A QoS-based FAP criterion for Indoor 802.11 wireless LAN optimization

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***Abstract*— Several softwares have been developed for computer-aided design of radio networks. The first constitutive element of such a tool is the propagation modelling algorithm. The second is the planning process providing positions and setup of access points. The last one concerning the frequency channel allocation problem (FAP) is the focus of this paper. Many works devoted to this problem exploit a graph-based modelling that leads to an under-constrained problem as interference between mobile nodes are not taken into account. In this paper a new QoS-based FAP criterion is formulated. This QoS criterion measures the overall throughput taking downlink interference into account. We show on an example that our FAP model outperforms usual graph-based FAP approaches concerning the effective SINR obtained at mobile nodes. Results are based on realistic simulations exploiting a simulator called WILDE (Wireless Lan DEsign) and implementing the MR-FDPF propagation algorithm.**

I. Introduction

With the current very fast development of wireless IEEE 802.11b or 802.11g local networks (wLAN), deployment engineers have to face an increasing interference level when increasing the number of access points (AP). Usual empirical frequency channel allocation (FAP) approaches use only 3 channels (typically 1,7,13) to compensate for the large overlap between adjacent channels in the ISM 2.4GHz band. On the one hand, it is obvious that getting interfence-free solutions with only 3 channels is utopian for large deployments. On the other hand dealing with all channels is not easy as it is in fact a complex combinatorial problem. A computer-aided approach is therefore the only way to manage efficiently the widely overlapping multi-channel spectrum of 802.11b/g.

In such a computer-aided approach, multiple APs configurations have to be evaluated, thanks to a propagation simulator, with respect to a predefined criterion. Finding a good criterion is precisely a hard task. Basically, criteria relying simply on radio coverage [18] fail to provide efficient solutions. But on the opposite, a planning process using a QoS based criterion involving the overall throughput while taking into account interferences and channel allocation would require a strong computational overload [2]. A good trade-off may be to treat AP planning and FAP as independent problems. It is in this framework that this paper focuses on the impact of interference modelling for robust channel allocation. It is thus assumed that the AP positioning is already done and the FAP is studied only on this predefined configuration. In section II, a reference FAP model is described after a short survey of usual FAP techniques. This section then proposes a new criterion taking interference into account. The main novelty in this criterion relies on the fact that the interference model is not computed for peer to peer AP radio links but also for mobile nodes in a downlink configuration. Furthermore, this approach also takes the cumulative nature of interference into account. The implementation of an optimization algorithm is proposed in section III, relying on a Tabu search meta-heuristic.

Because such an approach firstly relies on a robust propagation prediction tool, the propagation model used in this study is shortly described in section IV. Finally, an evaluation framework is proposed in section V. It should be noticed that a specificity of IEEE802.11 when compared to cell-phone systems holds in the fact that uplink and downlink share the same radio resource. The proposed approach is then evaluated both for downlink and uplink traffic. It is shown that including a realistic interference model in the FAP criterion leads to more robust FAP solutions because the interference level is reduced significantly for both APs and mobile receivers.

II. 802.11 channel allocation

A. FAP methods

Different FAP approaches can be found in the literature [16]:

- Maximum Service F-FAP: Maximizes the number of frequencies while minimizing interference level.
- Minimum Order MS-FAP: Penalizes the usage of frequencies in order to chose the cheapest one.
- Minimum Span MS-FAP: Minimizes the required bandwidth by minimizing the difference between the minimum and the maximum used frequencies.
- Minimum Interference MI-FAP: Maximizes the inter-channel spacing between close emitters.
- Fixed Spectrum FS-FAP: the same as MI-FAP but with a limited set of frequencies.

It is obvious that the 802.11 channel allocation problem falls in the last class, i.e. the FS-FAP modelling [16], [17]. For example in Europe the ISM Band at 2.4GHz is divided into 13 channels partially overlapping with each other leading to only 3 completely non overlapping channels. The FAP is often described with a graph-based model, nodes being the transmitters and edges the constraints (i.e. inter-cells interference level) [20], [27]. The cost of a solution is thus evaluated from the sum of each edge cost.

B. Interference taxonomy

Three different cases of interference can be established for two access points AP1 and AP2 as represented in figure 1 .

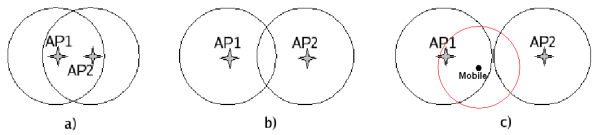

Fig. 1. Three interferences cases.

- case a: Each AP is located in the service area of another one.
- case b: Both service areas have a common region.
- case c: A mobile user located in the service area of one AP (either AP1 or AP2) may interfere with any mobile user associated to the other one.

The efficiency of any FAP approach is thus very sensitive to the interference model involved in the minimization criterion. Usual FAP are mainly based on the two following steps:

- Firstly, a graph is built by setting edges according to the radio link between each pair of APs,
- Secondly, a criterion is defined as the sum of the edge costs depending on the tested channel allocation.

The optimum frequency plan is the one minimizing this criterion.

C. Reference FAP criterion

This reference FAP algorithm only takes the simplest interference model described in Fig. 1-(a) into account. In this approach, interference distribution is modeled as a weighted graph whose nodes represent the APs placed in the environment [22]. Existance of an edge between two APs **A** and **B** relies on the quality of the radio link between them: these is an edge e if the access point **A** is in the carrier sense area of **B** and inversely.The cost assigned to each existing edge e is given by

$$\begin{aligned} C_e &= GAP - D_e \quad \text{if} \quad D_e < GAP \\ C_e &= 0 \quad \text{if} \quad D_e \geq GAP \end{aligned} \tag{1}$$

where GAP is the minimum distance (or gap) between 2 non overlapping channels and D_e the gap between both channels assigned to the nodes at the end of edge e. Typically, for a IEEE 802.11b network, GAP is fixed to 4. The global penalty cost function C_{ref} is the sum of the costs C_e assigned to each edge e of the graph.

D. A new QoS-based criterion

In usual algorithms [20], the interference model is in fact simplified because of two approximations. The first one neglects the cumulative nature of interference, each interferer being considered independently from each other. The second one holds in the fact that the interference levels are computed from the direct radio links between APs as described above. Such a model represents poorly realistic conditions of both uplink and downlink traffic.

- The former approximation leads to an under-estimation of the true interference level. The cumulative nature of interference has been widely evaluated in the context of GSM optimization showing its great impact. Initially neglected in the framework of wLAN planning, the actual growing size of wLAN deployed in more and more complex environments calls for a new point of view.
- The second approximation is done because only the APs' locations are known. Such a model is really unappropriate for WiFi like networks which share the same radio resources for uplink and downlink communications. The consequence is that both APs and mobile transmitters jointly produce interference at both APs and mobile receivers locations.

Because a complete interference estimation would need the knowledge of each mobile node location, our FAP interference criterion is rather based on interfering signals coming from transmitting APs evaluated at every possible receiving locations, including both mobile nodes and APs positions. The proposed criterion is more or less a downlink QoS-based criterion but improves as well downlink and uplink flows as illustrated in section V.

The second originality of our criterion holds in the fact that the criterion is based on a QoS measure. Indeed the chosen criterion aims to maximize the effective throughput in the network.

For the sake of clarity, let the environment be divided into regions of interest (ROI) defined as rectangular homogeneous areas. It is assumed that the mean received power is constant in each ROI. These ROI computed thanks to the MR-FDPF propagation simulator (see section IV), are called MR-nodes. The signal level from each AP is computed in each MR-node providing the SNR associated with each MR-node l according to:

$$(SNR_l)_{mW} = \frac{(F_l^{BS})_{mW}}{(P^n)_{mW}} \tag{2}$$

where F_l^{BS} is the power of the *best server* AP signal and P^n the AWGN noise mean power equal to $P^n = -92$ dBm for the 802.11b channel. SNR_l represents the best possible SNR one can obtain on the node l. This SNR supplies a mobile user with a given class of service. For instance, a 802.11b network having a SNR of 12 dB supplies a class of service of 11 Mbps data rate. To know the available theoretical data rate denoted D_l^{th}, SNR_l is compared to the standard SNR thresholds needed to guarantee emission rates of 1, 2, 5.5 and 11 Mbps.

Complementarily, having a given channel allocation scheme, the Signal to Interference plus Noise Ratio (SINR) is computed on each MR-node l according to:

$$(SINR_l)_{mW} = \frac{(F_l^{BS})_{mW}}{(P^n)_{mW} + (PI_l)_{mW}} \quad (3)$$

where $(PI_l)_{mW}$, defined as the total power of the N_I interfering signals at MR-node l, is given by:

$$(PI_l)_{mW} = \sum_{i=1}^{N_I} \nu(|c_{BS}, c_i|).[F_l^i]_{mW} \quad (4)$$

$\nu(|c_{BS} - c_i|)$ is the power rejection factor due to the distance between channels.
Table I gives the power rejection factor $p(|c_j - c_i|)$; $p(x) = -10log_{10}(\nu(x))$ in dB according to the gap between channels c_i and c_j.

$n = \|c_j - c_i\|$	0	1	2	3	4
P(n) for 802.11b	0 dB	2.25 dB	5.25 dB	9.9 dB	29.8 dB
P(n) for 802.11g	0 dB	3.9 dB	6.9 dB	12 dB	25.5 dB

TABLE I
POWER REJECTION FACTOR $P(n)$ DEPENDING ON THE GAP $n = |c_j - c_i|$ FOR BOTH 802.11B AND 802.11G.

The available data rate D_l^a provided by the SINR at MR-node l is computed and compared to the theoretical one D_l^{th}. If the available data rate D_l^a is lower than D_l^{th}, the MR-node l is considered jammed. The total jammed area A_I is computed as the total surface of jammed MR-nodes. The cost function is given by the percentage of jammed area for a given frequency plan.

$$C_{QoS}(S) = A_I / A_{total} \quad (5)$$

III. A TABU SEARCH ALGORITHM

First greedy algorithms based on hill climbing approaches have been used, but they have been shown to be really ineffective [22] as they only converge to local minima. Then the Tabu Search Algorithm has been developed to correct this local search problem by allowing non improving moves [13]. Other methods like Simulated Annealing or Genetic Algorithms [12] are also frequently used. Models based on Artificial Neural Networks or metaheuristic methods (like Ant Colony Optimization) have been developed too.

Our search algorithm relies on a *tabu search* metaheuristic firstly suggested by F.Glover [8]. It 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 of the method 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 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 is stored to prevent the search from cycling round on the same set of solutions. The key elements of the algorithm we chose to implement are inspired by [22]:

- *candidate solutions:* The representation of a frequency assignment S is given by the list of elements c_i containing the index of the channel assigned to transmitter i:

$$S = (c_1, c_2, ..., c_i, ..., c_N) \quad (6)$$

  N transmitters are considered.
- *Neighborhood:* The neighborhood of a solution is based on a function that binds a solution S to a set of neighbor solutions. The neighbor is herein defined such as a solution S_n is a neighbor of a solution S if one and only one channel $c_i, i \in [1, N]$ of S_n differs from S. The neighborhood of a solution of N transmitters with N_c channels is of $N \times N_c$ solutions, which is far less than the size of the global set of solutions: N_c^N. At each search iteration, the algorithm moves to the best solution chosen among the neighborhood of the current solution.
- *Tabu list:* This list stores the last moves carried out, which, for this reason, are forbidden. It can be referred to as the short-term memory that enables the algorithm to escape from local minima and withdraw cycling round during the search process. In this implementation, our tabu list stores a pair (t, c) where t is the transmitter and c the channel identifier. A solution of the neighborhood which has the channel c assigned to the transmitter t is tabu and can not be selected for the next search iteration. After a move from S_1 to S_2, the couple (t, c) that has been changed to get the new solution S_2 is stored in the tabu list.
  This short term memory has a length T that can be fixed or chosen randomly at each iteration. Montemanni et al. highlight in [22] the benefits of a dynamic length implementation that supports better convergence properties. At each iteration the length T of the tabu list is randomly chosen 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. The initial value of T is chosen in the same way.
- *Termination criteria:* The algorithm stops when one of the following termination criteria is satisfied:
  - the number of iterations has reached the maximum number of iterations n_{max},
  - the number of successive iterations without improvement of the cost function has reached a specified number NSA_{max},
  - the cost function returned value is equal to zero.
- *Parameter values:* The parameters used were tuned empirically after several tests as it is recommended in [5]. We fix $T_{min} = N/5$ and $T_{max} = N/2$ with N the number of transmitters. In the same way, we fix $NI_{max} = NSA_{max} = 1000$.

IV. RADIO COVERAGE PREDICTION MODELS AND AP PLANNING

The FAP modeling presented in section II and the results provided in section V heavily rely on the quality of the

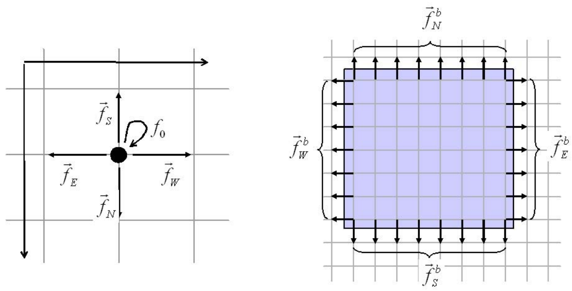

Fig. 2. This figure shows the usual ParFlow node (left), the MR-node (right), and their outward flows.

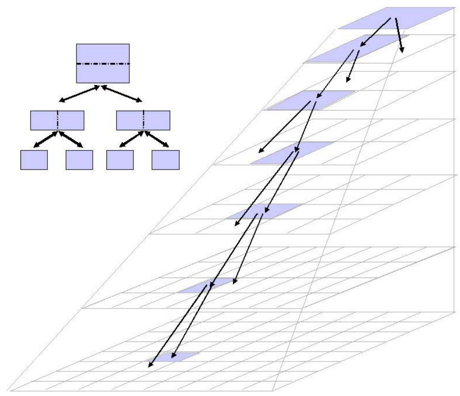

Fig. 3. The pyramidal structure.

simulations. The propagation model being used in this work is now described.

A. Usual Propagation models

Two different approaches have mainly been used depending on the applications:

a) Empirical models: They have firstly been devoted to outdoor environments. They are based on path-loss models as described, for instance, in [21], [24]. For Indoor environments, they suffer from a lack of accuracy because of the difficulty to take correctly the obstacles into account, although many efforts have been devoted to their improvement [3], [14].

b) Deterministic models: Ray tracing based approaches (see for instance [19], [26]), aim at computing a set of transmitted and reflected rays issued from the transmitter. Ray-tracing has been shown really efficient for urban or semi-open environments where only few significant diffractions and reflections hold for each ray. On the contrary, severe Indoor environments exhibit multiple diffraction and numerous reflections leading to a difficult trade-off between computational load and realism. This trade-off is the heart of more recent studies: image methods [1], [15], ray splitting [7], frustum ray tracing [25] and dominant path [28] are ones of them.

A discrete formulation approach has been recently proposed in [9]–[11]. This method is based on a peculiar finite difference approach using a frequency domain transmission line matrix (TLM) formalism. This method exploits the ParFlow theory developed by Chopard et al. [4] for GSM prediction in urban environment. A multi-resolution (MR) algorithm has been proposed for the frequency domain formulation of ParFLow (FDPF) equations leading to the MR-FDPF algorithm. The main elements of this approach are provided below. Its main advantage holds in the fact that all reflections and diffractions are taken into account, with no impact on the computational load.

B. MR-FDPF Model

In the ParFlow formulation the environment is discretized, each pixel having inward and outward flows associated with. The electrical field associated with each pixel is computed as the sum of all incoming flows. In steady-state, incoming flows in a node m are scattered according to the stationary scattering equation:

$$\begin{aligned} &\text{outward flows:} \quad \overrightarrow{F}(m) = \Sigma(m) \cdot \overleftarrow{F}(m) \\ &\text{inward flows:} \quad \overleftarrow{F}(m) = \mathcal{N}(\overrightarrow{F}(m)) + S(m) \end{aligned} \tag{7}$$

where $\Sigma(m)$ is the local scattering matrix, $\mathcal{N}(F(m))$ the vector of neighbor flows, and $S(m)$ the radiating source. Outward flows are illustrated in Fig.2(a).

Gorce et al. proposed in [9] to formulate a multi-resolution decomposition of the problem. The starting point is the definition of a multi-resolution (MR) node, as illustrated in Fig.2(b). A MR-node is a rectangular group of pixels having exchange flows on the border only. A scattering matrix can be associated with this node, allowing to compute outward flows as function of inward flows. The multi-resolution feature is obtained by a recursion that divides an initial MR-node, as illustrated in Fig.3. The MR recursion starts from the head-node encompassing the whole environment, and divides each MR-node into children nodes. Recursion stops when each branch is terminated by a standard ParFlow node (i.e. a pixel). A way to build a non regular binary tree to optimize the fit between nodes and walls and other obstacles has been presented in [6].

This method leads to a very efficient computational approach where the coverage calculation is split up into two stages:

- **The preprocessing stage:** Exploiting the environment characteristics, the binary tree is built and the scattering matrix of each MR-node is computed. This phase consumes the most computational and memory loads due to the needed successive matrix inversions. However this stage is done only once for an environment whatever the source location is.
- **The propagation stage:** In this stage coverage maps for each transmitter are computed. Starting from the source pixel, the father node of a source node is considered itself as a source node. Corresponding outward flows are computed from the child source node thanks to the upward matrices computed during the preprocessing. This is the bottom-up phase. When the head-node is reached,

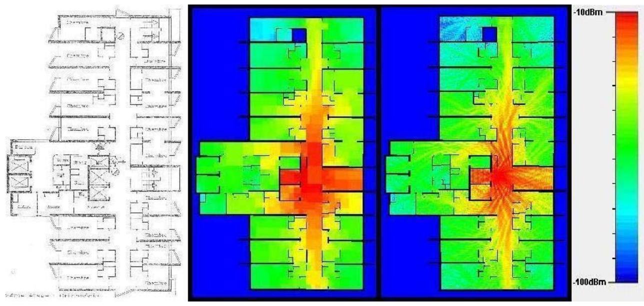

Fig. 4. left: a test environment, center: homogeneous MR-nodes coverage map, right: maximum resolution coverage map

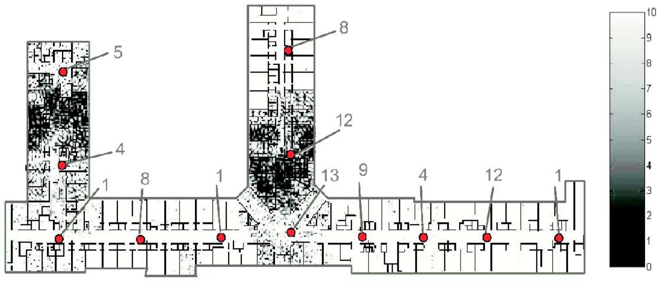

Fig. 5. SINR map for the best solution obtained with the Reference algorithm. The numbers on the figure correspond to the channel numbers. Gray points in the building correspond to potentially jammed mobile receivers.

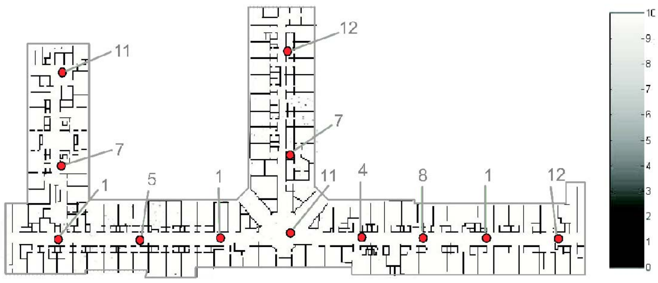

Fig. 6. SINR map for the best solution obtained with the QoS-FAP algorithm

the top-down phase consists in the propagation of inward flows of each source MR-node toward its children nodes. The process either ends at pixels, or stops at nodes having a predefined size.

This approach allows to reach quickly large homogeneous MR-nodes, referring to MR-nodes only containing free-space pixels only. It gives more sense to compute a mean power from inward flows over wide MR-nodes to save computational time. Figure 4 shows an example of a source coverage in a 20×30 meters environment at two different resolutions (homogeneous resolution and pixel resolution). The preprocessing computation time is measured at $4.3s$ while the source propagation time respectively equals to $3.6s$ at the pixel resolution and only to $0.5s$ at the homogeneous node level. In this figure, the good fit between both resolutions can be observed.

An experimental validation has been performed and simulations obtained after calibration exhibit a root mean square error (RMSE) of less than $5dB$ [23].

V. Results

A. Reference FAP and QoS-FAP algorithms results

Eleven APs have been placed in the environment as presented in Fig. 5. Ten runs of both Reference FAP and QoS-FAP process have been started on this problem instance.

Table II presents the mean value and the standard deviation of the reference cost function C_{ref} and the QoS-FAP cost function C_{QoS} computed with the 10 solutions obtained for both algorithms. $P(SINR > 10)$ is the percentage of surface area where the SINR is higher than 10 dB, allowing a data rate of 5.5 Mbps.

	Reference FAP		QoS-FAP	
	mean	σ	mean	σ
C_{ref}	37.7	0.8	-	-
C_{QoS}	36.4%	8.6	0.6%	0.3
$P(SINR > 10)$	76.5%	7.6	99.9%	0.1

TABLE II

Comparison between Reference FAP algorithm and QoS-FAP algorithm. Numerical results were obtained after 10 runs.

Table II highlights the efficiency of the QoS-FAP criterion. With QoS-FAP, a maximum global jammed area lower than 1% $(max(0.6 \pm 0.3))$ is obtained while the reference FAP criterion leads to a minimum global jammed area of 27.8% $(min(36.4 \pm 8.6))$. QoS-FAP obviously outperforms the Reference FAP algorithm and can enhance frequency plans.

The SINR map obtained with the best solution provided by the Reference FAP is represented on Fig. 5. As the criterion only takes interference between APs into account, only the AP locations are guarantee to be free of interference. The SINR map obtained with the best solution provided by the QoS-FAP is represented on Fig. 6. The potentially jammed receivers seen on Fig. 5 are no longer jammed on Fig. 6.

Thus, the quality of the QoS-FAP frequency plans allows to increase the density of APs in an environment and also guarantees high data rates for each cell.

B. Uplink SINR

To test the efficiency of our QoS-FAP result, it is worth to characterize how interference occur when the network is working. Therefore, a set of 12 users has been placed in the network and their coverage maps computed with our prediction model. For both channel assignments, a SINR map has been computed corresponding to uplink transmissions. Those maps are presented in Fig.7 and Fig.8. Users are represented by blue crosses and are linked to the AP providing the strongest signal.

Although our QoS-FAP approach is based on a downlink modeling, jammed area corresponding to these uplink transmissions remain sparse. The percentage of surface area where the SINR is lower than 10 dB is given by $P(SINR < 10) =$

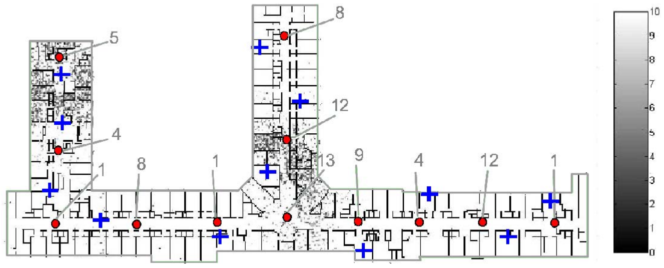

Fig. 7. Uplink SINR map for the best solutions of the Reference Algorithm

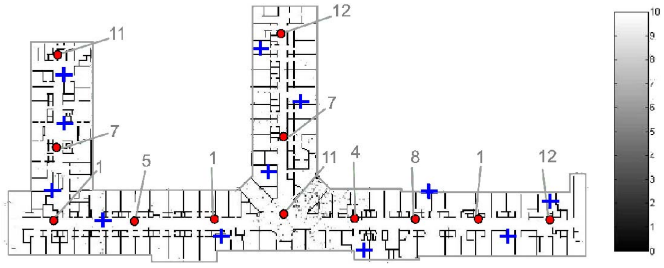

Fig. 8. Uplink SINR map for the best solutions of the QoS-FAP Algorithm

1.5% for the uplink context, whereas it is of $P(SINR < 10) = 0.5\%$ for the downlink one.

For the reference solution, the uplink jammed area is also comparable to the downlink jammed area as $P(SINR < 10) = 10\%$ in the uplink case and $P(SINR < 10) = 11\%$ in the downlink one.

VI. Conclusion

In this paper a tabu-based heuristic and a QoS-based interference criterion dedicated to the frequency assignment problem in wLAN deployments have been detailed. The criterion is based on a realistic interference model, expressed at mobile user positions. The proposed QoS-based FAP algorithm presented herein is interesting because it not only tries to maximize SINR, but ensures getting the best available class of service for a fixed AP distribution by minimizing the loss of overall throughput due to interference. It is shown on an example that the proposed QoS-FAP solution reduces as well the uplink and the downlink interference level.

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