An Evolutionary Approach to Resource Allocation in Wireless Small Cell Networks

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Abstract. In this paper we consider the problem of joint resource allocation, user association and power control for optimizing the network utility which is a function of users' data rates in a wireless heterogeneous network. This problem is shown to be NP-hard and non-convex. We propose an evolutionary algorithm to solve the problem. We show the gain of joint optimization over the scenarios with fixed power is considerable. Also in terms of computation time, our algorithm is substantially improved over the previously proposed algorithm by the authors.

Keywords: Small cell networks · Resource allocation · Optimization · Evolutionary algorithms

1 Introduction

As a promising technology to cope with ever growing demand for bandwidth intensive applications by the wireless users, small cells are supposed to bring the base stations to the close proximity of the users maybe in their homes or offices. Thousands or even more cells might be exploited within an area which was previously covered by a small number of cells. As a consequence, highly scalable algorithms are required in such densified networks for load balancing, power control and interference management, and channel (or time slot) allocation. For various reasons, the algorithms currently in use for conventional cellular networks should be revisited. For instance, unlike current cellular networks where statistically speaking the load variation of the cells is relatively minor (due to the law of large numbers), in small cells the load associated to a cell (particularly if conventional algorithms for user association are applied) may dramatically change over time. Also because of shorter distances between the transmitters interference mitigation and power management is more sensitive.

In [1,2], the optimization problem of joint resource allocation and user association for maximizing the network utility (which is a function of user data rates typically with proportional fairness consideration) is solved using some relaxations. Recently, the authors in [3] have studied a more general scenario where the power allocated for each resource at each base station is also an optimization variable and can be tuned. This problem is shown to be NP-hard and non-convex. In [3] a greedy algorithm is proposed to explore for the optimal solution. At each

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round of the algorithm a perturbation operator manipulates the solution found in the last iteration and if the new solution was better it updates the solution. Despite the considerable gain over the fixed power scenario in [1,2], the algorithm is very slow and hardly practical for a real time optimization of network parameters.

In this paper, an evolutionary algorithm to the optimization problem of joint resource allocation, user association and power control is introduced. This algorithm is substantially faster than the previously proposed algorithm in [3]. Not only the proposed algorithm converges faster but also it is possible to be parallelized over several processors as it is a population based algorithm where each solution within the population can be evaluated simultaneously on a distinct processor.

It should be noted that the problems of load balancing (see [4] for a comprehensive survey) and power control (see for instance [5,6,7] for a given set of transmitters and receivers) have been separately studied. However, unifying these problems within an identical framework is not straightforward at all. In the following the optimization problem and the proposed solution are described and evaluated via numerical experiments.

2 System Model and Problem Formulation

We study a wireless cellular network consisting of N users, M base stations and a set of K channels[1] available at each of the base stations. Cells are categorized to L tiers according to the range of their transmission power.We consider the downlink between the base stations and the users. The set of all users, all base stations, and all the channels which are identically available for association at each base station for association) are denoted by $\mathcal{U}$, $\mathcal{B}$ and $\mathcal{F}$, respectively. The subset of base stations belonging to tier l is denoted by $\mathcal{B}^l$.

In this paper we assume the power allocated to each frequency channel j from each base station k is an optimization variable and is denoted by P_k^j. The achievable rate for user i associated to base station k on channel j, denoted by c_{ik}^j, is typically a logarithmic function of signal to noise and interference ratio (SINR). In this paper we assume:

$$c_{ik}^j = \log(1 + \frac{P_k^j g_{ik}}{N_0 + \sum_{\ell:\ell\in\mathcal{B},\ell\neq k} P_\ell^j g_{i\ell}}) \tag{1}$$

where g_{ik} is the channel gain between base station k and user i, which includes path loss, shadowing and antenna gains and N_0 is the thermal noise power. We consider a snapshot of the network i.e. g_{ik} is assumed to be fixed which is similar to the assumption of [1,2].

We denote association of user i to base station k on channel j by x_{ik}^j where $x_{ik}^j = 1$ indicates the user is associated and j by $x_{ik}^j = 0$ otherwise. We use

[1] In this paper we consider an OFDM based system, however the algorithm proposed here can be extended to a time division multiple access system as well.

proportional fairness criterion in defining our objective function to maintain a balance between providing high data rates to the users and fairness in allocating network resources. It is shown in [8] that by maximizing the sum of logarithms of data rates the proportional fairness is achieved. Therefore, the optimization problem of joint resource allocation, user association and power control is formulated as follows.

$$\begin{aligned}
&\underset{P,X}{\text{maximize}} \qquad \sum_{i=1}^{N} \log c_i \\
&\text{s.t.} \\
&c_i = \sum_{k=1}^{M} \sum_{j=1}^{K} x_{ik}^j c_{ik}^j, \ \forall i \in \mathcal{U} \\
&c_{ik}^j = \log\left(1 + \frac{P_k^j g_{ik}}{N_0 + \sum_{\ell:\ell\in\mathcal{B},\ell\neq k} P_\ell^j g_{i\ell}}\right), \forall i \in \mathcal{U}, k \in \mathcal{B}, j \in \mathcal{F} \\
&x_{ik}^j \in \{0,1\}, \quad \forall i \in \mathcal{U}, \ k \in \mathcal{B}, \ j \in \mathcal{F} \\
&\sum_{i=1}^{N} x_{ik}^j \leq 1, \quad \forall k \in \mathcal{B}, \ j \in \mathcal{F} \\
&\sum_{k=1}^{M} x_{ik}^j \leq 1, \quad \forall i \in \mathcal{U}, \ j \in \mathcal{F} \\
&P_\ell^j \leq p_0^l, \quad \forall \ell \in \mathcal{B}^l, \ j \in \mathcal{F}
\end{aligned} \tag{2}$$

where P and X are the set of all P_k^j 's and x_{ik}^j's, respectively. The first and the second constraint identify the data received by each user i. The fourth constraint indicates that each channel at each base station can be allocated to one user at most. The fifth constraint ensures that a user is not associated to the same channel in more than one base stations. Finally, the last constraint applies an upper bound p_0^l to the transmission power in each tier l (which is an important constraint in real systems). As mentioned before this problem is non-convex, mixed integer and NP-hard as it is reduced to the problem of [1,2] if the power is fixed. In the next section we describe the proposed evolutionary algorithm to solve the formulated problem.

3 Evolutionary Algorithm

The algorithm evolves over a ceratin number of iterations and for a population $\mathcal{S}$ of size S. At each iteration for each member $s \in \mathcal{S}$ of the population one of the three perturbation operators $\mathcal{O} = \{O_1, O_2, O_3\}$ is chosen to manipulate s and generate $s' = O_i(s)$. Each member of the population results in a value for objective function $f(s) = \sum_s \log c_i$. If $f(s') \geq f(s)$, s is replaced with s', otherwise s remains in the population. It should be noted that any $s \in S$ is a solution satisfying the constraints in optimization problem 2. In the second phase of each iteration any member of the updated population is combined with a partner from the same population using a reproduction operator to generate a population of children who are the population for starting next iteration. In the following, the three operators, the reproduction operator, switching mechanism between operators for each member and the initialization of the algorithm are described in detail.

- **Operator 1 ($\mathcal{O}_1$):** This operator randomly chooses a channel from a random base station, say P_k^j and adds a random value from a Gaussian distribution subject to a ceiling for the transmission (if the new value exceeds the ceiling, the transmission power is updated to the ceiling value (*Power Control*).
- **Operator 2 ($\mathcal{O}_2$)** : Two frequency channels, say j_1 and j_2, from the same base station are chosen randomly and the users associated to these two channels (say i_1 and i_2, respectively) are swapped. In other words, j_1 is allocated to i_2 and i_1 is associated to j_2. It should be noted that when the power is fixed the schedule of resource allocation (the order which the frequency channels are allocated to users associated to the same base station) does not matter. However, in our work this schedule changes the SINR observed by the users and hence the network utility (*Resource Scheduling*).
- **Operator 3 ($\mathcal{O}_3$)**: The third operator randomly chooses a user i_1, a channel j_1 at base station ℓ_1 where currently is allocated to a user i_2. If channel j_1 has not been allocated to user i_1 from any other base station, i_2 is replaced with i_1. Otherwise, if channel j_1 has been allocated to i_1 at some other base station say base station ℓ_2, then channel j_1 is allocated to user i_2 at base station ℓ_2 and channel j_1 is allocated to ℓ_1 (*User Association*).
- **Operator Switching:** For any member of the population, we start from $\mathcal{O}_1$. If an operator $\mathcal{O}_i$ cannot improve the solution for τ successive iterations operator $\mathcal{O}_j$ is replaced where $j = (i+1) \mod 3$.
- **Reproduction Operator:** A fraction $\frac{1}{r}$ of the best solutions $\mathcal{S}' \subseteq \mathcal{S}$ (with highest utility function value) in the current iteration are selected and r replicas of each $s \in S'$ are placed in a new $\mathcal{S}$ (i.e. all the old members of S are replaced with these replicas). Any member $s \in \mathcal{S}$ is matched with a randomly chosen member $s' \in \mathcal{S}$. To combine s and s' to generate a child s" we use a crossover operator where each pair $< i : x_{ik}^j = 1, P_k^j >$ is chosen randomly from either s or s'. Therefore the child s'' is a random mix of the resource allocations in s and s'. If $f(s'') > f(s), f(s')$, s'' is replace with s.
- **Initialization:** We have chosen the solution found in [1,2] as the start point. This is reasonable as this solution is optimal for fixed power on all the channels within the same base station. All the members of the first iteration are set to the same solution.

As it can be inferred from the description of algorithm, it is different from standard evolutionary algorithms as it incorporates a greedy sub-algorithm within the main algorithm where at each round the solution selected for each member of the solution cannot be worse than the solution in the last generation. In other words, this algorithm can be named as a greedy-evolutionary algorithm.

In the next section we evaluate the performance of the algorithm via numerical experiments.

4 Numerical Experiments

In our simulations we evaluate the performance of the proposed algorithm and also we compare it to the algorithm proposed in [3]. Particularly we show that the proposed algorithm in the current paper is fundamentally faster both due to its faster convergence and also the possibility of running the algorithm over several processors. A set of $N = 100$ users and $M = 22$ base stations including $|\mathcal{B}^1| = 2$ macro base stations (first tier) and $|\mathcal{B}^2| = 20$ femtocell base stations (second tier) and $K = 20$ frequency channels available at each base station are considered. The users are spread over an $1000m \times 1000m$.

We assume the transmission power by the macro base station and femtocell base stations are upper limited by $P_k^j \leq 52dBm, \forall k \in \mathcal{B}^1, j \in \mathcal{F}$ and $P_k^j \leq 34dBm, \forall k \in \mathcal{B}^2, j \in \mathcal{F}$, respectively. To initialize the algorithm we assume all the transmission power for all the channels at each macro base stations and all the channels at each femtocell are set to be $P_k^j = 46dBm, \forall k \in \mathcal{B}^1, j \in \mathcal{F}$ and $P_k^j = 34dBm, \forall j, k \in \mathcal{B}^2$, respectively. We model the path loss as $L(d) = 30 + 37\log(d)$ and $40+34\log(d)$ for the macro and femtocell base stations, respectively where d is the distance between the transmitter and receiver. The thermal noise power is $\sigma_{noise}^2 = -104dB$ and the shadowing is assumed to be log normal random variable S with standard deviation $\sigma_{shadow} = 8dB$. Antenna gains for the first and second tiers are $g_A^1 = -15dBi$ and $g_A^2 = -5dBi$, respectively. The channel gain g_{ik} is assumed to be $g_A^l - L(d) + S$, $l = 1, 2$.

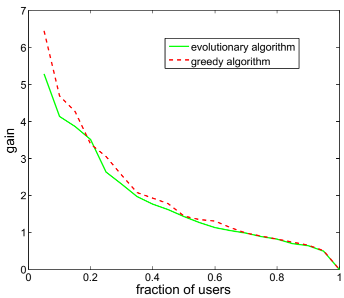

Fig. 1. Distribution of gain for the variants of the algorithm

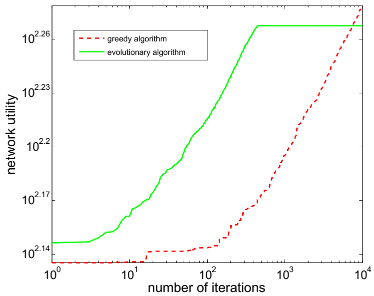

Fig. 2. Evolution of the network utility over iterations

In Fig. 1 we represent the distribution of the gain of the greedy algorithm in [3] and the proposed evolutionary algorithm in this paper over the optimization solution with fixed power assumption in [1,2]. As it can be observed the performance of the two algorithms are completely close. The average gain for

Table 1. Transmission power characteristics in the best solution found by the algorithm

	max power	min power	mean power
Macro cells	48.36	29.31	37.97
Femto cells	34.00	3.04	29.21

the evolutionary algorithm is 2.08. However, it should be noted that the current algorithm can be processed on 50 processors while the greedy algorithm should be only processed on a single machine as it is a sequential algorithm. However, not only because of the possibility of parallel computing but also because of the diverse pool of solutions generated at each round and reproduction the algorithm also converges in a dramatically less number of iterations. Fig. 2 shows the evolution of network utility in the evolutionary algorithm over 800 iterations and greedy algorithm over 10000 for iterations of the algorithm (we stopped the evolutionary algorithm after 800 iterations and fixed the solution for comparison). The evolutionary algorithm converges after nearly 400 iterations while the greedy algorithm finds a slightly better solution in about 10000 iterations. Therefore the difference in computation time is enormous and makes the evolutionary algorithm highly convenient in responding to the dynamics of the network.

Finally the maximum, minimum and average power in the solution found by the evolutionary algorithm are represented in table 1. The maximum power for the femtocells is matching with the upper limit on the power. Therefore, one can conclude that if the upper limit is removed it would be possible to obtain better solutions. However it should be noted for various reasons and according to radio communication regulations the transmission power cannot exceed a certain limit.

5 Conclusion

In this paper we proposed an evolutionary algorithm to the optimization problem of joint resource allocation, user association and power management in wireless small cell networks. The problem is NP-hard, non-convex and mixed integer. The proposed algorithm is substantially more efficient in terms of its computational time over the previously proposed algorithm by the authors. As a population based algorithm, the evolutionary algorithm in this paper can be run on several processors at the same time. Moreover, the algorithm itself converges dramatically faster because of it larger pool of solutions and reproduction.

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