Multiobjective QoS-oriented planning for indoor wireless LANs

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***Abstract*— This paper describes an automatic wireless LAN access points planning approach based on a multicriteria modelling and solving. A realistic and efficient wLAN planning approach can not only assess usual objectives based on radio coverage. It has to further implement a Quality of Service (QoS) constraint. In this work, a QoS criterion is defined as the mean available bandwidth per user, derived from a Markov-based performance evaluation model of the medium access control (MAC) layer behavior. Optimizing both coverage and QoS objectives results in finding the optimal trade-off between these concurrent criteria. Rather than optimizing a weighted sum of the optimization criteria that provides a single solution, it is herein proposed to develop a dedicated multicriteria search algorithm. Its main feature is to provide several solutions, each one representing a peculiar trade-off between the objectives. The planning process estimates for each solution the optimal number of APs and their placement. The AP's coverage is estimated with a powerful multi-resolution radio propagation simulator previously described. This paper presents results for a QoS oriented planning process providing a predefined minimum per-user throughput. The example provided herein applies for 200 users distributed over a 12600 m^2 building floor.**

I. Introduction

The wireless LAN (wLAN) planning problem is closely related to the cellular networks' planning problem. The main matter is to find a configuration of the access points (APs) that guaranties given qualities 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 emission 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, simple coverage constraints are not reliable enough and it becomes critical to develop automatic planning techniques based on radio-frequency propagation predictions. In the last decade, indoor wLAN planning mainly focused on coverage and cell-overlapping optimization [1][2]. Recent works [3], [4], [5] are now 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 considered 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], 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 [6], the available bandwidth of an AP is shown to be decreasing while the number of connected users increases. Defining an efficient QoS oriented criterion must take this feature of the medium access control (MAC) protocol into account. In this paper 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 [7]. 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 a non-interfering criterion. This objective favors the selection of solutions minimizing the number of adjacent cells. This reduces drastically the occurrence of remaining interferences after the channel assignment step. Of course, both criteria are balanced by a coverage criterion that ensures the basic coverage of the building.

The quality of the wLAN network relies on the optimization of several antagonist criteria and the optimal solution is the result of a fixed trade-off between them. Previous works mainly resolve the problem as a mono-objective optimization problem, either using continuous or combinatorial algorithms. In this case, a single optimization criterion is optimized. Results using continuous derivative-based and direct search algorithms [8][2] showed to be limited by the non-convex shape of the evaluation function. The use of linear programming was shown efficient [3] as it allows to take several criteria into account by defining a main objective and translating the others into constraints. But the linear programs obtained are complex to solve, what makes them inadequate for large environments. Main achievements have been obtained by the use of combinatorial metaheuristics [9],[2] as they better behave on large environments and are less sensible to the shape criteria.

All these works only provide a single optimal planning solution. If this solution doesn't suit the radio engineer, the whole search has to be started all over again with different settings. The wLAN planning problem can also be modeled as a multiobjective (MO) optimization problem [4] whose main feature is to get a set of Pareto optimal solutions, each one representing a different trade-off between the criteria. It is then possible to propose at the end of the search a set of solutions representing several alternatives to an engineer. The planning process described in this paper exploits a multiobjective optimization algorithm, based on a Tabu metaheuristic. It has been applied to optimise concurrently a coverage, a non-interfering and a QoS criterion.

Planning criteria are described in section II. Section III presents the implementation aspects by focusing on the propagation simulator and the multicriteria algorithm. Results and conclusion 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 access network efficiency, which mainly relies on the interference level between cells. Additionally, it is relevant to use a user-oriented objective which allows to control the access network deployment under operational constraints.

In section II-A, a generic formulation based on a penalty function is proposed for any criterion. The 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. Global formulation

Let be defined a discrete set of possible AP's positions. For each, the 2D coverage map is computed with the propagation simulator described in section III-A and for a representative set of test receiving areas defined by their left hand corner $p = (x, y)$ and dimension $s = (s_x, s_y)$ in pixels. For the sake of clarity, these blocks are numbered from 1 to L, and referred to as the blocks B_l in the following. The mean received signal power 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 value can simply be F_l^k for the coverage criterion, but it can also be the level of interference or the aggregate user throughput.

A penalty function

$$B_l \mapsto \mathtt{fp}(U_l) = \mathtt{fp}_l \tag{1}$$

estimates the quality of B_l regarding the value of U_l. The shape assigned to fp for a minimization problem is presented in Fig.1. 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 $\mathtt{fp}_l$ for each block B_l:

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

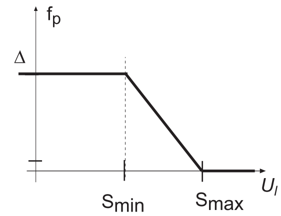

Fig. 1. Penalty function fp.

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. N_c is the number of blocks representing the whole environment.

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}. The thresholds are $S_{min} = S_1$ and $S_{max} = S_{11}$ standing for the minimum signal powers that ensure respectively a 1 Mbits/s and an 11 Mbits/s transmission rates. The maximum penalty Δ is thus $\Delta =\mid S_{11} - S_1 \mid$ leading to the following penalty function:

$$\mathtt{fp}_{cov}(F_l^{BS}) = \begin{cases} 0 & \text{for} \quad F_l^{BS} < S_{11}, \\ \mid S_{11} - F_l^{BS} \mid & \text{for} \quad S_{11} \geq F_l^{BS} > S_1, \\ \mid S_{11} - S_1 \mid & \text{for} \quad F_l^{BS} \leq S_1, \end{cases} \tag{3}$$

In this work, simulations are made with $S_1 = -94$ dBm and $S_{11} = -82$ dBm. These values come from the 802.11b Lucent Orinoco© PCMCIA receiver card specifications. Note however that this approach can easily be adapted to either $802.11g$ or $802.11a$ equipments by setting the thresholds accordingly.

C. Non-interfering 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 can not share efficiently the medium because the carrier sense mechanism doesn't work. With 802.11b equipments, there are few really not overlapping channels (3 or 4), and the frequency assignment problem (FAP) becomes untractable manually when the size of neighborhoods increases. A first glance would call for including the FAP into the optimization process. Therefore, either a FAP algorithm should run for each solution evaluation, or the channel number should be added as a variable into the combinatorial optimization problem [10]. Because 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 and nearly optimal two-step approach, a non-interfering criterion is introduced in the planning process. This criterion maintains a low number of adjacent cells, making an easier *a posteriori* FAP resolution.

The non-interfering criterion is based on the following penalty function. At B_l, received signal powers F_l^k, $k \in [1, N]$, exceeding the noise level N, are ordered from the strongest to the weakest:

$$F_l^{BS} \geq F_l^1 \geq \ldots \geq F_l^k \geq F_l^{k+1} \geq \ldots \geq N \qquad (4)$$

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 interferers are authorized for each block. Received signals are divided in 3 groups : the best server signal F_l^{BS} $(k = 0)$, adjacent signals $(1 < k \leq h)$ and interfering signals $(k > h)$. Herein, h is the number of utile signals and others are considered as interferers. The choice of the value of h is critical and reflects a trade-off between handover and FAP requirements.

Our goal is to maintain the power level of F_l^{h+1} under noise level N. The utility is thus defined as $U_l = F_l^{h+1}$ and the penalty function as:

$$\mathtt{fp}_I(F_l^{h+1}) = \begin{cases} 0 & \text{for} \quad F_l^{h+1} < N, \\ \mid S_{11} - F_l^{h+1} \mid & \text{for} \quad N \leq F_l^{h+1} < S_{11}, \\ \mid S_{11} - N \mid & \text{for} \quad F_l^{h+1} \geq S_{11}, \end{cases} \qquad (5)$$

The minimum threshold is $S_{min} = N$, the maximum threshold is $S_{max} = S_{11}$ and the maximum penalty is $\Delta = \mid S_{11} - N \mid$. Because in this formulation `fp` aims to minimize the interference level, `fp` is chosen as the vertical axis mirror function of those represented in Fig. 1.

This formulation has been adapted from [11] initially proposed in the framework of GSM cellular planning. In our simulations the noise level is fixed to $N = -98$ dBm and the number of adjacent signals is set to $h = 2$. This small value of h has been chosen 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 would be furthermore possible to add a connexity criterion as proposed in [11] to obtain more regular cell shapes. We disregarded such an approach because of the induced higher computational load.

D. QoS Criterion

In this paper, a QoS-based criterion implementing a *per-user throughput* constraint is proposed. Previous works introducing such a constraint considered a unique data rate for all nodes and a perfect bandwidth sharing between nodes, keeping constant the total bandwidth [3], [4], [5]. In a $802.11b$ network however several users share the bandwidth at 4 different data rates 1, 2, 5.5 or 11 Mbits/sand even more with $802.11g$ networks. Our contribution aims at introducing a more realistic sharing model.

Let firstly assume that each cell does not interfere with the other ones. This seems sensible as the non-interfering criterion defined above associated to an optimal channel assignment reduces co-channel interferences. Whatever, this assumption allows at least to obtain an upper-bound of the per-user throughput. All the users are divided into class of service groups, each group having its own aggregate throughput $D_1, D_2, D_{5.5}, D_{11}$. It is also assumed that the aggregate throughput of each service area $D_a, a \in \{1, 2, 5.5, 11\}$ is equitably distributed between the associated N_a users. The throughput d_l associated with a user located in B_l thus depends on the service area it belongs to, and is estimated by:

$$d_l = D_a/N_a \qquad (6)$$

The key point of this approach holds in the estimation of the aggregate throughput for each group. It relies on a stochastic performance evaluation model that estimates the aggregate throughput by solving a Markov chain problem describing the IEEE 802.11b MAC protocol [7].

Finally, the throughput per user is constrained to be higher than a limit ${D^*}_l$ for each block B_l, by the use of the following QoS penalty function:

$$\mathtt{fp}_{QoS}(d_l) = \max(({D^*}_l)_{dB} - (d_l)_{dB}, 0) \qquad (7)$$

where the throughput values are computed in dB ($d_{dB} = 10.\log(d_{bits})$) to get the same order of magnitude of the QoS criterion as the other ones. Here, the maximum penalty $\Delta = {D^*}_l$ is obtained when user throughput is null. Here, the utility is d_l, the minimum threshold $S_{min} = 0$ and the maximum threshold $S_{min} = ({D^*}_l)_{dB}$.

III. Implementation

A. The Propagation Simulation

In order to get realistic planning objectives, a fine propagation simulation tool is used [12]. It implements the Multi-Resolution Fourier Domain ParFlow (MR-FDPF) model [13], [14]. 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 [13] 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. 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 in (i,j) from AP numbered k is estimated over each block B_l defined by its left hand corner $p=(x,y)$ and its size $s=(s_x,s_y)$. This model has been experimentally assessed in Indoor environment, leading to a mean square error of about $5dB$ [12].

B. Multicriteria planning algorithm

The multicriteria algorithm looks for the number, the location and the emission power of the APs. Its aim is to minimise concurrently the three previously defined criteria: f_{cov}, f_I and f_{QoS}. This algorithm is derived from a standard Tabu metaheuristic. At each iteration, it aims at improving the quality of the current search front. This front is composed of the set of the solutions that dominate the other ones in the objective function space. When minimizing N criteria, a solution $\mathbf{x}$ dominates solution $\mathbf{y}$ if and only if:

$$\forall i \in [1,n] : f_i(\mathbf{x}) \leq f_i(\mathbf{y}) \wedge \exists j \in [1,n] : f_j(\mathbf{x}) < f_j(\mathbf{y}) \quad (8)$$

In our algorithm, the current search front $\mathcal{F}_c(i)$ at iteration i made of K solutions is expanded by computing a set of neighboring solutions. The non-dominated solutions of this neighborhood are selected and the optimal front $\mathcal{F}_{PP}$ is updated with these new solutions. The new current 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 valueR_{max}. 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:

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 non-dominated solutions of 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 $\mathcal{F}_{PP}$;*
   - *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 $\mathcal{F}_{PP}$;*
3) *Update of the Tabu list for each solution.*

The algorithm is stopped after a fixed number of iterations. It is necessary to select in $\mathcal{F}_{PP}$ a number K of solutions figuring significant and different trade-offs between the objectives. Selection is made in the evaluation functions space by the use of a sharing function defined by Srinivas and Deb in the N.S.G.A. algorithm [15]. 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 $\mathcal{F}_{PP}$ 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:

$$Sh(d(i,j)) = \begin{cases} 1 - \left(\frac{d(i,j)}{\sigma_{share}}\right)^2 & \text{if } d(i,j) < \sigma_{share} \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

A first assignment is done for all the solutions of $\mathcal{F}_{PP}$ and the best solution obtained is selected and removed with its neighborhood from the front. Then, the same process is iterated until the desired amount of solutions K is reached.

IV. Results

A. Test environment

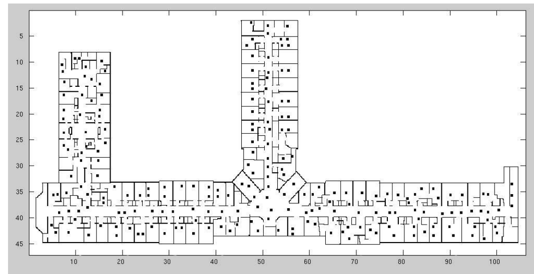

Fig. 2. Test environment and candidate AP locations

The test environment shown in figure 2 is the ground floor of a 12600 m^2 building. The M candidate positions ($M = 258$) have been chosen at the center of some selected blocks associated with the multi-resolution structure of the WILDE propagation simulator. A block in the pyramid is selected if and only if it is made of air and if its surface area S is bounded by $10m^2 < S < 80m^2$. The lower bound has been chosen to limit the density of potential APs locations and the upper bound to provide several locations within big rooms, as for instance in halls or patios. Larger homogeneous blocks are further divided and smaller blocks are disregarded. As selected blocks are only made of air, it seems sensible to assume that the radio coverage of a candidate AP placed in the center of a block is representative of the coverage of other APs in the same block. For this problem instance, emission power of the APs is fixed at 15 dBm and antennas are assumed omni-directional. Since the QoS criterion needs a repartition of simultaneous users, 200 users are assumed homogeneously distributed. 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}.

The algorithm starts with an initial solution of $N = 6$ APs randomly chosen over the full search space. Tabu lists' size is selected in an interval $I = [51, 129]$ according to [16]. Parameters R_{max} and K are set to $R_{max} = 2$ and $K = 10$ solutions.

B. Planning results

Figure 3 shows the Pareto front after 500 iterations where stars represent the 10 selected solutions. An iteration lasts 7 minutes to evaluate and classify 38 500 solutions in the neighborhood. Number N of APs and the values of the criteria for each selected solution are summarized in table I. Coverage maps of solutions 5 and 7 are provided in Fig.4.

Solution 5 presents really good coverage and throughput criteria, but the interference criterion is high due to the high number of APs. Solution 7 reveals to be the most promising one as all criteria present good values. Some other solutions present high values for one or two criteria. Therefore, we consider enhancing our search by only adding solutions to

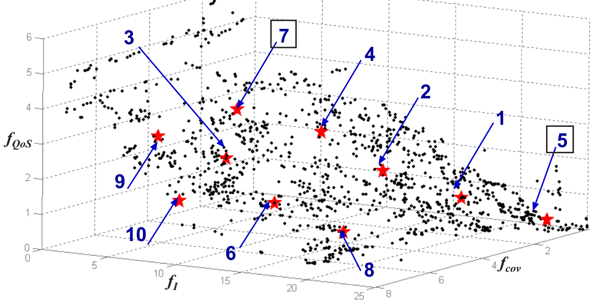

Fig. 3. Pareto front after 500 iterations

	N	f_{cov}	f_I	f_{QoS}		N	f_{cov}	f_I	f_{QoS}
1	12	0.81	17.20	0.73	6	11	4.15	9.82	0.95
2	10	1.29	12.26	1.39	7	8	2.53	3.76	3.03
3	9	3.86	5.60	1.97	8	11	4.20	15.08	0.36
4	9	1.54	8.10	2.35	9	8	5.34	3.40	2.81
5	15	0.06	22.11	0.16	10	10	5.67	5.67	1.13

TABLE I
CRITERIA VALUES FOR THE SELECTED SOLUTIONS

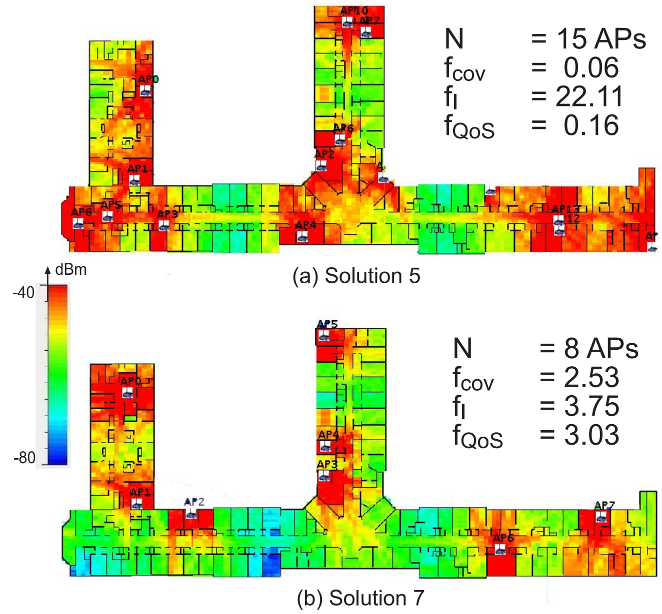

Fig. 4. Coverage maps of solutions 5 and 7.

the optimal front that present bounded criteria values. Nevertheless, the MO algorithm proved to be efficient in alternative solutions provision.

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 dedicated Tabu based multiobjective heuristic. In fact, this paper highlighted the advantage of a multiobjective approach which provides several alternative solutions to the radio engineer in a single optimization step. Planning results showed that the multiobjective search provides multiple interesting trade-offs between the criteria. Future work is firstly focusing on reducing the search duration. The most promising way concerns the introduction of strong dependencies in the Pareto fronts of each local Tabu search.

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