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Energy and Spectrum Efficient Resource Allocation in Two-Tier Networks: A Multiobjective Approach

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Abstract—In this paper we investigate the joint power and channel allocation problem in two-tier OFDMA femtocell networks using a multiobjective approach with focus on energy efficiency. Three main objectives are considered in our problem formulations namely, energy efficiency, spectral efficiency, and power consumption. To solve the multiobjective problems, we have utilized a non-dominated sorting genetic algorithm (NSGA-II) and an algorithm have been proposed to perform the resource allocation procedures. In this investigation, to preserve the quality service of users, we have applied a minimum data rate threshold for all users. Furthermore, we impose an interference threshold limit on each subchannel to protect the macrocell user quality of service. Finally, the simulation results figure out that we can achieve 30% better energy efficiency by trading the throughput by about 20%.

I. INTRODUCTION

Rapid increase in required data rate for different services on one hand and battery technology inabilities to keep pace with user demands on the other hand, lead to a large gap between data rate thirst services and batteries capacities. Furthermore, the study in [1] shows that indoor usage comprises approximately 50% of all voice calls and about 70% of data traffic. Consequently, regarding the operators interests to provide high data rate services, indoor coverage should be enhanced [2]. Femtocells as a heterogeneous network paradigm, have received much more interests rather than other solutions from both academia and industry [3]. Moreover, they introduce new technical challenges like co-tier interference and cross-tier interference [3]. In [4], in order to alleviate the effect of interference, specially in co-channel spectrum allocation, intelligent power and subchannel assignment is performed. The authors in [5], investigate the resource allocation for managing inter-tier interference in downlink direction. Furthermore, in [6], to attain a better throughput, a distributed energy efficient algorithm is proposed to mitigate the excessive interference.

Moreover, massive energy consumption of wireless systems is one of the most substantial obstacles for the next generation networks [7]. From the operators perspective, energy efficiency not only has significant economic benefits but also represents social responsibility in fighting climate change [8]. Consequently, green and energy efficient design has become a significant and bright research trend for the evolution of future wireless networks [9]. Therefore, it is imperative to shift the endeavor from pursuing optimal capacity to energy efficient design [10]. Many works in the literature are associated with

the problem of energy efficiency and resource allocation [11]–[17]. The authors in [11] proposed a model for subchannel and power allocation to minimize the transmit power of cells. Their algorithms offer significant performance improvements in terms of user outage probability and cell capacity in downlink direction, but the uplink resource allocation and its efficiency is not addressed. Also in [12], a joint subchannel and power allocation algorithm for the downlink of an Orthogonal Frequency-Division Multiple Access (OFDMA) network deployment is proposed to maximize the sum rate of all Femtocell User Equipments (FUEs) while guaranteeing the Macrocell User Equipments (MUEs) QoS. The authors in [13] formulated a max-min throughput problem using particle swarm optimization as a solution methodology. Power control strategies to manage minimum outage probability for femtocells is examined in [14] where the authors derived suboptimal resource allocation policy for femtocells in uplink direction. In their study, neither efficiency nor throughput and power consumption is considered. The authors in [15], proposed and formulated an optimization problem concerning joint channel assignment and power allocation to maximize the energy efficiency of OFDMA network without any femtocell, under user rate constraints. Also in [16], an energy efficient resource allocation for cognitive femtocell network is proposed using genetic algorithm. The authors in [17], formulated the energy efficiency optimization problem for two-tier heterogeneous networks consisting of a macro-cell and multiple small cells. Heterogeneous traffic model, beamforming and power allocation schemes are jointly considered to optimize the systems energy efficiency in download direction. To the best of our knowledge, the multiobjective problems of femtocell networks considering energy efficiency has not been addressed in the literature yet.

In this paper we have formulated the resource allocation problem for three objectives as mixed integer non linear problems (MINLPs) with focus on the energy efficiency. We have discussed the pros and cons of considering different objectives. First it is shown that the problems are MINLP, hence the optimal solution is intractable. We have utilized a powerful and well-known algorithm called, NSGA-II [18] to solve the problems. Then, we have introduced an algorithm for multiobjective optimization problems for heterogeneous networks that explicitly takes into account the energy efficiency. Next, we will turn our attention to the comprehensive

complexity analysis of the proposed algorithm is provided as well. It is demonstrated that unlike the main problem which is NP-hard and thus intractable, the proposed solution is polynomial with an acceptable convergence.

The rest of paper is organized as follows: in section II the considered system model is presented and the optimization problems are formulated. The solution methodology is introduced in section III. The simulation results are provided in section IV. Finally, the concluding remarks are summarized in section V.

II. SYSTEM MODEL AND PROBLEM FORMULATION

In our system model a macrocell with M users, overlaid with K femtocells and F Users in each femtocell. All FUEs share the same spectrum with each other and with MUEs. All FUEs demand a minimum required rate of R_u and are connected to a femtocell base station (FBS) with closed access mode. Further, channel models has three main parts, large scale fading that is chosen based on [19], small scale fading and shadow fading. We define $h_{k,u,n}^F$ and $p_{k,u,n}^F$ as channel gains and transmit power of u th FUE in k th femtocell on channel n , respectively. Channel gain and transmit power of MUE w to the FBS k in subchannel n is also denoted by $h_{k,w,n}^{FM}$ and $p_{w,n}^M$, where n, k, u, w are members of $\{1, \dots, N\}$, $\{1, \dots, K\}$, $\{1, 2, \dots, F\}$ and $\{1, \dots, M\}$, respectively. Thus, the received SINR at FBS becomes:

$$\gamma_{k,u,n} = \frac{p_{k,u,n}^F h_{k,u,n}^F}{\sum_{w=1}^M p_{w,n}^M h_{k,w,n}^{FM} + \sigma^2}. \quad (1)$$

The first term in the denominator of $\gamma_{k,u,n}$ is interference caused by MUEs on the subchannel n on the FBS k and the second term is thermal noise, which is denoted by σ^2 . The interference caused by nearby FUEs of neighboring femtocells as well as other cells interferences on subchannel n is absorbed in thermal noise. This assumption is acceptable because in sparse case deployment FBSs are working with very low power and the penetration loss is relatively high.

In this section three different optimization problems will be formulated but before that some notations should be defined. Total system throughput of all FUEs is defined as

$$C_{Tot} = \sum_{k=1}^K \sum_{u=1}^F \sum_{n=1}^N a_{k,u,n} c_{k,u,n} \quad (2)$$

where $a_{k,u,n}$ is a binary variable indicates whether the channel is occupied or not and $c_{k,u,n}$ is user data rate and follows the normalized Shannon capacity formula with respect to channel bandwidth and measured with bps/Hz:

$$c_{k,u,n}^F = \log_2(1 + \gamma_{k,u,n}). \quad (3)$$

Total power consumption of all FUEs is as follows:

$$P_{Tot} = \sum_{k=1}^K \sum_{u=1}^F \sum_{n=1}^N a_{k,u,n} p_{k,u,n} \quad (4)$$

where $p_{k,u,n}$ is transmitting power of user u in femtocell k on channel n .

Energy efficiency is a metric which quantifies how efficiently resources are used. In other words no power reduction or throughput enhancement is done, unless it is in line with energy efficiency. The normalized total energy efficiency of system, which is measured with $[bit/Hz]/joule$, is as follows:

$$EE = \frac{C_{Tot}}{P_{Tot}}. \quad (5)$$

A. Optimization Problem

The general form of the optimization problem is to maximize or minimize the objectives subject to some constraints. These constraints are defined as follows:

$$\sum_{u=1}^F a_{k,u,n} \leq 1 \quad \forall k, n \quad (6a)$$

$$a_{k,u,n} \in \{0, 1\} \quad \forall k, u, n \quad (6b)$$

$$\sum_{n=1}^N a_{k,u,n} p_{k,u,n} \leq P_{max}. \quad \forall k, u \quad (6c)$$

$$\sum_{n=1}^N a_{k,u,n} c_{k,u,n} \geq R_{k,u} \quad \forall u, k \quad (6d)$$

$$\sum_{k=1}^K \sum_{u=1}^F a_{k,u,n} p_{k,u,n} h_{k,u,n}^{MF} \leq I_n^{th}. \quad \forall n \quad (6e)$$

Accordingly, (6a) shows OFDMA is chosen as an access technology and (6b) indicates that $a_{k,u,n}$ is a binary variable which shows that whether a channel is given to a specific user or not. Maximum transmit power of each user is limited using (6c). Maximum tolerable interference level caused by all FUEs is confined by imposing the constraint (6e) on each subchannel. The interference constraint protects the MUEs QoS from service degradation. Moreover, each FUE requires the minimum data rate to be satisfied which is considered in the constraint (6d). To perform the resource allocation, perfect channel state information is required. Block fading is considered in this study and channel state information which is independent from one to another can be estimated at FBS and will be fed back to MBS. The objectives are optimized simultaneously with the equal gain thus the objectives have the same priority.

1) *Optimization Problem 1:* First problem aims at maximizing the total throughput and energy efficiency of the system. Throughput maximization requires using excess power thus it is in contrast with energy efficiency. Therefore, considering both of them as an objective, could illustrate the spectral and energy efficiency trade-off. Moreover, considering these conflicting objectives, ensures us that no excess power is consumed to reach a better throughput unless it will be efficient. The optimization problem, which is called SE-EE, is as follows:

$$\max_{a_{k,u,n}, p_{k,u,n}} C_{Tot} \quad (7)$$

$$\max_{a_{k,u,n}, p_{k,u,n}} EE \quad (8)$$

$$\text{subject to (6a) to (6e)} \quad (9)$$

It is worth mentioning that throughput plays an important part in EE equation. Hence, while considering EE and C_{Tot} at the same time, we have put more effort on throughput because it appears in the nominator of energy efficiency as well. Also, if we fix the throughput, then maximizing the energy efficiency is equivalent to minimizing the power consumption, so the final power vector provided by the algorithm is the best solution amongst the all power vectors with the same throughput.

2) *Optimization Problem 2:* In the second optimization problem, we minimize the total power consumption and maximize the energy efficiency of the system. This problem is applicable to downlink direction which is a noteworthy problem for green communication. Also, in uplink direction it saves the battery life of devices which is a critical point for users. To refer this problem we use the notation PE-EE and the problem is as follows:

$$\min_{a_{k,u,n}, p_{k,u,n}} P_{Tot} \quad (10)$$

$$\max_{a_{k,u,n}, p_{k,u,n}} EE \quad (11)$$

$$\text{subject to (6a) to (6e)} \quad (12)$$

Unlike the energy efficiency and spectral efficiency, these objectives do not show the trade off all the time. In other words, minimizing power is not always equivalent to maximizing the energy efficiency as will be discussed later. This problem, put more focus on energy efficiency while ignoring the throughput maximization.

3) *Optimization Problem 3:* This problem has been considered in literature [20]. In [20] the authors try to maximize the total throughput while minimizing the total power consumption. These contradictory objectives are chosen wisely; however, there is no guarantee that system utilizes the resources efficiently. We refer to this problem as SE-PE.

$$\max_{a_{k,u,n}, p_{k,u,n}} C_{Tot} \quad (13)$$

$$\min_{a_{k,u,n}, p_{k,u,n}} P_{Tot} \quad (14)$$

$$\text{subject to (6a) to (6e)} \quad (15)$$

Considering the EE formula (5), single objective solutions tries to provide the maximum throughput with minimum power consumption which is similar to our objectives but it results only one solution which is one of the possible solutions existing in the optimal set. In other words, our method will provide us with a set of solutions and also a freedom to choose between them while the solution of single objective problem is a member of the pareto optimal set. This is one of the advantages of multiobjective problems comparing to the single objective ones.

III. SOLUTION METHODOLOGY: NSGA-II ALGORITHM

Complex intrinsic of resource allocation problems, motivates us to take advantage of heuristic techniques to obtain approximate solutions in polynomial time. Two major approaches have been utilized to solve the optimization problems. The gradient based method which requires the computation of objective functions and constraints derivatives and

heuristic algorithms [18], [20]. The latter algorithm suits well for optimization problems with conflicting objective functions rather than problem with one objective function. There are many ways in dealing with multiobjective optimization problems, such as linear sum method. These methods convert the original problem with multiple objectives into a single-objective optimization problem. Commonly, some approximations are performed to solve the problem using these methods which yields to only one sub-optimal solution while heuristic algorithms are alternative approaches with Pareto-optimal solutions in one single simulation run due to working with a population of solutions [18]. Another reason for opting such methods is their ability to find spread of solutions as well. Hence to avoid the complexity of objective and constraints derivatives meanwhile to reach a Pareto-optimal set instead of single solution we have opted a well known algorithm called non-dominated sorting genetic algorithm NSGA-II as a solution methodology of our problems.

NSGA-II is a fast and elitist multiobjective evolutionary algorithm based on a non-dominated sorting approach. The utilized mechanism in NSGA-II to preserve the diversity is the best between the schemes studied in [18]. Therefore, NSGA-II is one of the best option to handle the multi objective problems. Before comprehensive explanation of the main loop some concepts must be clarified according to the procedures of NSGA-II shown in algorithm 1. Multiobjective problems yields in set of solutions, therefore, the concept of dominance is introduced to compare the solutions. Given two solutions X and Y, solution X dominates solution Y, if considering all the objectives, X is not worse than Y and at the meantime there exists at least one objective in X that is strictly better than Y. Crowding distance is metric that in some sense measures the congestion of the solutions near each solution. Using this parameter, algorithm can maintain the diversity of the solutions. In this approach there is no need for any user-defined parameter for maintaining the diversity.

For each objective, by calculating the average distance of two neighbor solution on either side of particular solution, a density estimation of solutions is attained. For all objectives the crowding distance must be calculated. To compute the crowding distance the population is sorted in ascending order and then for each objective the boundary solutions are assigned an infinity value while the other solutions are given a value equal to the absolute normalized difference in the function values of two neighboring solutions. The sum of individual crowding distance values resultant to each objective, is the overall value of crowding distance. A solution with a smaller value is in a more congested area so we can use it to compare the density of the solutions near each particular point.

A. Multiobjective Resource Allocation Algorithm

The pseudocode of NSGA-II is provided in algorithm 1. In this algorithm, for clarity, we ignore the first iteration description and other iteration's scheme, e.g. i_{th} , will be explained. First, the generated populations at $(i-1)th$ loop are sorted using non-dominated sorting algorithm. To do so, each

solution must be assigned a non-dominated rank and crowding distance value. Selection part, is devoted to choose the N_p best solutions between all generated populations. Best solutions are the one with lower non-dominated rank and if two solutions have the same non-dominated rank, higher crowding distance value will be taken into account. Afterwards, Crossover and Mutation, as two basic operators of genetic algorithm, are performed with parameters of P_c and P_m , respectively. In the last step, new offsprings are combined with parents, to produce the new generation with $2N_p$ population, for the next iteration. This procedure is continued until the loop counter reaches to the maximum iteration number (N_i). The final solutions are the members of first front. First front is a set of acceptable solutions who are called pareto optimal set. Based on different criteria, best solution can be selected. We have opted the solution which is the median of all results in the first front.

Algorithm 1 The resource allocation scheme using NSGA-II

```

1: Set initial parameters:
2:    $N_i, N_p, P_c$ , and  $P_m$ 
3:   Generate parent set, randomly.
4:   Offspring set =  $\emptyset$ 
5: for  $i = 1: N_i$  do
6:   a. Non dominated sorting:
7:     i. Rank
8:     ii. Crowding distance
9:   b. Selection: Select  $N_p$  best solutions
10:  c. Bitwise crossover (with probability of  $P_c$ )
11:  d. Multi point mutation (with probability of  $P_m$ )
12:  e. Combine offspring with parents,
13:     to make  $2N_p$  individuals
14: end for

```

B. Complexity Analysis

The complexity analysis of different stage of NSGA-II algorithm is evaluated in [18]. To evaluate the total complexity of algorithm the objective functions computation complexity must be considered. FKN computation is needed to evaluate each objective for each individual, hence at each generation total complexity becomes $O(N_p KFN)$ and non-dominated sorting of the solutions requires $O(O_b N_p^2)$ computations, as well. The complexity of other parts are dominated by non-dominated sorting and objective evaluations part. For instance, the crowding distance computation has the complexity of $O(O_b \log_2 N_p)$ and sorting the population for crowding distance comparison has the complexity of $O(N_p \log_2 N_p)$. Fast nondominated sorting has reduced the time complexity at cost of increasing the required storage from $O(N_p)$ to $O(N_p^2)$. Thus, the total complexity of algorithm become $O(G[N_p KFN + O_b N_p^2])$, where G is number of generation, O_b is number of objectives and N_p is number of individuals in each generations. The problem is NP-hard and thus intractable while the proposed solution is polynomial. The complexity of optimal exhaustive search is $O(K^{N^F})$ thus compared to exhaustive search, NSGA-II has better complexity.

IV. SIMULATION RESULTS

To evaluate the proposed algorithm in the system we assume that there are 50 active MUEs that share the same bandwidth of $B = 10$ MHz with FUEs. Also, the macrocell and femtocell radii are set to 500 m and 20 m, respectively. We have used indoor femto channel models with given parameters in suburban deployment based on [19]. The number of channels is set to 50 and the number of femtocells is set to $K = 20$ with $F = 4$ users in each one. MUEs, FUEs, and FBSs are distributed uniformly throughout their associated cell. Maximum transmit power in uplink, P_{max} , is set to 23 dBm. The minimum required rate of all FUEs is set to 9 bps/Hz. Thermal noise is considered as a zero mean Gaussian random variable with variance of σ^2 and power spectral density of $N_0 = -174$ dBm/Hz, so $\sigma^2 = (W/N)N_0$. The NSGA-II parameters including number of individuals, iterations, probability of mutation (P_m) and crossover (P_c) are set to 100, 150, 0.03, and 0.9, respectively.

In Fig. 1 the convergence performance of proposed algorithm for different problems is investigated. For this simulation, we have opted the median solution in pareto optimal set with $Ith = -101$ dBm. Generally in multiobjective problems each objective should sacrifices its optimum value to achieve a better value for the other objectives. To investigate this, single objective problems are also added so that it would be possible to compare the results with upper and lower bounds.

Interestingly, in terms of efficiency as depicted in Fig. 1a, EE-PE outperforms the others because power and energy efficiency are two compatible objectives so the less power consumed, the higher energy efficiency is obtained. Also, SE-EE offers the best throughput among the other objectives, as is illustrated in Fig. 1b. Due to no effort in maximizing throughput, EE-PE has the least achieved throughput meanwhile users are satisfied with their data rates. According to the Fig. 1c, EE-PE consumed the least power and SE-PE performs worse than EE-PE but better than a SE-EE where power consumption is not included in objectives. To further investigate the trade-offs, Fig. 1 illustrates the penalty and the cost for the system when you consider different objectives at the same time. The gap between the single objective case and multiobjective cases shows how much we should pay as a penalty, to optimize the other objectives as well. For instance in Fig. 1a, considering throughput degrades the energy efficiency performance considerably. Also in Fig. 1c, by comparing minimizing power and EE-PE, it can be seen that system should consume more power to gain energy efficiency. Therefore, minimizing power is not equivalent to maximizing energy efficiency.

In Fig. 2, the pareto optimal set of EE-SE is depicted, so that one can have an overview on the final fronts of algorithm. It also illustrates that utilizing the available resources, NSGA-II could come up with remarkable improvement in energy efficiency as well. This result also illustrates the fundamental tradeoff between energy efficiency and throughput which is in line with [9].

Tolerable interference level on each channel, have an effect

(a) Energy Efficiency of System

(b) Total Throughput of System

(c) Total Power Consumption of System

Fig. 1: Convergence performance of proposed algorithm

Fig. 2: Pareto optimal set of EE SE problem

Fig. 3: System energy efficiency for different interference level

on the total system performance which is explored in Fig.3. In the interval of -120 dBm to -105 dBm system is infeasible. Around $I_{th} = -105$ dBm, an abrupt change occurred because the system become feasible. In Fig.3 after a sudden change, the energy efficiency level reach to the steady state with a slightly increasing trend. By increasing the interference threshold, FUEs has more fidelity to adjust their power to maximize their objectives. On the other hand, I_{th} is not neither the critical constraints thus the final solution is bounded by other constraints.

By deploying more femtocells, one can utilize the advantages of small cells but it may have effect on total system performance. This issue is investigated in Fig.4 where it can

be seen that by increasing the number of femtocells, system experiences the degradation in EE for all the scenarios. When the more femtocells are deployed, the more interference is brought into each channel. Therefore, the optimum channels in term of channel gain may be saturated by interference so they are not available for some users. As a result, users must use more power on other channels and energy efficiency will be dropped. According to the Fig.4b and Fig.4c, both power consumption and throughput is increased but regarding the Fig.4a their ratio is decreasing which means that deploying more femtocells is not always beneficial for the system in terms of energy efficiency.

By considering the maximum allowable interference limit, we protect the system from high system degradation. It is newsworthy to examine the effect of femtocell deployment on MUEs QoS in terms of their maximum achievable rate. To probe this issue, first each MUE is given its best channel and then we assume that they transmit their maximum allowable power. Fig.5 illustrates the aggregate achievable rate of all MUEs. It can be seen that by deploying more femtocells maximum achievable rate of MUEs will decline. When the number of femtocells are not high, say 10 or 20, their corresponding interference is low therefore MUEs can reach to very high data rate. As the number of femtocells become larger, in almost all channels, the interference is near to its upper bound and MUEs reach to the lower data rate than before. It is noteworthy to point out that, from a point the MUEs rates do not decline because in all channels the interference reach to their upper bound and thus no degradation is allowed for FUEs. Using this fact, it is possible to set a minimum limit for MUEs rate and find the maximum number of deployed femtocells. Moreover, PE-EE performs better than the other problems because it tries to use less power and consequently produce less interference.

V. CONCLUSION

In this paper, the multiobjective resource allocation problem for OFDMA based femtocell networks in uplink direction is considered. The final solutions must satisfy the minimum required rate of all users. To protect the system from extra interference, the maximum tolerable interference level on each channel is taken into account. Three main objective

(a) Energy Efficiency

(b) Total Power Consumption

(c) Total System Throughput

Fig. 4: Femtocell user performance Vs. Number of femtocells

Fig. 5: Maximum achievable spectral efficiency of MUEs

functions were considered namely, energy efficiency maximization, throughput maximization, and power minimization. We discussed on pros and cons of choosing different objective functions to attain an overview on effect of each objectives. By considering the trade off between objectives, EE-PE or SE-EE are the best objectives. The latter suits well for the cases with high data rate services and the former is a proper choice in cases where the system is under strict limitation of power consumption and has to save energy as much as possible. Furthermore, the effect of deploying more femtocells on the maximum achievable rate of macrocell users is investigated. Finally, simulation results demonstrated that maximizing throughput or minimizing the power individually, are not the most efficient way to allocate the available resources while including energy efficiency as one of objectives ensures us that the resources are utilized in an efficient way. Moreover, there is always a penalty if you consider spectral efficiency while optimizing the energy efficiency.

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