Efficient Usage of Renewable Energy in Communication Systems using Dynamic Spectrum Allocation and Collaborative Hybrid Powering

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***Abstract*—In this paper, we introduce a new green resource allocation problem using hybrid powering of communication systems from renewable and non-renewable sources. The objective is to efficiently allocate the power delivered from the different micro-grids to satisfy the network requirements. Minimizing a defined power cost function instead of the net power consumption aims to encourage the use of the available renewable power through collaboration between the base stations within and outside the different micro-grids. The different degrees of freedom in the system, ranging from assignment of users to base stations, possibility of switching the unnecessary base stations to the sleep mode, dynamic power allocation, and dynamic allocation of the available bandwidth, allow us to achieve important power cost savings. Since the formulated optimization problem is a mixed integer-real problem with a non-linear objective function, we propose to solve the problem using the Branch and Bound (B&B) approach which allows to obtain the optimal or a suboptimal solution with a known distance to the optimal. The relaxed problem is shown to be a convex optimization which allows to obtain the lower bound. For practical applications with large number of users, we propose a heuristic solution based on decomposing the problem into two sub-problems. The users-to-base stations assignment is solved using an algorithm inspired from the *bin-packing* approach while the bandwidth allocation is performed through the *bulb-search* approach. Simulation results confirm the important savings in the non-renewable power consumption when using the proposed approach and the efficiency of the proposed disjointed algorithms.**

***Index Terms*—green communications, smart grids, efficient bandwidth allocation, power efficiency, renewable energy, branch and bound.**

I. INTRODUCTION

The dramatic increase of power generation costs and the increasing awareness about effects of carbon emissions resulted in a serious focus on reducing power consumption when designing modern industrial systems [1–4]. As a result, the development of techniques that can still achieve high system performances while minimizing energy consumption has been the design focus of various networking systems, including sensor networks [5–8], cognitive radio networks [9–12], femtocell networks [13–16], cloud networks [17–19], and others.

Relying on renewable energy sources has been one of the promising solutions to reduce carbon emissions [20, 21], but their limited availability makes them unreliable for long term use. With the technological advances achieved in improving their energy efficiency, renewable sources contributed about 19% of the global world energy consumption in 2012 [22].

With the continuous growth in telecommunications market, communication systems become one of the biggest power consumers and CO_2 producers with an amount representing 2% of the global CO_2 emissions in the world [23]. In 2014, radio access networks contributed about 84 TWh in the total world energy consumption and about 170 $Mto\ CO_2e$ in the total carbon emissions [24]. Those numbers are expected to exponentially increase in the coming years with the continuous growth of the telecommunications market driven by the multiplication and variation of the telecommunication services and the exponential increase of the required Quality of Service (QoS). According to [25, 26], base stations (BSs) are the highest components in terms of power consumption in the mobile networks. It is responsible for about 60% of the total power consumption. For that, many research attempts [27, 28] have focused on reducing BSs' energy consumption through efficient resource allocation, increasing collaboration between BSs to serve users, optimizing the geographical positions taking into consideration the distribution of the served users, and improving the use of renewable sources.

In this work, we consider a communication system where BSs connected to different micro-grids cooperate to minimize the global power cost while ensuring a reliable service to the requesting users. Each micro-grid is equipped with renewable sources but has the ability to procure non-renewable power from the main grid when needed. The main task is to optimize resource allocation through collaboration between BSs to satisfy the required QoS of the different users while minimizing the non-renewable energy consumption by profiting from the available renewable power. The challenge consists in determining the users' assignment to BSs depending on their relative channel gains as well as the renewable power availability at each micro-grid.

Our joint users assignment and resource allocation problem is formulated as a mixed-integer real problem with non-linear objective function and constraints. Solving this type of

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problems is often challenging, especially with large number of variables. In our initial work [29], we proposed a heuristic approach based on dividing the problem into two tasks, users assignment task and resource allocation task, and proposed an adequate algorithm for each task. In this paper, we complement it with a study of an optimal solution using convex relaxation of the problem and the branch and bound method. This method allows to obtain a solution with a known distance to the optimal but its high computational cost makes it impractical for real implementation. Thus, we show that the heuristic solution represents a good alternative that achieves a trade-off between optimality and complexity.

A. Literature Review

Developing green communications is one of the major challenges of the communication networks for 5G systems [30]. A recent survey [31] studied different works on using renewable sources to power BSs and showed their efficiency for a reliable communication system. Authors in [32] proposed to power BSs using solar energy while in [33], they focused on dimensioning the battery and the photovoltaic panel used to supply BSs. Using hybrid renewable is shown to increase the energy efficiency by taking advantage of the different renewable power sources. In this topic, different scenarios of hybrid wind-solar powering of the BSs were studied in the literature [34–36]. One of the limits of renewable sources is the discontinuity of the power generation which affects reliability of the service. Thus, hybrid renewable and non-renewable powering is required. The emergence of smart grids represents an opportunity to enhance power usage in telecommunication systems by exploiting the dynamic power pricing information. In a recent survey, Erol-Kantarci and Mouftah [37], showed the great savings that could be achieved through the use of smart grid capabilities in optimizing powering communication networks. In addition, it was remarked that only few research groups have focused on optimizing the use of smart grids in communication systems. Of these works, Bu *et al.* [38] presented a study of the best scheme to power base stations using smart grid with consideration of real-time power prices provided by the smart grid and pollution level resulting from the power generation while Ghazzai *et al.* [39] presented a complete framework for a smart-grid powered LTE system and introduced a power allocation strategy based on evolutionary algorithms. Turning BSs to sleep mode is one of the strategies that attracted a lot of attention. For this purpose, Holtkamp *et al.* [40] proposed an optimized radio resource allocation algorithm where the achieved gain ranges between 20 to 40% depending on the load, the proposed algorithm includes a sleep mode duration estimation, resources sharing and antenna configuration. Micallef *et al.* [41] proposed to switch BSs to sleep mode when the traffic load decreases, the focus of this work is how to select the set of BSs to be switched to sleep mode. Serving the same main purpose of the previous reference, Saker *et al.* [42] proposed two switching to sleep mechanisms for base stations, the first is dynamic and depends on the real time load and the second is called semi-static where resource allocation is planned for longer time periods.

B. Contributions

In this paper, we propose to solve a joint users-to-BS assignment and resource allocation problem for a group of BSs clustered into a number of micro-grids, where each micro-grid is powered through hybrid renewable and non-renewable power sources. The objective is to minimize the total cost of procurement in the network while guaranteeing the required QoS for the users in the system.

The contributions of this paper are summarized as follows:

1) A green resource allocation architecture using hybrid powering of the communication system from renewable and non-renewable sources.
2) Exploiting the optimal performance using the relaxation approach based on the branch and bound method to present an ϵ-to-optimal solution.
3) Proposing a suboptimal solution based on di-associating the problem into two sub-problems; one for the users-to-BSs assignment and the other for the resource allocation and proposing efficient heuristic algorithms to solve each of them.
4) Taking into consideration the possibility of switching BSs to the sleep mode by studying a powering model that contains this capability and studying its effect on power cost savings.
5) Studying the effect of the distribution of the renewable power availability on the achieved cost gains.

The remaining of this paper is organized as follows. Section II introduces the system model and micro-grid powering architecture. Section III gives the mathematical problem formulation of the system and models that govern the power cost in the system. Then, in Section IV we present how to exploit the B&B method to find the optimal solution while in Section V, we detail and analyze the proposed heuristic algorithms for resource allocation. Following that, we present a performance analysis of the presented algorithms through extensive simulations in Section VI. Finally, the conclusion is drawn in Section VII.

II. System Model

We consider a set of L base stations aiming to serve K users through N sub-channels ($N >> K$). We assume that the base stations are connected through M power-grids where each micro-grid m powers a group of L_m base stations. Each micro-grid uses renewable power to generate electricity needed to feed the connected base stations. In addition to that, it is responsible for purchasing the back-up power from the main grid when needed as shown in Fig. 1.

It is to be noted that BSs' clustering method into the micro-grids is out of the scope of this paper. But, results of this work could be exploited to optimize the clustering of the BSs. We consider to focus on the instantaneous management of the available power. Thus, we assume that BSs do not have the ability to stock power. The available instantaneous renewable power at a micro-grid m is denoted by P_m^{renew} assumed to incur free cost of usage while the non-renewable power has a unitary cost denoted α_m per power unit. Thus, the cost of the power consumed by each micro-grid is equal to the cost of

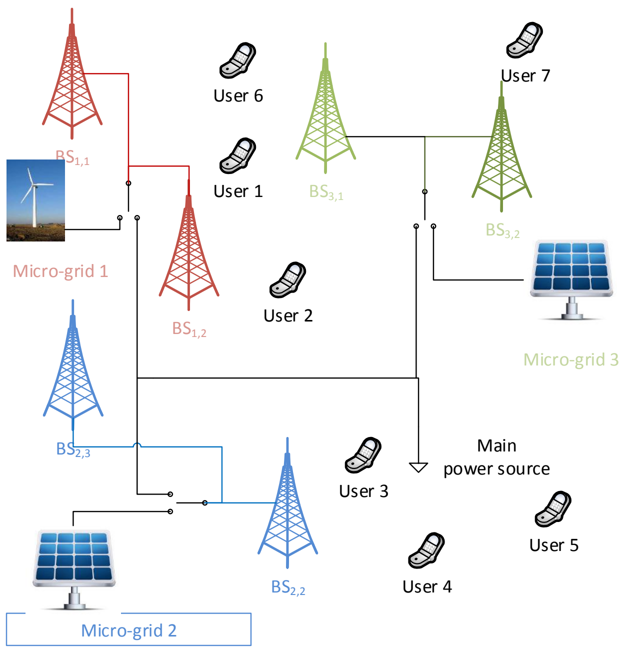

Fig. 1. System powering architecture

the power consumed by all BSs belonging to the micro-grid exceeding the available renewable power. Mathematically, the cost of the power at the micro-grid m is written as

$$C_m = \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+, \tag{1}$$

with $[x]^+ = \max(x, 0)$ and where P_l represents the power consumption of the base station l, $b_{m,l}$ is an index of the base stations connected to the micro-grid m (i.e., $b_{m,l} = 1$ if base station l is connected to micro-grid m and $b_{m,l} = 0$, otherwise), and P_m^{renew} represents the generated renewable power at this micro-grid.

We consider a simplified model for the base station power P_l. According to Arnold *et al.* [43], the power consumption of a base station consists of basically two components. The first term is a function of the transmitted power which depends on the served users while the second is independent of the load and serves to ensure powering of the base station and ensuring some functionalities such as cooling. Thus, assuming a linear model function of the transmitted power, the base station power can be written as follows

$$P_l = \xi_l \sum_{k=1}^{K} a_l^{(k)} P_l^{(k)} + P_l^{idle}, \tag{2}$$

where $a_l^{(k)}$ is the assignment index for users to base stations (i.e., $a_l^{(k)} = 1$ if the k-th user is served by the base station l and $a_l^{(k)} = 0$, otherwise), $P_l^{(k)}$ is the power transmitted by base station l to the k-th user, and ξ_l is the amplification factor for the transmitted power by the base station l and P_l^{idle} is the power consumed by the l-th base station when idle.

III. Problem Formulation

The aim of our work is to improve the usage of the available renewable power in different micro-grids through collaboration between the base stations in the same micro-grid and in different micro-grids. Consider Eq. (1), the total cost of the procured non-renewable power by all micro-grids can be written as follows:

$$C = \sum_{m=1}^{M} \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+. \tag{3}$$

The Quality of Service (QoS) is ensured by a minimum throughput r_k^{req} that needs to be guaranteed for each user k for its successful communication. The QoS may differ from one user to another depending on the user's running applications. The minimum rate constraint for each user is expressed as

$$R(k) \geq r_k^{req}, \tag{4}$$

where $R(k)$ is the achieved throughput by user k, given by

$$R(k) = \sum_{l=1}^{L} a_l^{(k)} \; b_c \; n_l^{(k)} \; \log_2 \left(1 + \frac{P_l^{(k)} \; g_l^{(k)}}{N_0 \; b_c \; n_l^{(k)}} \right), \tag{5}$$

where $n_l^{(k)}$ is the number of sub-channels allocated to user k, b_c is the sub-channel bandwidth, $g_l^{(k)}$ is the channel gain between the base station l and the user k assumed to be the same for all sub-channels (fast fading variations are not considered as we target relatively large time-slot transmissions), and N_0 is the noise power density. To avoid interference, we assume channel re-use not allowed and all sub-channels shared orthogonally between all base-stations. Thus, an additional constraint is considered for sub-channels' sharing

$$\sum_{l=1}^{L} \sum_{k=1}^{K} a_l^{(k)} n_l^{(k)} \leq N. \tag{6}$$

Then, the problem consists of minimizing the cost function under minimum rate per user constraint, total bandwidth constraint, and the assumption that each user must be served only from one base station which can be written mathematically as follows

$$\min_{\left\{a_l^{(k)}, n_l^{(k)}\right\}_{\substack{1 \leq l \leq L \\ 1 \leq k \leq K}}} \quad \sum_{m=1}^{M} \alpha_m \left[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \right]^+ \tag{7a}$$

$$\text{s.t.} \quad \sum_{l=1}^{L} a_l^{(k)} b_c n_l^{(k)} \; \log_2 \left(1 + \frac{P_l^{(k)} \; g_l^{(k)}}{N_0 b_c n_l^{(k)}} \right) \geq r_k^{req}, \quad \forall k \tag{7b}$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K} \; a_l^{(k)} n_l^{(k)} \leq N \tag{7c}$$

$$\sum_{l=1}^{L} \; a_l^{(k)} = 1, \quad \forall k. \tag{7d}$$

The last constraint is added to indicate that each user is served by only one base station. In this case, the allocated power is deduced from the rate constraint (13d) as follows

$$P_l^{(k)} = a_l^{(k)} \left(2^{\frac{r_k^{req}}{n_l^{(k)} b_c}} - 1 \right) \frac{N_0 b_c n_l^{(k)}}{g_l^{(k)}}. \tag{8}$$

The optimization problem (7) is a non-linear mixed integer-real minimization problem to determine the assignment of each user to the best BS in addition to the number of sub-channels per user and the allocated power. The objective is to ensure the required data rates for all users while minimizing the consumption power cost by profiting from the available renewable power in the different micro-grids and variability of the channels' gains between the different users. In conventional power allocation problems, users-to-BSs assignment depends mainly on the channel gains between the users and the BSs (i.e., each user will be assigned to the BS with the best channel gain). In our problem, the dependency of the cost function on the available renewable power makes the problem more challenging. In addition, further power cost reductions are possible by using adaptive bandwidth allocation on the cost of an additional complexity in the problem solving.

IV. Optimal solution using branch and bound method

As dynamic spectrum, power allocation and user to base station assignment problem is a mixed integer non-linear optimization problem with a large number of variables, then finding the optimal solution is a challenging task. For this type of problems, branch and bound method is shown to provide an ϵ-to-optimal solution with a worst case exponential time but a less complex average time and a minimum time of polynomial complexity [44]. The method is proposed by A. H. Land and A. G. Doig in 1960 [45] as a non-heuristic global optimization method for non-convex problems. Its basic idea consists of partitioning the set of feasible solutions into smallest subsets. Then, recursively, compute an upper bound and a lower bound for each subset and a global upper and lower bounds. The dimension of the problem is reduced rapidly by pruning the subset of feasible sub-problems by eliminating the branches where a global upper-bound is better than the branch lower bound. The algorithm of this method is described as follows

1) Compute an upper bound (U) and a lower bound (L) for the problem: The upper bound can be computed using one of the heuristic proposed algorithms or as a randomly selected solution, and the lower bound can be computed using a relaxation method.
2) If the found lower bound is a feasible solution then it is the searched solution, otherwise create two branches by fixing one of the binary variables one time to zero (B_1) and one time to one (B_2).
3) Compute lower bounds (L_1, L_2) and upper bounds (U_1, U_2) for B_1 and B_2, respectively.
4) Set U to min(U_1, U_2) and then if L_1 is greater than U then prune B_1 and if L_2 is greater than U then prune B_2.
5) Repeat the previous steps recursively until finding a solution within ϵ distance to the optimal (i.e., the difference between lower bound and upper bound is less than ϵ), or parsing all the branches.

Eliminating the unfeasible branches reduces the complexity of the algorithm. For instance, if one variable $a_l^{(k)}$ is fixed to 1, using the constraint that $\sum_{l=1}^{L} a_l^{(k)} = 1$, all variables $a_{l'}^{(k)}, \forall k' \neq k$ are set to 0. In addition, the choice of the binary variable to fix is also important. Usually, the variables with equal probabilities to the binary values are fixed firstly and their two possible branches are parsed (i.e, the variable for which the real solution is the closest to 0.5). The fixing for 1 is done first since it requires less computation as $L-1$ variables are eliminated.

The challenging task in this approach is obtaining the lower-bound. We use a convex relaxation of the problem by converting the users-to-BS assignment binary variables $a_l^{(k)}$ into real variables (relaxed variable) and adding constraints that require the relaxed variables to be between zero and one. We show in the Appendix that the relaxed problem is convex. Solving the relaxed problem is still challenging as the relaxation of the binary variables produces a problem with high dimensionality ($3 \times K \times L$ variables to be solved). Observing the dependence of the bandwidth and the users-to-BS assignment variables, we proceed with a variable change (9) that reduces the number of variables by one-third. Thus, we propose a new variable $x_l^{(k)}$, representing the percentage of sub-channels used by user k through the l-th BS:

$$x_l^{(k)} = a_l^{(k)} n_l^{(k)} \tag{9}$$

Using the property that $\sum_{l=1}^{L} a_l^{(k)} = 1, \ \forall k$, the original variables are re-obtained from the new joint variable as follows

$$n_l^{(k)} = \sum_{l=1}^{L} x_l^{(k)} \tag{10}$$

$$a_l^{(k)} = \frac{x_l^{(k)}}{\sum_{l=1}^{L} x_l^{(k)}} \tag{11}$$

In addition, in order to derive easily the Lagrangian of the problem we introduce a new variable C_m defined as follows

$$C_m = \max \left\{ \sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew}, 0 \right\} \tag{12}$$

The relaxed problem is then written as follows

$$\min_{\left\{P_l^{(k)}, x_l^{(k)}\right\}_{\substack{1 \leq l \leq L \\ 1 \leq k \leq K}}} \quad \sum_{m=1}^{M} \alpha_m C_m \tag{13a}$$

$$\text{s.t. } C_m \geq \left[\sum_{l=1}^{L} \sum_{k=1}^{K} b_{m,l} P_l^{(k)} - P_m^{renew} \right] \ \forall m \tag{13b}$$

$$C_m \geq 0 \tag{13c}$$

$$\sum_{l=1}^{L} x_l^{(k)} \ \log_2 \left(1 + \frac{P_l^{(k)} \ g_l^{(k)}}{N_0 x_l^{(k)}} \right) \geq r_k^{req}, \quad \forall k \tag{13d}$$

$$\sum_{l=1}^{L} \sum_{k=1}^{K} \ x_l^{(k)} \leq N \tag{13e}$$

As proven in the Appendix, the relaxed problem is convex. Thus, the primal and dual problem solutions are identical given the slackness condition which is guaranteed in our case (existence of at least one feasible solution). Then, by introducing non negative dual variables β, $\{\lambda_1...\lambda_m\}$, $\{\gamma_1...\gamma_m\}$, and $\{\mu_1...\mu_K\}$, the Lagrangian function is given by

$$\begin{aligned} L = & \sum_{m=1}^{M} \alpha_m C_m \\ & + \sum_{m=1}^{M} \lambda_m \Big(\sum_{l=1}^{L} \sum_{k=1}^{K} b_{m,l} P_l^{(k)} - (P_m^{renew} + C_m) \Big) \\ & + \beta \Big(\sum_{l=1}^{L} \sum_{k=1}^{K} x_l^{(k)} - N \Big) - \sum_{m=1}^{M} \gamma_m C_m \\ & + \sum_{k=1}^{K} \mu_k \Big(r_k^{req} - \sum_{l=1}^{L} x_l^{(k)} \log_2 \big(1 + \frac{P_l^{(k)} \theta_l^{(k)}}{x_l^{(k)}} \big) \Big). \end{aligned} \tag{14}$$

Then primal feasibility K.K.T conditions are inferred from the Lagrangian derivatives as follows

$$\gamma_m = \alpha_m - \lambda_m \tag{15a}$$

$$\beta - \mu_k \Bigg[\log\big(1 + \frac{P_l^{(k)} \theta_l^{(k)}}{x_l^{(k)}}\big) - \frac{P_l^{(k)} \theta_l^{(k)}}{x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}} \Bigg] = 0 \tag{15b}$$

$$\lambda_m b_{m,l} - \frac{\mu_k \theta_l^{(k)}}{\Big(1 + \frac{P_l^{(k)} \theta_l^{(k)}}{x_l^{(k)}}\Big)} = 0, \tag{15c}$$

where $\theta_l^{(k)} = \frac{g_l^{(k)}}{N_0}$, while the complementary slackness conditions are given by

$$\lambda_m \Big(\sum_{i=1}^{L} \sum_{k=1}^{K} b_{m,l} P_l^{(k)} - (P_m + C_m) \Big) = 0, \quad \forall m \tag{16a}$$

$$\mu_k \Big(\sum_{i=1}^{L} x_l^{(k)} \log_2 \Big(1 + \frac{P_l^{(k)} \theta_l^{(k)}}{x_l^{(k)}}\Big) - r_k^{req} \Big) = 0, \quad \forall k \tag{16b}$$

$$\gamma_m C_m = 0, \quad \forall m \tag{16c}$$

$$\sum_{i=1}^{L} \sum_{k=1}^{K} x_l^{(k)} - N = 0. \tag{16d}$$

Then we define

$$A_m = \sum_{i=1}^{L} \sum_{k=1}^{K} b_{m,l} P_l^{(k)} - P_m^{renew}, \tag{17}$$

such that $C_m = \max(A_m, 0)$

A sub-gradient algorithm is then implemented, where the dual variables are iteratively solved in the outer loop to satisfy the slackness conditions while in the inner loop the K.K.T conditions are solved to determine the primal variables $P_l^{(k)}$, $x_l^{(k)}$, and C_m.

In particular, in the case where C_m is greater than zero, we can deduct from (16c) that $\gamma_m = 0$ and from (15a) that $\lambda_m = \alpha_m$. Then, we solve (15b) and (15c) to obtain $x_l^{(k)}$ and $P_l^{(k)}$ function of the Lagrangian parameters while in the other case where $C_m = 0$ (i.e., $A_m < 0$); we can deduct from (16a) that $\lambda_m = 0$, $x_l^{(k)}$ and $P_l^{(k)}$ can be then be freely chosen such that we keep $C_m = 0$, then we increase the power $P_l^{(k)}$ and decrease the used bandwidth $x_l^{(k)}$ for the BSs l belonging to the micro-grid m (i.e., $b_{l,m} = 1$).

V. Disjoint Users and Channels Assignment

As the problem is complex and even, the optimal solution presented earlier is impractical for large number of users/channels, we then propose a suboptimal efficient approach. We divide the problem into two sub-problems. First, we assume constant bandwidth allocation among all users and focus on assigning the users to BSs. Then, we optimize the allocated bandwidth to further optimize the cost of the power consumed by profiting from dynamic spectrum assignment. The two algorithms are incorporated successively in a two-step iterative algorithm.

A. Users-to-BS assignment

In this part, we consider a fixed bandwidth sharing between the users and we focus on determining the assignment of users to the BSs. The optimal solution to determine the best users-to-BS assignment is to perform an exhaustive search of all the possible assignments and take the combination that incur the least total cost. Obviously, this is not a practical solution as its complexity is exponential. Alternatively, we propose a polynomial approach based on the *bin-packing* to determine the users that will be assigned to each base station. In our case, the BSs represent the bins while the users are the objects to be packed. The difference, is that objects occupy different volumes depending on the pack as the power consumed differs from a BS to another. Our metric criterion for the decision is the resultant global power cost in the whole network. Thus, each user will be assigned to the base station incurring the lowest power cost according to Eq. (3). As in usual *bin-packing* algorithms, the order of packing objects influences the obtained performance. For that, we propose two approaches:

- **Random users assignment:** In this approach, we simply assign the users in a random order. Although, this method is limited in performance, it is suitable for online assignment as we need to assign users in their order of request of service without waiting for all users to search for the best order of assignment.
- **Best users assignment:** In this approach, as described in Algorithm 1, we search for the user that will incur the lowest power cost by checking with all users. Then, assign it and repeat the procedure until assigning all users. Although the complexity is multiplied by a factor capped by the number of users (we need to parse, at each step, all users and compute the resultant power cost), this process notably enhances the performance as the order of assignment of the users is very important to efficiently use the renewable power in the micro-grids.

Algorithm 1 Users-to-base stations assignment.

INPUT: Number of sub-channels per user: $\{n_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

OUTPUT: Users-to-BSs assignment: $\{a_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

repeat
  for all users $k = 1 : K$ **do**
    Determine base station l_k to be assigned to user k incurring lowest power cost: $l_k = \arg\min_l c_l^{(k)}$
  end for
  Assign user k^* such that $k^* = \arg\min_k c_{l_k}^{(k)}$
until All users assigned

B. Bandwidth Allocation

Dynamic spectrum allocation has shown its importance for power savings. Thus, we propose to assign the bandwidth adaptively between the users in order to further reduce the global power cost. As discussed earlier, solving the global problem optimally is computationally complex, therefore we propose to use an iterative two-step algorithm. In the first step, we optimize the users-to-BSs assignment similarly to the previous section. While in the second step, we propose to optimize the bandwidth allocation. For the bandwidth allocation, inspired by the bubble sort, we propose an algorithm that consists of searching recursively the best possible sub-channels changes until convergence. At each step, we parse all users and search, for every user, the best channel swap with another user that results in the largest reduction in power cost. We apply that change and restart the search again until no further power savings could be achieved.

Algorithm 2 Bandwidth allocation.

INPUT: Users-to-BSs assignment: $\{a_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

OUTPUT: Number of sub-channels per user: $\{n_l^{(k)}\}_{\substack{1\le l\le L\\ 1\le k\le K}}$.

repeat
  for all users $k_1 = 1 : K$ **do**
    search for the best sub-channel swap with another user k_2 such that:

$$k_2 = \arg\min_{k_2} C(n_l^{(k_1)} \Leftarrow n_l^{(k_1)} + 1, n_l^{(k_2)} \Leftarrow n_l^{(k_2)} - 1)$$

  end for
until no possible cost decrease ($k_2 = k_1,\ \forall k_1$).

VI. Performance Analysis

A. Complexity Analysis

1) Branch and Bound Algorithm: The branch and bound proceeds with a tree binary search over the branches which are the binary variables until finding the optimal solution. Thus, its worst case complexity is proportional to $2^{L\times K}$. This should be multiplied by the cost of computing the lower bound denoted by C_r. For the best case, the solution can be found through a single evaluation of the lower bound if a feasible solution is

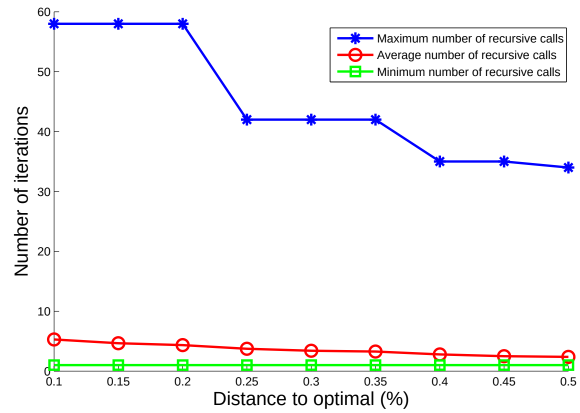

Fig. 2. B&B number of recursive calls as a function of the distance to optimal solution for $K = 10$ users.

found from this step. It is shown that this approach performs much better in practice by pruning the branches rapidly using the feasibility constraints. For our problem, the condition of having only one BS to serve a user helps to eliminate rapidly the branches. For instance, if a BS l_1 is shown to serve a user k, all other branches of BSs $l_2 \neq l_1$ serving the user k.

In order to show the practical complexity of this approach, we consider a small scenario with $K = 10$ users, $M = 2$ micro-grids, and $L = 3$ BSs and compute the number of iterations to find an ϵ-to-optimal solution for different values of ϵ. Fig. 2 shows that the minimum, average, and maximum number of iterations function of ϵ. We observe that the average is much closer to the minimum than the maximum which proves the efficiency of the pruning method.

2) Two-Step Algorithm: For the users-to-BS assignment Algorithm 1, the number of iterations needed to perform the assignment of all users is linear as a function of the number of users and the number of BSs in the network. The easiest way to implement Algorithm 1 is to perform two loops, one on the users and one on BSs. Additionally, the operations inside the loops does not exceed the computing of a simple function and a comparison. Thus, the complexity of Algorithm 1 is $O(K \times L)$ when not considering the outer loop (random user selection algorithm) and it will be multiplied by the number of users when considering the outer loop (best user selection).

For the bandwidth allocation, we need first to go through all users, and to search for the best sub-channel swap with another user. The search operation is performed by going through all possible swaps and this is by going through all users and all sub-channels. Since sub-channels are all identical in terms of gains, and without considering the repeat loop, we will have K^2 comparisons and K^2 possible swaps. In the best case we need to perform the previously described operations only one time before deducing that there is no cost decrease. In the worst case, we need to perform the previous operations as much as the number of the sub-channels. Then the worst case complexity is $N \times K^2$.

Thus, the complexity of the whole algorithm will be the sum of the complexities of these two steps multiplied by the number of iterations needed to converge denoted by N_{iter}.

Via simulations, we verify the convergence of this two-step algorithm within few iterations not exceeding 10.

To resume, we present in Table I, the complexity of the different algorithms.

B. Simulation Results

We consider a circular area of diameter 6 Km where K users and L base stations are placed randomly. The channel gains are derived based on the pathloss model $g_l^{(k)} = c_0 \left(\frac{d_0}{d_{l,k}}\right)^\eta$, where c_0 is the channel gain for the reference distance d_0, $d_{l,k}$ is the distance between the base-station l and the user k, and η is the pathloss set to 3. We consider a total bandwidth $B = 20$ MHz divided into sub-channels of per sub-channel width $b_c = 15$ KHz. The noise power is taken -120 dBm/Hz. The minimum required throughput rate per user is set to $r_k^{req} = 50$ $Mbps$. We consider that the base stations are grouped into $M = 4$ micro-grids so each micro-grid supplies two base stations. We assume that the non-renewable power cost, α_m, is equal for all micro-grids to focus on the effect of the renewable power availability. The renewable power P_m^{renew} is set such that it is sufficient to serve an average number of users for the average spatial distribution in the network. To illustrate the results, we consider the scenario where renewable power is not considered in optimization and compute the incurred power cost and consider that as a reference. We represent the obtained performance as the relative cost gain with comparison to this reference cost.

Fig. 3 illustrates the normalized power cost gain as a function of the number of users in the network for the B&B method with $\epsilon = 0.8\%$. The method shows good performance as known distance (at most ϵ) to optimal solution in the way that it keeps closer to the optimal (black curve) than to ϵ-to-optimal limit (red curve).

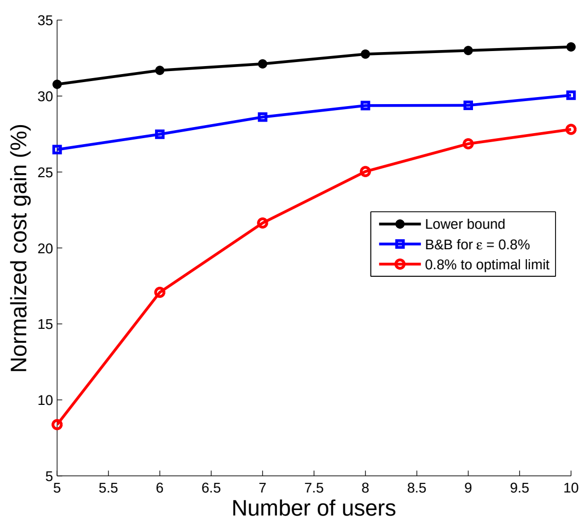

Fig. 3. Power cost gain as function of the number of users for optimal, B&B ϵ-to-optimal, and ϵ-to-optimal cost gain distance.

The performance of the heuristic algorithms are firstly compared to the ϵ-to-optimal results obtained by the B&B method. Due to the computational complexity of the B&B method, we restrain the simulations to a small number of users in this comparison. Fig. 4 shows the power cost gain as a function of the number of users for B&B method, *best user selection* algorithm and *random user selection* algorithm with optimized bandwidth. Through this analysis, we show that the best user selection algorithm combined with an optimized bandwidth allows to obtain less than 0.8% to optimality while the random user selection algorithm is slightly farther than this bound.

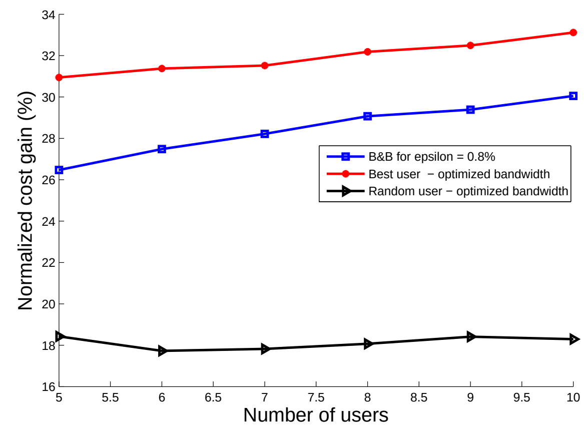

Fig. 4. Power cost gain as a function of the number of users

Since one of the advantages of the heuristic algorithms is its ability to solve the problem with more degrees of freedom, we study in the next simulations the performance of the proposed algorithms when considering a larger number of users (100 to 200 users). Fig. 5 illustrates the normalized power cost gain as a function of the number of users in the network with different heuristic algorithms. First, we note the net cost gain achieved by incorporating additional features in the optimization algorithm. In particular, the best user selection method for the users-to-BSs assignment outperforms the random selection. In addition, optimizing the allocated bandwidth for each user allows further cost savings. Second, as the number of users requesting to be served increases, the cost gain decreases due to the increase of the consumed power which, at a certain step, harvests all the available renewable power. In this case, the problem reduces to a total power minimization problem and our approach becomes limited in performance compared to the optimal approach.

One important factor that impacts the obtained performance is the available non renewable power in the micro-grids. For that, we denote the non renewable to renewable consumed power ratio by ρ and represent it in Fig. 6 as a function of the number of users. As expected, the bandwidth optimized algorithms allows to reach lesser ratios than algorithms with uniform bandwidth which means lesser consumption of non-renewable energy and higher utilization of the renewable sources. The users' selection algorithm also helps in enhancing the usage of the renewable resources as the best selection method reaches lesser ratio than the random user selection.

In order to show the optimality of the proposed algorithms

TABLE I
ALGORITHMS COMPLEXITY

Algorithm	best case	worst case	average
Random user selection with Uniform bandwidth	$L \times K$	$L \times K$	$L \times K$
Best user selection with Uniform bandwidth	$L \times K^2$	$L \times K^2$	$L \times K^2$
Random user selection with Optimized bandwidth	$(2K^2 + L \times K)N_{iter}$	$(2N \times K^2 + L \times K)N_iter$	-
Best user selection with Optimized bandwidth	$(2K^2 + L \times K^2)N_{iter}$	$(2N \times K^2 + L \times K^2)N_iter$	-
B&B method	C_r	$2^{L*\times K} * C_r$	$L \times K \times C_r$

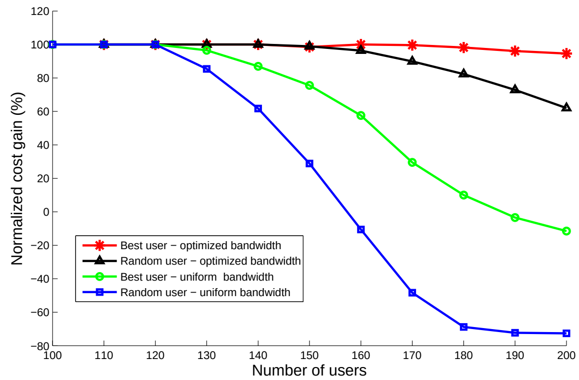

Fig. 5. Relative power cost gain as a function of the number of served users with constant renewable power for all micro-grids.

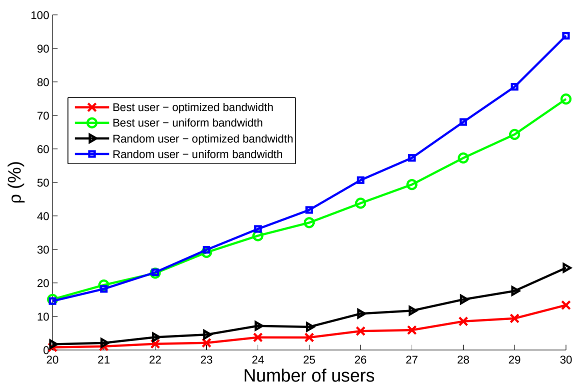

Fig. 6. Non renewable to renewable consumed power ratio in the network as a function of the number of users.

for such a practical scenario (large number of users), we consider the case where the renewable power is not available at all (i.e., $P_m^{renew} = 0, \forall m$). In this case, the problem reduces to exactly the same as the total power minimization which we took as a reference for computing the cost gains. We present the results in Fig. 7 which shows that without bandwidth optimization the best user selection algorithm incurs a loss of around 10% while adding the bandwidth optimization allows a gain between 30 to 45% which represents the net gain of the dynamic allocation of the bandwidth.

In the previous figures, we studied configurations where the same renewable power amount is available in each micro-grid. In the following, we propose to study a more practical scenario where the available renewable power is variable across the different micro-grids. We present in Fig. 8 the cost gain with

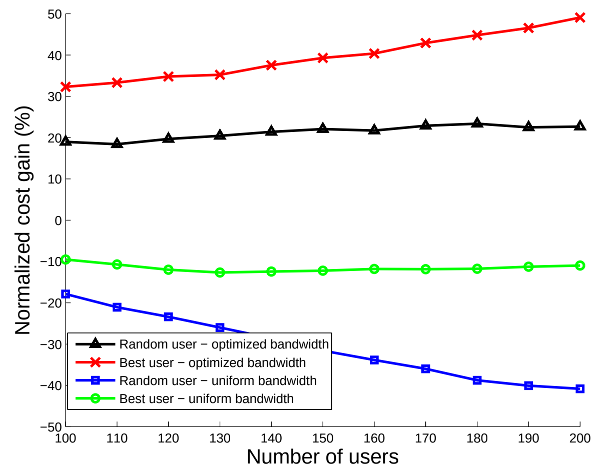

Fig. 7. Algorithms optimality: relative power cost gain when renewable power is not available.

increasing variability of the renewable power level across the micro-grids. We note that with the best user assignment algorithm, the cost gain increases when the variance increases. This is explained by the fact that the order of assignment of users-to-BSs becomes more important in this case than in the equal renewable case for which, due to the random distribution of users, optimal assignment will be most likely based on channel gains rather than renewable power availability.

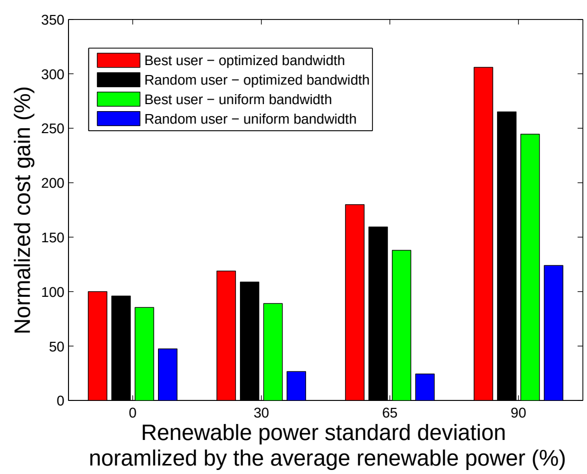

Fig. 8. Cost gain percentage as a function of the renewable power standard deviation for $K = 150$ users.

In Fig. 9, we vary the number of micro-grids while keeping the same number of base stations and the same total renewable power over all micro-grids to observe the effect of collaboration between the base stations. As the number of micro-grids increases, the cost gain is expected to decrease as in the random users assignment due to non-possibility of exchanging energy between BSs. But, with the best user assignment, the gain remains approximately constant. The algorithm succeeds to compensate the loss incurred by the absence of collaboration between BSs by classifying the users before assigning them.

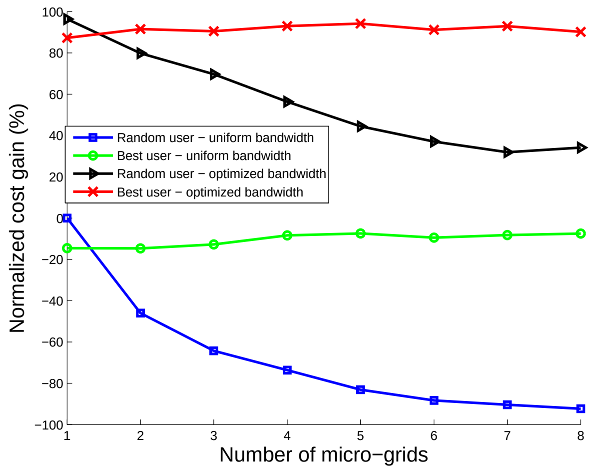

Fig. 9. Cost gain percentage for different number of micro-grids for $K=200$ users.

The possibility of switching base stations to the sleep mode when not serving any users could help in saving the power. We consider a new model for the BS power where the component independent from the load in the BS power consumption model given by Eq. (2) is divided now into two terms; one term that is consumed only if the BS is serving users called (P_l^{on}) and one for the power consumed even in sleep mode (P_l^{idle}). The new model is given by

$$P_l = \xi_l \sum_{k=1}^{K} a_l^{(k)} P_l^{(k)} + P_l^{on}\Big(\sum_{k=1}^{K} a_l^{(k)} > 0\Big) + P_l^{idle}, \quad (18)$$

The effect of the sleep mode is studied in Fig. 10. We vary the percentage of power that could be saved through this sleep mode and represent the power cost savings that could be achieved. The normalized power cost gain slightly increases with the increase of the power needed to turn the BSs on as further savings could be achieved when this amount increases. Hardware limitations due to components needed always ON and system instability for long-term due to recurrent switch of BSs limit the gains of this capability in practice.

In order to further enhance the performances of the proposed algorithms, we propose to use a new objective function when evaluating the power cost during the users-to-BSs assignment task. This new objective includes the consumed renewable energy at each micro-grid weighted with the degree of consumption of the renewable energy in each micro-grid.

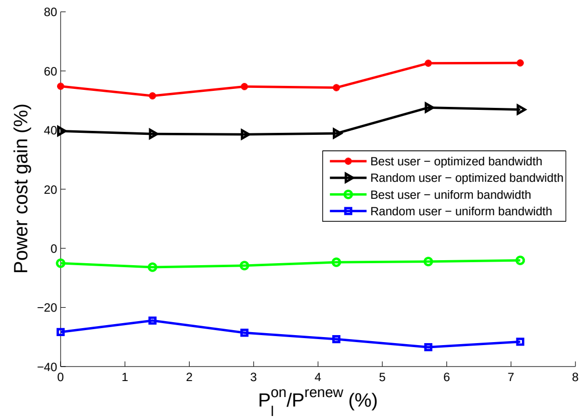

Fig. 10. Effect of sleeping mode: power cost gain as a function of the power needed to turn the BS ON for $K=20$ users.

Mathematically, this objective is written as follows

$$\begin{aligned} O = &\sum_{m=1}^{M} \alpha_m \Big[\sum_{l=1}^{L} b_{m,l} P_l - P_m^{renew} \Big]^+ \\ &+ \sum_{m=1}^{M} \omega_m \min\Big\{ \sum_{l=1}^{L} b_{m,l} P_l ; P_m^{renew} \Big\}, \end{aligned} \quad (19)$$

where ω_m is the weight affected to the micro-grid and computed as follows

$$\omega_m = \frac{P_m^{renew} - \min\Big\{ \sum_{l=1}^{L} b_{m,l} P_l ; P_m^{renew} \Big\}}{\sum_{m'=1}^{M} P_{m'}^{renew} - \min\Big\{ \sum_{l=1}^{L} b_{m',l} P_l ; P_{m'}^{renew} \Big\}} \quad (20)$$

Consider the configuration where a different renewable power amounts are available in each micro-grid, Fig. 11 shows the power cost gain function of the number of users for two objective functions. The first is the one given by Eq. (3) (FOF), while the second is given by Eq. (19) (SOF). The final power cost gain is always evaluated using Eq. (3) which is our effective cost measure. The figure shows an improvement on the power cost gain up to 3% depending on the number of users when using the new objective function.

VII. Conclusion

We have introduced in this paper a new model for powering base stations using hybrid renewable and non-renewable power sources. While base-stations are clustered in groups of micro-grids, we proposed to minimize the global power cost while satisfying the users' requirements through cooperation between BSs in the same micro-grids and between the different micro-grids. Two approaches are presented. The first aiming an ϵ-to-optimal solution based on the branch and bound method, then a suboptimal two-step algorithm using efficient heuristics for the users-to-BSs assignment and bandwidth allocation tasks. Important power cost gains are achieved through the proposed approaches due to the better usage of the renewable powers across the micro-grids to serve the users.

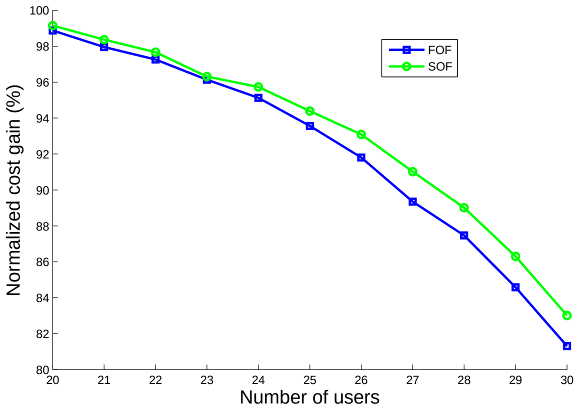

Fig. 11. Effect of the objective function: relative power cost gain as a function of the number of users when considering the new objective function.

Relaxed problem convexity proof

In the relaxed problem (13) the objective function is convex since it is the maximum of two convex functions and all constraints, except constraint (13d), are linear, that is why it will be sufficient to prove the convexity of the minimum rate constraint (13d) to prove the convexity of the whole optimization problem. This is equivalent to proving that the function $r\left(\{P_l^{(k)}, x_l^{(k)}\}_{l=1..L}\right)$ defined as,

$$r\left(\{P_l^{(k)}, x_l^{(k)}\}_{l=1..L}\right) = \sum_{l=1}^{L} x_l^{(k)} \ \log_2\left(1 + \frac{P_l^{(k)} \ g_l^{(k)}}{N_0 x_l^{(k)}}\right), \tag{21}$$

is concave for all $k = 1..K$.

The Hessian of this function is written as follows

$$H = \begin{bmatrix} H_{1,1} & 0 & \cdots & \cdots & \cdots & 0 & 0 \\ 0 & \ddots & \ddots & & & & \vdots \\ 0 & \ddots & \ddots & 0 & & & \vdots \\ \vdots & & \ddots & H_{m,n} & \ddots & & 0 \\ \vdots & & & 0 & \ddots & \ddots & \vdots \\ 0 & & & & \ddots & \ddots & 0 \\ 0 & 0 & \cdots & 0 & \cdots & 0 & H_{M,N} \end{bmatrix}, \tag{22}$$

where the block matrices $H_{m,n}$ are defined as

$$H_{m,n} = \begin{bmatrix} \frac{\partial^2 r}{\partial x_l^{(k)2}} & \frac{\partial^2 r}{\partial x_l^{(k)} \partial P_l^{(k)}} \\ \frac{\partial^2 r}{\partial x_l^{(k)} \partial P_l^{(k)}} & \frac{\partial^2 r}{\partial P_l^{(k)2}} \end{bmatrix} \tag{23}$$

Since H is a block diagonal matrix thus it is sufficient to prove that all the $H_{m,n}$ are definite negatives to conclude that H is a definite negative since the eigenvalues of H are the concatenation of all the eigenvalues of the matrices $H_{m,n}$. Thus, let us compute the eigenvalues of $H_{m,n}$.

For that, we start by computing the partial derivatives in (23) to get

$$\frac{\partial^2 r}{\left(\partial x_l^{(k)}\right)^2} = -\frac{\left(P_l^{(k)} \theta_l^{(k)}\right)^2}{\log(2) x_l^{(k)} \left(x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}\right)^2} \tag{24a}$$

$$\frac{\partial^2 r}{\partial x_l^{(k)} \partial P_l^{(k)}} = \frac{P_l^{(k)} \theta_l^{(k)2}}{\log(2) \left(x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}\right)^2} \tag{24b}$$

$$\frac{\partial^2 r}{\left(\partial P_l^{(k)}\right)^2} = -\frac{x_l^{(k)} \theta_l^{(k)2}}{\log(2) \left(x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}\right)^2} \tag{24c}$$

where $\theta_l^{(k)} = \frac{g_l^{(k)}}{N_0}$.

Then the $H_{m,n}$ matrices are given by:

$$H_{m,n} = \frac{\theta_l^{(k)2}}{\log(2) \left(x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}\right)^2} \begin{bmatrix} -\frac{P_l^{(k)2}}{x_l^{(k)}} & P_l^{(k)} \\ P_l^{(k)} & -x_l^{(k)} \end{bmatrix} \tag{25}$$

The sum of the eigenvalues of the $H_{m,n}$ matrix is given by its trace as follow:

$$trace\left[H_{m,n}\right] = -\frac{\theta_l^{(k)2}}{\left(x_l^{(k)} + P_l^{(k)} \theta_l^{(k)}\right)^2} \left(\frac{P_l^{(k)}}{x_l^{(k)}} + x_l^{(k)}\right), \tag{26}$$

and the product of the eigenvalues is given by its determinant

$$\det\left[H_{m,n}\right] = 0. \tag{27}$$

Since the determinant of the Hessian matrices are null and the traces are negative, then the Hessian matrices $H_{m,n}$ are semi-definite negative and thus matrix H is also semi-definite negative. Thus, we conclude that the rate function is concave and the rate constraint is convex.

References

[1] M. Ben Ghorbel, B. Hamdaoui, R. Hamdi, M. Guizani, and M. NoroozOliaee, "Distributed dynamic spectrum access with adaptive power allocation: Energy efficiency and cross-layer awareness," in *IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS)*, April 2014, pp. 694–699.

[2] D. Dechene and A. Shami, "Energy-aware resource allocation strategies for lte uplink with synchronous harq constraints," *IEEE Transactions on Mobile Computing*, no. 99, pp. 1–1, 2014.

[3] M. Ben Ghorbel, B. Khalfi, B. Hamdaoui, and M. Guizani, "Power allocation analysis for dynamic power utility in cognitive radio systems," in *IEEE International Conference on Communications (ICC)*, Jun. 2015.

[4] M. Guizani, B. Khalfi, M. Ben Ghorbel, and B. Hamdaoui, "Large-scale cognitive cellular systems: resource management overview," *IEEE Communications Magazine*, vol. 53, no. 5, pp. 44–51, May 2015.

[5] B. Hamdaoui and P. Ramanathan, "Sufficient conditions for flow admission control in wireless ad-hoc networks," *ACM SIGMOBILE Mobile Computing and Communications Review*, vol. 9, no. 4, pp. 15–24, 2005.

[6] X. Wang, D. Wang, H. Zhuang, and S. Morgera, "Fair energy-efficient resource allocation in wireless sensor networks over fading TDMA channels," *IEEE Journal on Selected Areas in Communications*, vol. 28, no. 7, pp. 1063–1072, September 2010.

[7] S. Ehsan, B. Hamdaoui, and M. Guizani, "Radio and medium access contention aware routing for lifetime maximization in multichannel sensor networks," *IEEE Transactions on Wireless Communications*, vol. 11, no. 9, pp. 3058–3067, 2012.

[8] N. Chakchouk, B. Hamdaoui, and M. Frikha, "WCDS-induced routing for data-aggregation in wireless sensor networks," in *First International Conference on Communications and Networking (ComNet)*. IEEE, 2009, pp. 1–6.

[9] M. NoroozOliaee, B. Hamdaoui, and K. Tumer, "Efficient objective functions for coordinated learning in large-scale distributed osa systems," *IEEE Transactions on Mobile Computing*, vol. 12, no. 5, pp. 931–944, 2013.

[10] Y. Belkasmi, A. Kobbane, M. Koutbi, and J. Ben-Othman, "Channel allocation strategies in opportunistic-based cognitive networks," in *8th International Wireless Communications and Mobile Computing Conference (IWCMC)*. IEEE, 2012, pp. 872–877.

[11] B. Hamdaoui, "Adaptive spectrum assessment for opportunistic access in cognitive radio networks," *IEEE Transactions on Wireless Communications*, vol. 8, no. 2, pp. 922–930, 2009.

[12] M. Ben Ghorbel, B. Hamdaoui, M. Guizani, and B. Khalfi, "Distributed learning-based cross-layer technique for energy-efficient multi-carrier dynamic spectrum access with adaptive power allocation," *IEEE Transactions on Wireless Communications*, vol. PP, no. 99, pp. 1–1, 2015.

[13] N. Chakchouk and B. Hamdaoui, "Uplink performance characterization and analysis of two-tier femtocell networks," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 9, pp. 4057–4068, 2012.

[14] A. Hatoum, N. Aitsaadi, R. Langar, R. Boutaba, and G. Pujolle, "Fcra: Femtocell cluster-based resource allocation scheme for ofdma networks," in *IEEE International Conference on Communications (ICC)*. IEEE, 2011, pp. 1–6.

[15] B. Hamdaoui, M. Elaoud, and P. Ramanathan, "A delay-based admission control mechanism for multimedia support in ieee 802.11e wireless lans," *Wireless Networks*, vol. 15, no. 7, pp. 875–886, 2009.

[16] A. Hatoum, R. Langar, N. Aitsaadi, R. Boutaba, and G. Pujolle, "Qos-based power control and resource allocation in ofdma femtocell networks," in *IEEE Global Communications Conference (GLOBECOM)*. IEEE, 2012, pp. 5116–5122.

[17] T. Taleb and A. Ksentini, "Follow me cloud: interworking federated clouds and distributed mobile networks," *IEEE Network*, vol. 27, no. 5, pp. 12–19, 2013.

[18] M. Dabbagh, B. Hamdaoui, M. Guizani, and A. Rayes, "Energy-efficient cloud resource management," in *INFOCOM workshop on Mobile Cloud Computing*. IEEE, 2014, pp. 386–391.

[19] M. Bagaa, T. Taleb, and A. Ksentini, "Service-aware network function placement for efficient traffic handling in carrier cloud," in *IEEE Wireless Communications and Networking Conference (WCNC)*. IEEE, 2014, pp. 2402–2407.

[20] H. Al Haj Hassan, L. Nuaymi, and A. Pelov, "Renewable energy in cellular networks: A survey," in *Online Conference on Green Communications (GreenCom)*, Oct 2013, pp. 1–7.

[21] M. Marsan, G. Bucalo, A. Di Caro, M. Meo, and Y. Zhang, "Towards zero grid electricity networking: Powering bss with renewable energy sources," in *IEEE International Conference on Communications Workshops (ICC)*, June 2013, pp. 596–601.

[22] P. S. REN21, *Renewables 2014: Global Status Report*. REN21 Secretariat Paris, France, 2014.

[23] C. A. Chan, A. F. Gygax, E. Wong, C. A. Leckie, A. Nirmalathas, and D. C. Kilper, "Methodologies for assessing the use-phase power consumption and greenhouse gas emissions of telecommunications network services," *Environmental Science & Technology*, vol. 47, no. 1, pp. 485–492, 2013, pMID: 23211093. [Online]. Available: http://dx.doi.org/10.1021/es303384y

[24] A. Fehske, G. Fettweis, J. Malmodin, and G. Biczok, "The global footprint of mobile communications: The ecological and economic perspective," *IEEE Communications Magazine*, vol. 49, no. 8, pp. 55–62, August 2011.

[25] A. Chatzipapas, S. Alouf, and V. Mancuso, "On the minimization of power consumption in base stations using on/off power amplifiers," in *IEEE Online Conference on Green Communications (GreenCom)*, Sept 2011, pp. 18–23.

[26] C. Han, T. Harrold, S. Armour, I. Krikidis, S. Videv, P. M. Grant, H. Haas, J. Thompson, I. Ku, C.-X. Wang, T. A. Le, M. Nakhai, J. Zhang, and L. Hanzo, "Green radio: radio techniques to enable energy-efficient wireless networks," *IEEE Communications Magazine*, vol. 49, no. 6, pp. 46–54, June 2011.

[27] X. Ge, X. Huang, Y. Wang, M. Chen, Q. Li, T. Han, and C.-X. Wang, "Energy-efficiency optimization for mimo-ofdm mobile multimedia communication systems with qos constraints," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 5, pp. 2127–2138, Jun 2014.

[28] X. Ge, B. Yang, J. Ye, G. Mao, C.-X. Wang, and T. Han, "Spatial spectrum and energy efficiency of random cellular networks," *IEEE Transactions on Communications*, vol. 63, no. 3, pp. 1019–1030, March 2015.

[29] M. Ben Ghorbel, T. Touzri, B. Hamdaoui, M. Guizani, and B. Khalfi, "Joint users-channels assignment for efficient use of renewable energy in hybrid powered communication systems," in *IEEE Global Communications Conference (GLOBECOM)*, Dec. 2015.

[30] X. Ge, H. Cheng, M. Guizani, and T. Han, "5g wireless backhaul networks: challenges and research advances," *IEEE Network*, vol. 28, no. 6, pp. 6–11, Nov 2014.

[31] H. Al Haj Hassan, L. Nuaymi, and A. Pelov, "Renewable energy in cellular networks: A survey," in *IEEE Online Conference on Green Communications (GreenCom)*, Oct 2013, pp. 1–7.

[32] N. Tekbiyik-Ersoy, E. Uysal-Biyikoglu, K. Leblebicioglu, and T. Girici, "Kalman prediction based proportional fair resource allocation for a solar powered base station," in *21st Signal Processing and Communications Applications Conference (SIU)*, April 2013, pp. 1–4.

[33] V. Chamola and B. Sikdar, "Resource provisioning and dimensioning for solar powered cellular base stations," in *IEEE Global Communications Conference (GLOBECOM)*, Dec 2014, pp. 2498–2503.

[34] G. Schmitt, "The green base station," in *4th International Conference on Telecommunication - Energy Special Conference (TELESCON)*, May 2009, pp. 1–6.

[35] S. Paudel, J. Shrestha, F. Neto, J. Ferreira, and M. Adhikari, "Optimization of hybrid pv/wind power system for remote telecom station," in *International Conference on Power and Energy Systems (ICPS)*, Dec 2011, pp. 1–6.

[36] M. Marsan, G. Bucalo, A. Di Caro, M. Meo, and Y. Zhang, "Towards zero grid electricity networking: Powering bss with renewable energy sources," in *IEEE International Conference on Communications Workshops (ICC)*, June 2013, pp. 596–601.

[37] M. Erol-Kantarci and H. Mouftah, "Energy-efficient information and communication infrastructures in the smart grid: A survey on interactions and open issues," *IEEE Communications Surveys & Tutorials*, vol. 17, no. 1, pp. 179–197, Firstquarter 2015.

[38] S. Bu, F. Yu, Y. Cai, and P. Liu, "Dynamic operation of bss in green wireless cellular networks powered by the smart grid," in *IEEE Global Communications Conference (GLOBECOM)*, Dec 2012, pp. 5201–5205.

[39] H. Ghazzai, E. Yaacoub, M.-S. Alouini, and A. Abu-Dayya, "Optimized smart grid energy procurement for lte networks using evolutionary algorithms," *IEEE Transactions on Vehicular Technology*, vol. 63, no. 9, pp. 4508–4519, Nov 2014.

[40] H. Holtkamp, G. Auer, S. Bazzi, and H. Haas, "Minimizing base station power consumption," *IEEE Journal on Selected Areas in Communications*, vol. 32, no. 2, pp. 297–306, February 2014.

[41] G. Micallef, P. Mogensen, and H.-O. Scheck, "Cell size breathing and possibilities to introduce cell sleep mode," in *European Wireless Conference (EW)*, April 2010, pp. 111–115.

[42] L. Saker, S.-E. Elayoubi, and T. Chahed, "Minimizing energy consumption via sleep mode in green base station," in *IEEE Wireless Communications and Networking Conference (WCNC)*, April 2010, pp. 1–6.

[43] O. Arnold, F. Richter, G. Fettweis, and O. Blume, "Power consumption modeling of different base station types in heterogeneous cellular networks," in *Future Network and Mobile Summit*, June 2010, pp. 1–8.

[44] S. Boyd and J. Mattingley, "Branch and bound methods," *Notes for EE364b, Stanford University*, pp. 2006–07, 2007.

[45] A. H. Land and A. G. Doig, "An automatic method of solving discrete programming problems," *Econometrica: Journal of the Econometric Society*, pp. 497–520, 1960.

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