Power Savings with Data Rate Guarantee in Dense WLANs

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***Abstract*—We investigate the problem of minimising power consumption in dense Wireless Local Area Networks (WLANs), by optimally establishing the association of User Terminals (UTs) to Access Points (APs). This management allows to switch off some APs, granting important power savings, while at the same time guaranteeing to satisfy the data rate requirements of all UTs. The considered WLAN power minimization problem can be formulated as an Integer Linear Programming (ILP) model and can be in principle solved by any commercial optimization solver. However, the problem is NP-hard and, as we show through thorough computational tests, even a last generation state-of-the-art solver like IBM ILOG CPLEX can have difficulties in finding solutions of good quality in short amount of time, as required in real WLAN deployments. As a consequence, we propose two new fast heuristic algorithms for WLAN power minimization. Furthermore, we show that, in some cases, also a proper setting of the parameters of CPLEX can compute solutions associated with good power savings in a reasonable time.**

***Index Terms*—Wireless LAN; Power Efficiency; Resource Allocation; Integer Linear Programming; Network Management; Heuristics.**

I. Introduction

Dense WLANs are usually deployed where a lot of users require WiFi access to the Internet (e.g., public locations and large enterprises). In these scenarios, besides coverage, a relevant design target is to provide enough capacity for the large amount of traffic generated by the users. The solution is to increase the density of APs (in the order of 0.01 AP/m^2). In this scenario, the design of efficient reconfiguration algorithms, aimed at reducing the power consumption of the WLAN infrastructure, is of paramount relevance, since it may lead to a relevant cost reduction.

Most (or even all) of the currently deployed enterprise dense WLANs are continuously operated at full power, i.e. all the APs are always on and their transmission power is set to the maximum possible value. This leads to a considerable energy wastage, because the same power is employed at the peak hours (e.g., 11 AM of weekdays) and during the off-peak periods (e.g., nights and weekends).

In this work, we address the problem of saving power, taking into account the generated traffic, while satisfying the data rate requirements of the users. To achieve this goal, we operate at the network management level by establishing a suitable association UTs-APs, in order to select the APs that can be turned off.

In the first step of our study, we formally characterize the WLAN system, in order to detail all the system-level features in their more general form, without performing any kind of approximations or simplifications. The WLAN system characterization is then used to propose an Integer Linear Programming (ILP) model, which formulates the optimization problem of reconfiguring the WLAN network for power minimization. The resulting WLAN power minimization problem is NP-hard and even state-of-the-art commercial optimization software can solve to optimality only instances of the problem of moderate size. Therefore, in the second part of our study we investigate the adoption of alternative, fast and computationally efficient, heuristic solution approaches, in order to be able to tackle larger instances.

To cope with the complexity of the ILP model solution, in this paper we carry out two kinds of analysis. The first one is devoted to evaluate at what extent the ILP model, when solved by a commercial optimization solver, can be actually useful to compute solutions for realistic scenarios, in a time that is acceptable from the engineering perspective. In our case, this is carried out by using the sophisticated state-of-the-art optimization solver IBM ILOG CPLEX, studying different settings of the solver parameters, and evaluating the quality of the computed solutions. Indeed, the ILP model for the WLAN power minimization problem can be solved, *at least in principle*, by any commercial optimization solver, such as IBM ILOG CPLEX. However, the problem can result hard to solve even for CPLEX, when the size of the instances increases: CPLEX can find difficulties in identifying feasible solutions of satisfying quality in a short amount of time and presents a very slow convergence to an optimal solution. Such a performance

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is unacceptable for real-world deployment of WLANs, where the time factor is critical: since the conditions of the network vary over time, an optimal solution computed after a large amount of time would result useless, since in the meantime the network conditions would have changed radically.

To tackle such an unsatisfactory performance of CPLEX, in this paper we propose two new heuristics which are able to determine solutions of high quality, often near to the optimal ones, in much shorter time than CPLEX, especially in dense scenarios. The second computational analysis that we make is thus devoted to evaluate the performance of two new heuristics as a computationally efficient alternative to the direct use of a commercial solver. CPLEX and the two heuristics are compared in terms of quality of the returned solutions, evaluated in terms of power consumption, and also in terms of computational time.

In summary, the main contributions of this paper are the following. We first give a general characterization of the WLAN system and state an ILP model that takes into account all the system features. Then, we propose two heuristics to solve the problem. Furthermore, we study the performance of CPLEX when dealing with the ILP in realistic network scenarios and perform a comparison of its performance with that of the proposed heuristics.

The rest of the paper is structured as follows. The next Section reviews the state-of-the-art of energy-efficient resource allocation in WLANs. Section III illustrates the analytical model of the WLAN system and the ILP formulation to the problem. Section IV describes the proposed heuristics, whereas Section V presents the simulation analysis involving both CPLEX and the heuristics. Finally, we draw conclusions in Section VI.

II. Related work

The literature on energy efficiency in WLANs is conspicuous, as well as the one on the different approaches used to obtain power savings. We review here some works which are particularly relevant for our study.

A first approach is based on the concept of *Resource on Demand* (RoD). In a dense WLAN, RoD means that APs dynamically switch on and off based on users' need for capacity. A seminal work on this topic is [1] by Jardosh et al., who proposed a strategy to dynamically power on/off APs depending on the resource demand of the users. This approach has been translated into a working testbed, proving the feasibility of the idea and the related energy gains. However, the strategy is based on empirical considerations, has no guarantees of optimality, and is tested on a very small network. Based on actual data traffic, Meo et al. [2] investigate the users' behaviour in accessing the WLAN and formulate a stochastic characterisation of it. They propose a simple model that describes the RoD strategies and use it to study the system performance that is evaluated in terms of AP activity and inactivity periods, AP switching frequency, and energy saving. Through an experimental analysis, they show that RoD strategies for dense WLANs are feasible and effective in trading-off the contrasting needs of saving energy and guaranteeing a smooth network operation and a high quality of service. However, the experimental analysis is limited to a small network composed of a few APs and a few tens of UTs.

To save power consumption of APs, radio-on-demand WLAN techniques are proposed for example in [3]. Power savings is achieved using APs' sleep interval with length dynamically selected taking into account the offered load during different parts of a day (peak hours, off-peak hours). Recently, Hyeontaek Oh et al. [4] have proposed a novel sleep mechanism that dynamically sets bounds of sleep duration considering traffic arrival rate and traffic delay requirements at a given time. However, such works do not consider the bandwidth of the AP capacity and the link quality between APs and devices in a Green WLAN. Differently from the mentioned works, the Quality of Service (QoS) is taken into account in our study: to satisfy the user data rate requirements of a user, in our model we can turn on an AP even if its utilisation is low.

Finally, we mention the work of Garcia-Saavedra et al. [5], who studied the trade-off between energy and throughput optimisation in case of heterogeneous user devices. Even if the authors present an exact analytical model, then they simplify it due to its complexity. In any case, the addressed problem is different from ours, since it targets the energy consumption of the user devices in a single WLAN, rather than consumption of the overall WLAN infrastructure.

III. The system model

The physical problem considers a set $\mathcal{J}$ of deployed APs that must serve a set $\mathcal{I}$ of UTs. Each UT $i \in \mathcal{I}$ requires a data rate w_i that must be provided by exactly one AP. As shown in our previous analysis [6], the power P_j consumed by the generic AP j can be essentially ascribed to two major components. There is a constant component b_j, which is bound to the mere fact that the device is powered on. In addition, there is a variable component a_j, which accounts for the so-called "airtime", i.e. the fraction of time the device is either transmitting or receiving frames. It is weighted by a constant "wireless" factor, say p^w, which accounts for the power drain of the radio front–end for the transmission and reception operations. The two components are combined so that the power P_j can be expressed as:

$$P_j = b_j + p^w\, a_j \qquad \forall j \in \mathcal{J}. \tag{1}$$

Other parameters characterising the WLAN system are the data rates (or capacities) r_{ij} available between the UT i and the AP j, for $i \in \mathcal{I}$ and $j \in \mathcal{J}$. They depend on the physical properties of the system (e.g., the position of the UT i and the AP j, the transmission power, the radio propagation rules). To keep the notation simpler, we shall assume that the links are symmetric, i.e. $r_{ij} = r_{ji}$, for $i \in \mathcal{I}$ and $j \in \mathcal{J}$.

In an actual scenario, both user movements and capacity fluctuations due to radio channel variability should be taken into account to establish the available r_{ij} over the time. As an example, UTs can roam across the service area and this has a direct impact on the link capacities r_{ij}, which are a function of the distance between the UT i and the AP j, for $i \in \mathcal{I}$ and $j \in \mathcal{J}$. However, here we assume to be able to determine a solution, and to implement it, before significant variations in the network conditions happen. In particular, we assume to be on average in an almost static scenario, as in the case of corporate environments (see [1]), where we can assume that the network conditions do not vary in a time scale of one-two hundreds of seconds. Consequently, putting a time limit lower than 100s to determine a WLAN solution, we can reasonably assume that the UTs are static while solving the problem and that the data rates, estimated before the solution starts, are certain.

Under the stated conditions and assumptions, the problem to be solved thus consists in deciding what APs to power on and to which powered-on AP to assign each UT (each UT must be assigned to exactly one AP), so as to satisfy the data rate requirements of all UTs and the capacity constraints. The goal is to minimise the overall power consumption of the APs.

A. The problem formulation

The WLAN power optimization problem introduced above can be formulated by means of the following ILP model, formerly introduced in [7]. The model is based on two sets of binary decision variables:

- x_{ij}, which is set to 1 if UT i is assigned to AP j, and to 0 otherwise, $\forall i \in \mathcal{I},\ j \in \mathcal{J}$;
- y_j, which is set to 1 if AP j is powered-on, and to 0 otherwise, $\forall j \in \mathcal{J}$.

As indicated before, the objective is to minimise the total power consumption:

$$z = \min \sum_{j\in\mathcal{J}} P_j = \min \sum_{j\in\mathcal{J}} \left\{ b_j\, y_j + p^w \sum_{i\in\mathcal{I}} \frac{w_i}{r_{ij}}\, x_{ij} \right\}, \tag{2}$$

where the airtime a_j has been expressed in terms of the variables x_{ij}:

$$a_j = \sum_{i\in\mathcal{I}} \frac{w_i}{r_{ij}}\, x_{ij}. \tag{3}$$

The minimisation is subject to the constraints:

$$\sum_{j\in\mathcal{J}} x_{ij} = 1 \qquad i \in \mathcal{I} \tag{4}$$

$$\sum_{i\in\mathcal{I}} \frac{w_i}{r_{ij}}\, x_{ij} \le y_j \rho_j \qquad j \in \mathcal{J} \tag{5}$$

$$x_{ij} \in \{0,1\} \qquad i \in \mathcal{I}, j \in \mathcal{J} \tag{6}$$

$$y_j \in \{0,1\} \qquad j \in \mathcal{J}\ . \tag{7}$$

Equations (4) are the single assignment constraints imposing that each UT must be assigned to exactly one AP. Equations (5) are the capacity constraints. They impose that the *load* of each AP $j \in \mathcal{J}$, which is defined as the sum in the left-hand-side of the constraint (5) related to j, be at most $\rho_j \le 1$. They also ensure that no UT is assigned to powered-off APs. It is worth emphasizing that these constraints imply $w_i \le \rho_j r_{ij}$, $i \in \mathcal{I}, j \in \mathcal{J}$, and consequently, since $\rho_j \le 1$, they also imply $w_i \le r_{ij}$ for any UT i associated with an AP j. In other words, constraints (5) guarantee that the computed solution satisfies the data rate requirements for all the users. Finally, (6) and (7) declare the decision variables.

IV. Heuristic Algorithms

To tackle the unsatisfactory performance of state-of-the-art solvers, similarly to other works (e.g., [8]), in this section we introduce two new computationally efficient heuristics, which can very fast find solutions of high quality and can be used in real WLAN applications.

A. A clustering heuristic approach

In order to solve the problem in a few hundreds of seconds, also for network scenarios composed of a high number of UTs and APs, we present a first heuristic based on the observation that the network scenario can be spatially divided into subareas. In particular, since the distance between a UT and an AP is a key parameter for determining the data rate necessary for the requested service, the idea is to decompose the overall network into clusters of UTs and APs, and then to solve each resulting subproblem of the ILP model described in Section III-A. The solutions obtained by solving the subproblems, which are smaller and easier to solve than the overall problem, are then combined to determine a solution to the overall problem. We call this heuristic "*CHER*" (Clustering HEuRistic - see Algorithm 1).

The number of the clusters has been determined experimentally by considering the trade-off between performance and computational time. In particular, in the simulation analysis presented in the next section, we will show the results for different values of K.

It is worth mentioning the relevance of the cycle used to determine the load limit of each AP j when j is

Algorithm 1 CHER - Clustering HEuRistic

```
1: Calculate the Distance Matrix, where the element (i, j) contains the distance between UT i (row) and AP j (column)
2: Consider the row i of the Distance Matrix as the features list of UT i
3: Set the number of clusters K;
4: Determine UTs and APs belonging to each cluster
5: for k = 1 to K do
6:     for each AP in cluster k do
7:         Calculate the amount of "potential" load given by the UTs nearest to the considered AP in cluster k
8:     end for
9: end for
10: for each AP do
11:     for k = 1 to K do
12:         Calculate the load limit ρ_{j,k}
13:     end for
14: end for
15: for k = 1 to K do
16:     Solve the ILP model restricted to the subproblem defined by cluster k
17: end for
```

associated with cluster k, also denoted as $\rho_{j,k}$. Indeed, the clustering procedure assigns each UT to exactly one cluster. On the contrary, an AP can be associated with different clusters. This implies that, for a particular AP associated with more clusters, the capacity constraint (5) is certainly satisfied in each subproblem, whereas the sum of the loads given by the different clusters to which the AP belongs might violate its capacity constraint. To avoid this, the strategy implemented within the cycle of lines 10-14 in Algorithm 1 computes the $\rho_{j,k}$ values related to an AP j, for each cluster k where j is present, as the ratio between the "potential" load of the AP in k and the sum of "potential" loads of the AP over all the clusters. The "potential" load is estimated as the sum of the load offered by the UTs having the considered AP as the nearest one.

Also observe that, depending on the network scenario, the clustering algorithm could generate subareas where one of the subproblems is unfeasible, even if the whole network scenario indeed admits a feasible solution. However, in the dense network scenarios considered in the simulation analysis we did not experience this kind of unfeasibility issue.

B. A two-phase heuristic approach

The second heuristic is based on the idea of exploiting the linear feature of the AP power model function (1), and the realistic assumption that $b_j > p^w$. As shown in [9], these conditions suggest traffic consolidation as the right strategy to obtain power savings. Hence, the proposed heuristic tries to find a good quality solution, near to the optimal one, performing two phases: 1) associating each UT i with the AP j with the minimum $\alpha_{i,j} = \frac{w_i}{r_{ij}}$ value (i.e., minimizing the AP power consumption due to the variable component with parameter p^w); 2) trying to consolidate the traffic (i.e., trying to switch off some APs in order to save the constant part b_j of the AP power consumption).

The heuristic is therefore made up of two main phases, one for each strategy. The first phase is reported in Algorithm 2. In the following the application of only this part will be denoted as "*MinDist*". When MinDist finds a feasible solution, we can start the second phase, aimed at consolidating the traffic in order to switch off some APs, as detailed in Algorithm 3. In the following, the overall two-phase heuristic will be indicated by the name "*HECTIC*" (HEuristiC for TraffIC Consolidation).

V. SIMULATION ANALYSIS

The simulation analysis has been carried out by using MATLAB R2015b and CPLEX 12.6.3 running on a MacBook Pro with 2.9 GHz Intel Core i5 CPU with 16 GB RAM memory. The goal of the experimentation is to analyse the performance of the two proposed heuristics. In addition we investigate a suitable setting of some CPLEX parameters, which allows one to convert the exact approach, consisting in solving the ILP model in Section III-A to optimality, into what we call an *approximation* approach, and compare the performance of the heuristics and of the approximation CPLEX based approach from the perspective of the trade–off between power consumption and computational time.

Three different performance parameters have been considered: the power consumption of the network, denoted by *PC*, the computational time required to compute a solution, denoted by *CT*, and the number of APs which are switched off in the considered solution, denoted by *NOFF*. Each performance parameter has been evaluated by solving 50 independent instances, obtained by randomly generating the positions of the UTs and the APs in the considered area. For each performance parameter we report both the mean value and the 95% Confidence Interval (CI). Since MinDist uses the most common association strategy (i.e., each UT is associated with the AP with the best received signal), we can assume the performance obtained with this strategy as reference.

The main achievements of the simulation analysis can be summarised as follows:

1) with suitable configuration settings, the approximation CPLEX based approach is able to obtain solutions providing interesting power savings in an acceptable computational time;

Algorithm 2 HECTIC - Phase I

Initialize $y_j := 1$ all j
for $i = 1$ to $|I|$ **do**
  set $x_{ij} := 1$ for j given by $\min_j \alpha_{i,j}$;
end for
$ULIST$ = {Set of APs not satisfying constraint on the load}
Sort the $ULIST$ in descending order of the load.
repeat
  Select $\widehat{j}$ from the $ULIST$
  $UT2M$ = {Set of UTs with $\alpha_{i,\widehat{j}} \neq \infty$ sorted in increasing values of α}
  $IndexUT2M = 2$
  Select $\widehat{i}$ as $UT2M(IndexUT2M)$
  $PAAP$ = {Set of APs where $\widehat{i}$ can move sorted in increasing order of $\alpha_{\widehat{i},j}$ }
  $indexPAAP = 2$
  repeat
    Select the Potential New AP $PNAP$ as $PAAP(indexPAAP)$
    if Load constraint of $PNAP$ is satisfied **then**
      Move $\widehat{i}$ from $\widehat{j}$ to $PNAP$
    else
      Increment $indexPAAP$
      if $indexPAAP > |J|$ **then**
        $\widehat{i}$ cannot be associated to a new AP
        Try with another UT
      end if
    end if
  until $\widehat{i}$ is associated to a new AP or $indexPAAP > |J|$
  if $indexPAAP < |J|$ **then**
    Remove $\widehat{j}$ from the $ULIST$
  else
    The problem is Infeasible
  end if
until ULIST is empty or $indexPAAP > |J|$

Algorithm 3 HECTIC - Phase II

$AP2OFF$ = {Set of turned on APs sorted in increasing values of load}
repeat
  Select the $APtryOFF$ from the $AP2OFF$
  $UT2APtryOFF$ = {Set of UTs connected to $APtryOFF$ sorted in decreasing values of $\alpha_{i,APtryOFF}$}
  repeat
    Select $UT2MOVE$ from $UT2APtryOFF$
    $ArrAP$ = {Set of APs sorted in increasing order of $\alpha_{UT2MOVE,j}$}
    repeat
      Try to move the $UT2MOVE$ to one of APs in $ArrAP$
      if the movement of $UT2MOVE$ is not possible **then**
        $APtryOFF$ cannot be switched off
      else
        Remove $UT2MOVE$ from $UT2APtryOFF$
      end if
    until A new AP is found for $UT2MOVE$ or movement is not possible
  until $UT2APtryOFF$ is empty or $APtryOFF$ cannot be switched off
  if $UT2APtryOFF$ is empty **then**
    Switch off $APtryOFF$, Update the sorted set $AP2OFF$
  end if
until all APs in the $AP2OFF$ list are considered

2) the proposed heuristics, in dense WLAN scenarios, show a very good performance depending on the ratio $\frac{|I|}{|J|}$.

A. Simulation settings of network scenarios

The area of each considered scenario is a square of side 100 m. Four different scenarios have been considered. Each scenario is characterised by a higher number of APs and UTs, which have been set by imposing the ratio $\frac{|I|}{|J|} = 10, 50$, and the density of the APs $\frac{|J|}{m^2} \in \{0.001, 0.005, 0.01\}$.

The positions of the APs and of the UTs in each instance are randomly determined as follows. Firstly, we divide the test area into a regular grid of $|\mathcal{J}|$ squares. Then, the APs are placed one per square, with their coordinates chosen randomly within the square. The set of the UTs is also split into $|\mathcal{J}|$ subsets and the elements of each subset are randomly spread over each square. This strategy ensures enough uniformity in the placement of the UTs and of the APs, so as to mimic a corporate scenario and to avoid heavily unbalanced instances.

The data rate requirement of each UT has been randomly generated from a uniform distribution in the range $[270, 330]$ Kbps.

Concerning the evaluation of the $r_{i,j}$ starting from the distance $d_{i,j}$ between a UT i and an AP j, in general it can be determined by means of two steps. Firstly, the received power is estimated starting from the transmitted power and the path loss model, which takes into account the propagation properties of the considered network scenario. In the simulation analysis, we considered the COST-231 multi-wall path loss model for indoor, with non-LOS environments [10]. By assuming that all the APs are in the same floor, the path loss model in dB is: $PL(d_{i,j})_{dB} = P_{ref} + L_C + 10log_{10}\frac{d_{i,j}}{d_0} + n_w L_w + n_c L_c$, where P_{ref} is the reference free space value evaluated at the distance d_0, and L_C is a constant loss term (set to 14.2 dB). The integer n_w and n_{cl} are the number of walls and columns in $d_{i,j}$ respectively. These numbers are estimated assuming to have a mean distance between walls of 8 m and between columns of 20 m. The terms L_w and L_{cl} denote the loss in dB added by each single wall (set to 1.4) and column (set to 2).

The transmission capacity has been calculated as follows:
i) if the received power in the link (i, j), P_{Rij}, is higher than a sensitivity threshold γ_{ij}, then $r_{ij} = 0$. Thus, $j \in \mathcal{J}$ can only be assigned to $i \in \mathcal{I}$ when its radiated power P_{Rij} remains above γ_{ij};
ii) otherwise, the SNIR (Signal to Noise plus Interference Ratio) is calculated and the capacity r_{ij} is extracted. Examples of curves reporting the relation between the capacity and the SNIR can be found in [11], [12]. In addition, an experimental study where the "capacity vs. transmitted power" curves are estimated for different system configurations is presented in [13]. If $r_{ij} \leq r_{max}$, then r_{ij} is set to r_{max}, which represents the maximum rate achievable by any physical connection.

In the simulation study, we set $r_{max} = 54$ Mbps according to the 802.11g standard, and the sensitivity thresholds $\gamma_{ij} = -121dBm$. The setting of the parameters for the power consumption model is $p_w = 11$ w and $b_j = 24$ w for all APs. All these parameters refer to the data sheet of [14], and to the results shown in [15].

B. Simulation Results

We analysed the results obtained with the six scenarios obtained by the combination of the two parameters $\frac{|I|}{|J|} \in \{10, 50\}$, and the AP density $\frac{|J|}{m^2} \in \{0.001, 0.005, 0.01\}$. However, for sake of clarity we report here only the results showing the main achievements. The others are not shown since they simply confirm the conclusions reported in the following.

Impact of CPLEX configuration setting. Concerning the study devoted to evaluate the impact on the performance of different settings of the solver CPLEX, we consider the following parameters:

- the relative tolerance on the gap between the best integer objective function value and the objective value of the best node remaining, denoted as (EG); it provides an estimate of the distance of the solution returned by the optimization solver with respect to an optimal solution;
- the maximum time, in seconds, given to the solver for computing a solution, denoted as Time Limit (TL).

This analysis considers the scenario with the highest number of variables that CPLEX was able to solve, i.e. $|J| = 50$ and $|I| = 2500$. Three alternative settings have been considered. Two have the default EG value (10^{-4}) and differ in the TL (TL=200 s and TL=1800 s, respectively). The third setting associates TL=1800 s with $EG = 0.05$. Notice that these alternatives, which have been set based on a preliminary analysis carried out with the default parameter settings of CPLEX, turns out the exact approach, consisting in solving the ILP model to optimality, into what we call an *approximation CPLEX-based* approach.

The results in terms of mean values and 95% CI are summarised in Table I for all the algorithms except CHER. The results clearly show that accepting a solution with $EG = 0.05$ allows to reduce the computational time of one order of magnitude, with a loss in terms of power consumption less than 2% with respect to the solution with $TL = 1800$s. Furthermore, HECTIC provides a solution in a few hundreds of ms, with a power saving of 8% with respect to the one provided by MinDist.

It is worth noting that the optimisation with $EG = 0.05$ permits to save the 30% of power consumption with respect to the solution of MinDist. However, this relevant power saving is possible only if we are able to wait for a few tens of second before establishing the association AP-UT and what APs to switch off. The analysis of the NOFF parameter clearly shows the ability of CPLEX to switch off a significant number of APs, which is about twice that obtained with HECTIC.

The GAP parameter reported in the table is the optimality gap EG certified by the solver when it stops after having reached the arrest condition (either having reached the time limit TL or the requested optimality gap EG). We can observe that running the solver for 1800 s does not reduce considerably the GAP with respect to the one obtained by setting TL = 200 s.

The power consumption results obtained with CHER for different number of clusters are reported in Figure 1. To solve the subproblem related to each cluster, we set TL=1800 s and $EG = 0.05$. To simplify the comparison with the results shown in Table I, the figure also reports the results obtained by solving the whole scenario with CPLEX (using the setting $TL = 1800$s and $EG = 0.05$). These results correspond to the curve denoted as `FSol_G5`. We report also the curves corresponding to HECTIC and MinDist. The figure shows that CHER allows to achieve about the 10% of power savings with respect to the one guaranteed by HECTIC for a number of clusters equal to 15. However, this result is obtained with a computational time of about 5s, as shown in Fig.2.

It is relevant to note that, for $K < 12$, CHER does not provide advantages with respect to the solution of the whole problem via the CPLEX settings TL=1800 s and $EG = 0.05$. This result is due to the fact that in about the 10% of the independent distributions of

PP	TL=200s	TL=1800s	TL=1800s $EG = 0.05$	HECTIC	MinDist
CT	200.11±0.06	1802.9± 2.69	37.62± 77.74	0.300± 0.111	0.293 ± 0.107
PC	867.47± 9.62	866.54 ± 0.70	882.14 ± 22.53	1161.3± 44.99	1262.7 ± 66.22
NOFF	24.94±0.48	24.96±0.39	24.35±0.48	12.85±1.84	8.72 ± 2.68
GAP	2.24 ± 1.03	2.13 ± 0.18	3.85 ± 2.47	–	–

Table I
PERFORMANCE COMPARISON FOR DIFFERENT CPLEX SETTINGS - MEAN VALUES AND 95% C.I. - 50 APS, 2500 UTS, SQUARE OF SIDE 100 M

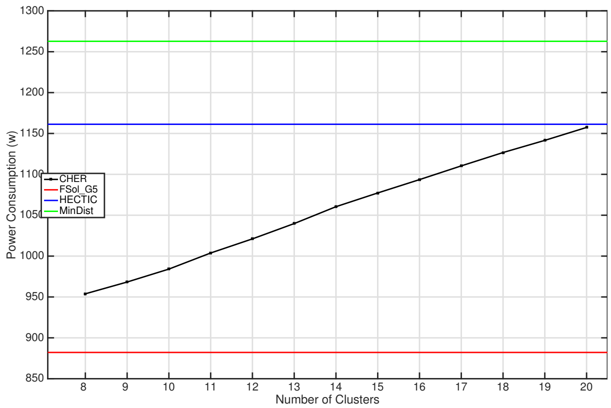

Figure 1. Power vs. K - 2500 UTs, 50 APs in a square of side 100 m - Mean Values

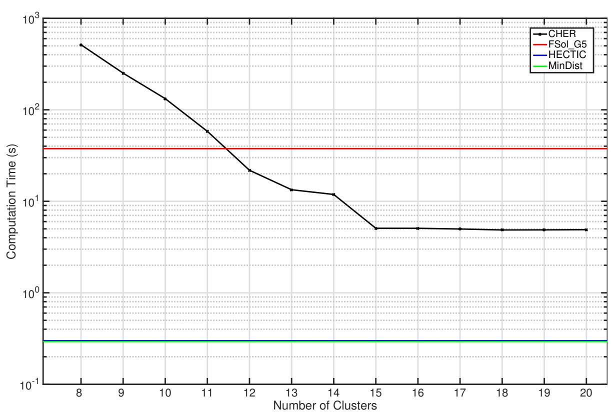

Figure 2. Time vs. K - 2500 UTs, 50 APs in a square of side 100 m - Mean Values

the APs and UTs, we have observed one cluster whose solution requires more than 1000 s. In some cases, for this particular cluster the Time Limit is achieved.

Scenario with the highest AP density (0.01 AP/m^2). In the case of the most dense WLAN scenario analysed in this study, i.e. with 100 APs in the considered area, CPLEX was able to solve the whole problem only for $|I| = 1000$, while for 5000 UTs the number of variables is too high to be managed by the solver. Figures 3 and 4 show the results obtained for $|I| = 1000$ in terms of PC and CT, respectively. We can observe that CHER provides high power savings with respect to HECTIC, with an acceptable CT. Indeed, for $K = 20$ in about 4 s, CHER is able to find a solution with a power savings of about 57% w.r.t. HECTIC.

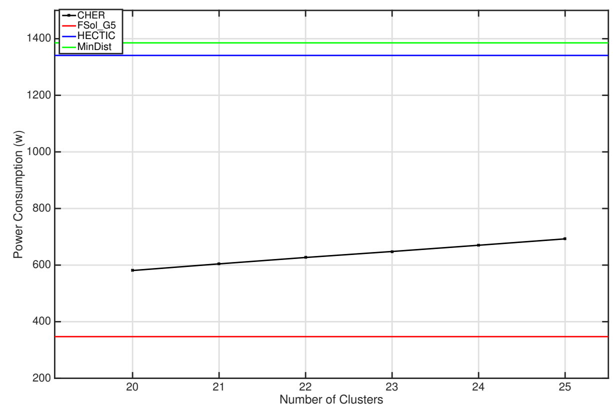

Figure 3. Power vs. K - 1000 UTs, 100 APs in a square of side 100 m - Mean Values

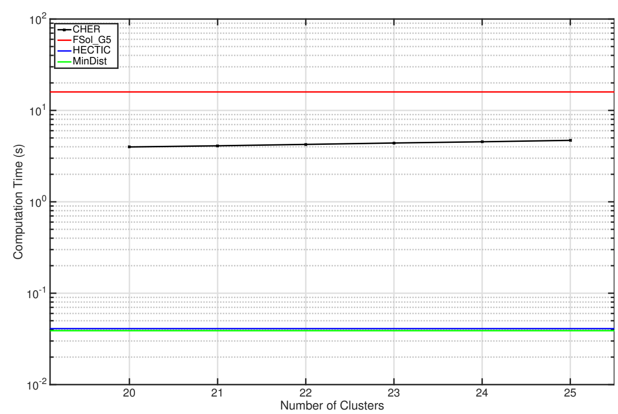

Figure 4. Computation Time vs. K - 1000 UTs, 100 APs in a square of side 100 m - Mean Values

Concerning the scenario with 5000 UTs, we can observe in Figure 5 that we need about 25 s to have a solution from CHER. This solution is achieved with $K = 25$ and generates a power savings of about 13% w.r.t. HECTIC, as shown in Figure 6.

The comparison of these two results confirms a general trend observed for all the scenarios: CHER provides higher power savings for lower $\frac{|I|}{|J|}$ ratio. In this situation, for each UT there are different AP association alternatives that can satisfy its data rate requirement. Thus, CHER is able to find a solution for each cluster subproblem very fast. Consequently, CHER can determine a solution near to the one obtained by solving the whole network scenario, in less than 5 s. On the contrary, when the $\frac{|I|}{|J|}$ ratio is higher, some subproblems can be hardly solved given the constraints on the AP capacity, which imply the satisfaction of the data rate requirements of each UT. In this case, the advantages of CHER w.r.t. HECTIC are less evident.

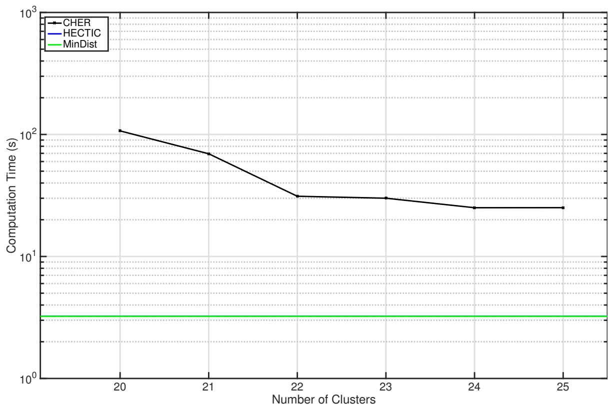

Figure 5. Computation Time vs. K - 5000 UTs, 100 APs in a square of side 100 m - Mean Values

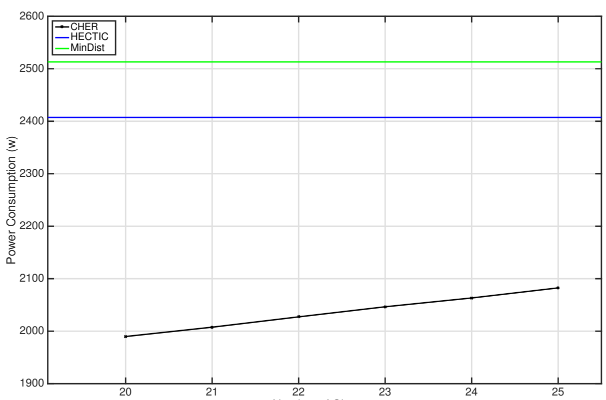

Figure 6. Power vs. K - 5000 UTs, 100 APs in a square of side 100 m - Mean Values

VI. Conclusion

We have addressed the optimization problem of power consumption minimization in dense WLANs, pointing out the limits of solving the resulting ILP model even by using a state-of-the-art solver like CPLEX. Given the unsatisfying performance of CPLEX, we have proposed two heuristic solution algorithms which can determine solutions of high quality very rapidly, and therefore can be used in real WLAN applications. We have also shown that, in some cases, also an approximated CPLEX based-approach can compute acceptable solutions in a reasonable amount of time. As future work, we plan to investigate refined integration of the new heuristics with branch-and-cut algorithms (see e.g., [16]) and study the extension of the heuristics to a multiband robust optimization case (see e.g., [17]), addressing the uncertainty of data rates.

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