments) to compute the coverage of each AP candidate, thanks to the MR tree. This time is comparable to the time needed with a standard empirical model, but rendering all the multiple reflection and diffraction effects. Furthermore, 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 (see Fig.3), and the received power F_l^m is estimated for each one. This model has been experimentally assessed for Indoor environments, leading to a mean square error between signal power measurements and predictions of about $5dB$ [15].

B. Simulation setup

The proposed multi-objective algorithm has been launched on a 12600 m^2 environment depicted in Fig.3. A set of $M = 256$ candidate APs and a set of $L = 499$ regions of interest have been defined. Candidate AP locations are represented by black dots on Fig.3 placed at the center of previously selected blocks of the MR-FDPF model. The RI elements all belong to the indoor parts of the building and create a complete partition of its surface area. 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 - PIV 2.4GHz with 1Go of RAM.

An 802.11b network is considered and the threshold values of Table II-C.1 are used for the coverage criterion. The interference criterion is computed with $h = 1$ allowed interfering signal. The QoS criterion assumes a uniform distribution of 200 users and the target throughput per user ${T_l}^*$ is set to 256 $Kbits/s$.

The multi-objective Tabu search has a search front $\mathcal{F}_c(i)$ of $K = 15$ solutions and each Tabu list has a duration of $[M/5\ ,\ M/2]$ (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.

C. Results

The results obtained with this multiobjective approach are summarized in Tab. II. For each of the $N_{opt} = 15$ selected solutions, the following figures are given:

- the number N of APs,
- the values of the criteria $f_{cov},\ f_I,\ f_{QoS}$ and f_{QoS}^I,
- the percentage p_{cov} of covered area,
- the percentage p_I of interfered area after channel allocation,
- the average throughput per user T_m.

T_m is obtained after channel assignment by averaging the throughput T_l of each region RI_l computed with the Markovian performance evaluation model of [11]. In this case, T_l is also estimated thanks the complete SINR knowledge, as done for the modified QoS criterion f_{QoS}^I. These results show that the more APs are placed, the better the throughput per user is but the worse the interference level gets. But a good channel allocation algorithm is able to strongly reduce the influence of interference on throughput. With this set of solutions, the end user of the planning tool is able to choose a solution that either guaranties high throughput with numerous APs or reduce network cost with a still good transmission quality. Solution 4 suits well in the first case, while solution 9 looks competitive in the second onem with only 7 deployed APs. Figure 4 shows the coverage map and the distribution of the service areas for solution 9.

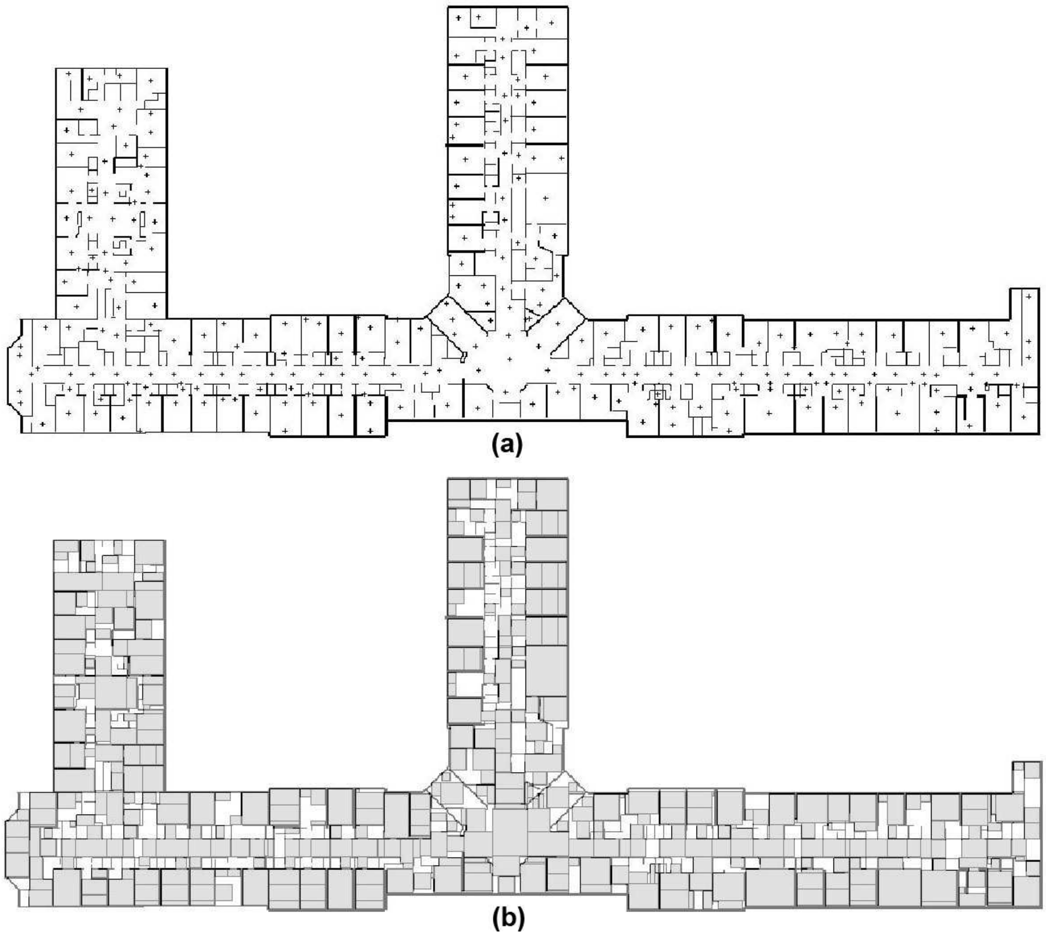

Fig. 3. Test environment of 12600 m^2: (a) Distribution of the $M = 256$ candidate AP locations. (b) Distribution of the $L = 499$ regions of interest (blocks provided by the propagation tool).

VI. Discussion

The automatic WLAN planning framework presented here relies on both realistic models for coverage, interference and QoS estimations and a challenging multiobjective search approach. The main benefit of such multiobjective approach is to provide the engineer the opportunity to choose a solution that balances the network objectives according to his specific needs.

Based on existing work devoted to WLAN planning, three generic criteria dealing with coverage (or radio link), interference limitation, and resource sharing have been used. It has been shown that the optimization of such a problem is truly a multiobjective problem. Finding a good solution heavily relies on the choice of the scaling parameters when performing a conventional mono-objective implementation. In this work, recent results in multiobjective optimization have been used to provide a general framework

Solution	N	f_{cov}	f_I	f_{QoS}	f_{QoS}^I	p_{cov}	p_I	T_m
1	15	0.0	12.5	0.0	0.3	100%	18%	261 Kbits/s
2	14	0.5	11.7	0.3	1.6	99 %	23%	298 Kbits/s
3	13	0.6	12	0.08	0.9	98 %	17%	260 Kbits/s
4	11	0.0	11.2	0.5	1.3	100 %	12.5%	259 Kbits/s
5	9	0.0	9.7	1.0	1.1	100 %	16%	219 Kbits/s
6	9	0.6	11	0.6	0.9	99 %	6 %	242 Kbits/s
7	8	0.0	7.6	1.6	1.6	99.5%	1.1%	198 Kbits/s
8	8	1.2	7.7	1.5	2.2	97 %	8.3%	178 Kbits/s
9	7	0.0	5.6	2.1	2.1	100 %	9.6%	172 Kbits/s
10	6	0.0	3.8	3.0	3.0	99.5%	0.0%	145 Kbits/s
11	6	0.9	2.1	3.5	3.5	96 %	0.0%	145 Kbits/s
12	5	1.5	0.8	4.8	4.8	93 %	0.0%	105 Kbits/s
13	5	0.2	2.7	3.5	3.5	99.5%	0.0%	117 Kbits/s
14	4	0.6	0.1	5.0	5.0	99 %	6.5%	78 Kbits/s

TABLE II

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

for finding good deployment solutions. In this approach, channel allocation has been postponed to a second stage for mainly two reasons. The first one concerns the computational load as including a channel variable in the optimization problem leads to a strong computational overload. The second reason not above mentioned is that the FAP can be introduced [10] as a dynamic process. Although few details are only provided, some constructors provide now APs having the ability of choosing dynamically the proper frequency. Such dynamic resource allocation are efficient only if cells does not overlap excessively. This is precisely the aim of our model.

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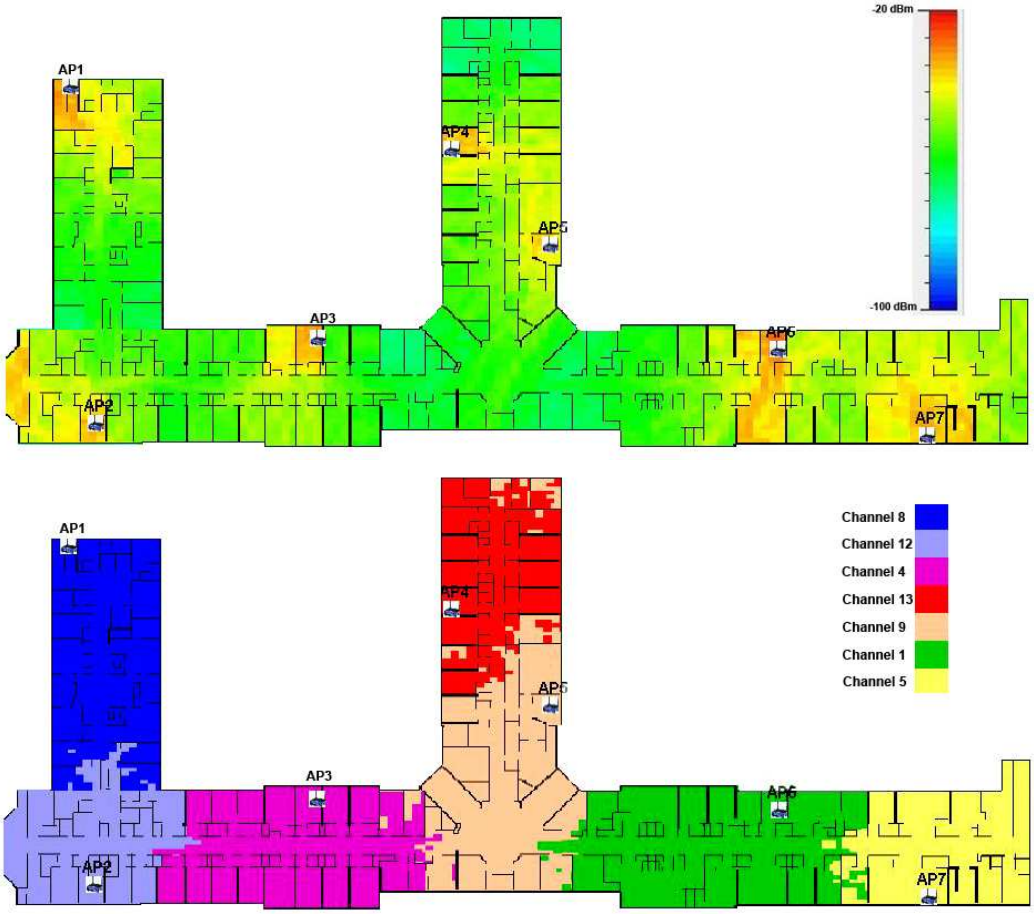

Fig. 4. Coverage map (top) and distribution of the service areas (bottom) of solution 9.

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