Multiobjective Subchannel and Power Allocation in Interference-Limited Two-Tier OFDMA Femtocell Networks

Nitin Sharma, Divyakumar Badheka, and Alagan Anpalagan

***Abstract*—The cochannel deployment of femtocells in a macrocell network is a cost-effective and efficient way to increase network coverage and capacity. However, such deployment is exigent due to the presence of inter- and intratier interference and the ad hoc operation of femtocells. Motivated by the flexible subchannel allocation capability of orthogonal frequency-division multiple access, in this paper, we consider the problem of joint subchannel and power allocation in both the uplink and downlink of a two-tier orthogonal-frequency-division-multiplexing-based femtocell network. It is a multiobjective optimization problem that aims to maximize the throughput of all users, simultaneously increasing the power efficiency of femtocell base stations. Interference to macrocell users is kept below a certain tolerable threshold. The minimum-rate requirements of delay-sensitive users are also taken into consideration. The problem is solved using nondominated sorting genetic algorithm version II, and the results are compared with the existing solution.**

***Index Terms*—Femtocells, multiobjective optimization, nondominated sorting genetic algorithm version II (NSGA-II), orthogonal frequency-division multiplexing, power allocation.**

I. Introduction

FEMTOCELLS are miniature versions of the standard base stations. They are low-power base stations designed to facilitate cellular communication in areas where the received power from a macrocell base station (MBS) is not adequate to support the active users, or the demand for cellular communication is very high, and one MBS is not adequate to meet the requirements. They have a typical coverage of 10–100 m and are mainly used in small business offices or homes.

Orthogonal frequency-division multiple access (OFDMA)-based femtocells have been already considered in major wireless communication standards, e.g., long-term evolution (LTE)/LTE Advanced [1]. Due to the scarcity of spectrum, operators prefer spectrum sharing between macrocells and femtocells rather than orthogonal deployments [2]. Spectrum sharing can be performed in the region of large number of active users. However, there is a great chance of increased cross-tier signal interference in such a spectrum-sharing system [3]. Therefore, resource allocation for minimizing cross-tier interference has become an important research area in order to enhance performance and has attracted much attention within the telecommunication industry and academia.

Interference management in two-tier networks faces many practical challenges such as the lack of sufficient coordination between the MBS and femtocell base stations (FBSs), scalability, security, and limited availability of backhaul bandwidth. Recently, several works [4]–[10] dealing with the interference management problem for two-tier femtocell networks have been reported. In [4], a noncooperative power allocation with signal-to-interference-plus-noise ratio (SINR) adaptation was used to alleviate the uplink interference suffered by macrocells, whereas in [5], a Stackelberg-game-based power control was formulated to maximize femtocell's capacity under cross-tier interference constraints. However, subchannel allocation was not considered there. In [6], a joint subchannel and power-allocation algorithm was proposed to maximize total capacity in dense femtocell deployments. In [7], a Lagrangian approach was used to allocate power in an orthogonal-frequency-division-multiplexing-based femtocell network. In [2], the distributed subchannel and power allocation for cochannel-deployed femtocells was modeled as a noncooperative game, for which a Nash equilibrium was obtained based on a time-sharing subchannel allocation.

Zhang *et al.* in [8] proposed a convex-pricing-based resource-allocation algorithm with the aim of improving the energy efficiency of two-tier cochannel femtocell networks. The subchannel allocation and power control problem was modeled as a noncooperative game, where both the transmit power and circuit power were considered. In [9], a distributed utility-based downlink power control algorithm was proposed. This algorithm used the firefly algorithm in order to find the optimal power settings that can maximize the value of utility functions for macrocells and femtocells based on the factor of area spectral efficiency. In [10], Shen and Lok investigated the problem of cross-tier and intercell interference for a two-tier femtocell network. In this investigation, the macro- and femtotiers were assumed to share the same spectrum, and the femtotiers were further assumed to use a closed-access scheme. The game theory and variational inequality theory were used to achieve femtotier optimality and reduce cross-tier interference quickly. However, in these works, joint subchannel and power allocation with users' quality of service (QoS) and cross-tier interference considerations were not studied. In [11],

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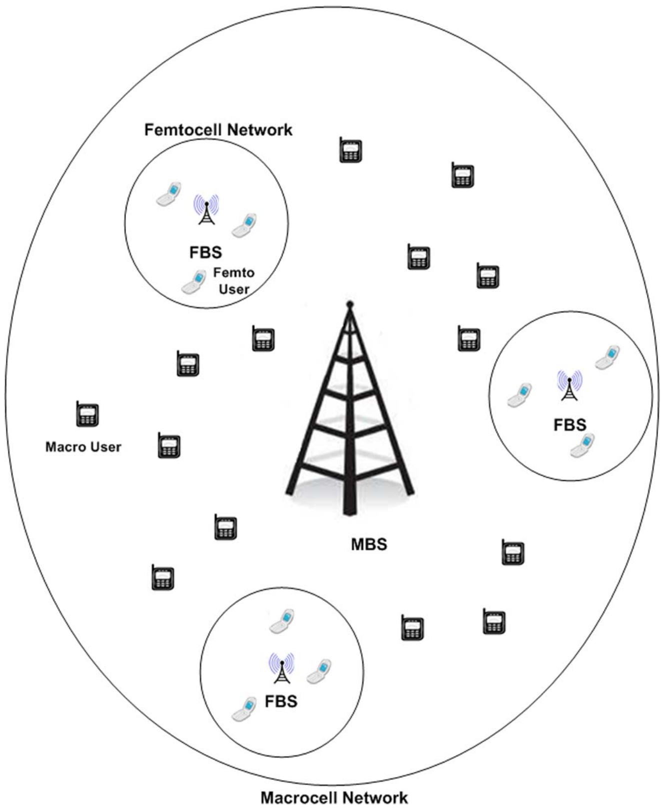

Fig. 1. System model.

a distributed modulation and coding scheme, subchannel and power allocation that supports different throughput constraints per users, was proposed, but only a single-tier network was considered.

Femtocells should be able to support the minimum requirements for delay-sensitive users, such as video calling, online multimedia, etc., while maintaining the capacity of delay-tolerant users [12]. In this paper, the problem of resource allocation in OFDMA not only includes the power allocation for maintaining the minimum required SINR but also considers the maximum total power utilization available at FBSs (maximum efficiency). The delay-sensitive users have a minimum QoS requirement [13], whereas the delay-tolerant users do not have any such requirements. After including the constraints of power budget and maximum interference temperature level, we optimize the multiobjective problem formulated using the second version of nondominated sorting genetic algorithm (NSGA-II).

The remainder of this paper is organized as follows: Section II provides the system model and the required mathematical model for the optimization problem under consideration. In Section III, we briefly discuss the NSGA-II algorithm used for power and subchannel allocation. Section IV presents the simulations results and their comparison with existing methods. Conclusion and future directions are given in Section V.

II. System Model

As shown in Fig. 1, we consider a two-tier femtocell system with total of K number of cochannel FBSs overlaid with a macrocell. It is assumed that femtocells are deployed in suburban areas, with each femtocell employing the closed-access scheme, where an FBS only serves users that are members of a particular closed subscriber group. Further, we assume that there is, at most, one scheduled active user during each signaling time slot at any given frequency band (e.g., one frequency subband in an OFDMA-based femtocell). Each femtocell serves F users, and the number of users in a macrocell is M. The OFDMA-based femtocell system has a bandwidth of B Hz, which is equally divided into N subchannels. The channel fading of each subchannel is assumed to be the same within a subchannel, but may vary across different subchannels, and we assume that it is composed of large-scale fading (path loss) and small-scale fading (frequency-selective Rayleigh fading).

We first calculate the results for the uplink case and extend them to the downlink case. We model the SINR as

$$\Upsilon^F_{k,u,n} = \frac{p^F_{k,u,n} g^F_{k,u,n}}{p^M_{w,n} g^M_{k,w,n} + \sigma^2} \quad (1)$$

where $\Upsilon^F_{k,u,n}$ is the SINR at the kth $(k \in \{1, 2, \ldots, K\})$ FBS from its uth $(u \in \{1, 2, \ldots, F\})$ user at the nth $(n \in \{1, 2, \ldots, N\})$ subchannel. $p^F_{k,u,n}$ is the transmit power of the uth user belonging to the kth femtocell on the nth subchannel. $g^F_{k,u,n}$ is the channel gain from femtocell user u to its FBS k on subchannel n. $p^M_{w,n}$ is the transmit power of macro user $w \in \{1, 2, \ldots, M\}$ on the nth subchannel to the MBS. $g^M_{k,w,n}$ is the channel gain on subchannel n of macro user w to femtocell k, and σ^2 is the additive white Gaussian noise (AWGN) power. We assume that the interference between femtocells is negligible [14], [15] as they are transmitting much lower power [14] than MBS and separated by a larger distance to cause any significant interference. Hence, we only consider the interference caused by femtocell users on macrocell users. Using Shannon's normalized capacity formula (after dividing by B), we can write

$$C^F_{k,u,n} = \log_2\left(1 + \Upsilon^F_{k,u,n}\right) \quad (2)$$

where $C^F_{k,u,n}$ is the capacity of femtocell user u in the k femtocell on subchannel n.

Further, it was shown in [5] that the resource-allocation approach for the uplink can be applied to the downlink with appropriate modifications. The structure of the downlink femtocell system is almost identical to that of its uplink counterpart, with only difference being the notation of channel power gains. The problem formulation for the downlink transmission thus can be easily obtained by replacing the uplink channel power gains in (1) with the corresponding downlink counterparts. Therefore, the resource-allocation algorithm for the uplink transmission can be directly used for its downlink counterpart. However, since there are no direct links between the mobile users and FBS, the channel state information and the interference required in the optimal design must be exchanged between them through the MBS.

A. *Optimization Problem Formulation*

Our aim is to maximize the sum capacity of all users in the femtocells while satisfying the constraints of QoS. The subchannel and power allocation will be decided by these quality factors. Our objectives (OBs) are to maximize the total throughput and minimize the difference between FBS power budget and actual FBS power usages, i.e.,

$$\text{OB1}: \max_{a_{k,u,n}, p^F_{k,u,n}} \sum_{k=1}^{K} \sum_{u=1}^{F} \sum_{n=1}^{N} a_{k,u,n} C^F_{k,u,n} \tag{3}$$

$$\text{OB2}: \min_{a_{k,u,n}, p^F_{k,u,n}} \sum_{k=1}^{K} \sum_{n=1}^{N} a_{k,u,n} p^F_{k,u,n} - P_{Tot} \tag{4}$$

subject to

$$\begin{aligned}
&\text{C1}: p^F_{k,u,n} \geq 0, \ \forall\, k, u, n \\
&\text{C2}: \sum_{n=1}^{N} a_{k,u,n} C^F_{k,u,n} \geq R_u, \ \forall\, k, \ \forall\, u \in DS_k \\
&\text{C3}: \sum_{k=1}^{K} \sum_{u=1}^{F} a_{k,u,n} p^F_{k,u,n} g^{MF}_{k,u,n} \leq I^{th}_n, \ \forall\, n \\
&\text{C4}: \sum_{u=1}^{F} a_{k,u,n} \leq 1, \ \forall\, k, n \\
&\text{C5}: a_{k,u,n} \in \{0, 1\}, \ \forall\, k, u, n.
\end{aligned}$$

The first objective is to maximize the total capacity of all the femtocell users. The second objective is to maximize the resource/power utilization of the FBS. Here, $a_{k,u,n}$ is an identifier, with $a_{k,u,n} = 1$, which means that in the kth femtocell, the uth user is assigned the nth subchannel; otherwise, it is zero. It ensures that no two users in a femtocell are allocated the same subchannel. P_{Tot} is the sum of the maximum power that all femtocells can transmit. DS_k and DT_k are the set of delay-sensitive and delay-tolerant users in femtocell k with $|DS_k| + |DT_k| = F$ and $DS_k \cap DT_k = \varnothing$ [13]. C1 ensures that the power allocated to each allocated subchannel in all femtocells is greater than zero. Constraint C2 fulfills the QoS requirement of the delay-sensitive users. The capacity of delay-sensitive users should be more than a given minimum R_u. In the constraint C3, $g^{MF}_{k,u,n}$ is the channel gain on subchannel n, from femtocell user u in femtocell k to the MBS. I^{th}_n is the maximum interference temperature level that is tolerable. This constraint restricts the use of only those subchannels by femtocells users whose assignment keeps the interference caused to macrocell users below I^{th}_n. C4 and C5 imply that no two users, in the same femtocell, are assigned the same subchannel or that no two users can share a particular subchannel within a femtocell.

III. Allocation Using NSGA-II

The traditional methods used for solving optimization problems can be divided into two broad groups: gradient-based and random methods. The main advantage of the genetic algorithm (GA) over the gradient-based methods is that it eliminates the computation of derivatives of the objective function and constraint equations. The random methods are usually referred to as guided random methods, such as GA, simulated annealing algorithm, which are suitable for problems with multiple variables.

A. GA

GA [16] is an efficient numerical optimization method, and it mimics the natural behavior of evolution, in terms of "*survival of the fittest*," to search for the optimal solution to a given problem. GAs enable efficient search in the solution space of any function so as to obtain a solution set that optimizes an objective function. Parallelism with the natural selection process includes three major steps: selection, crossover, and mutation. Every individual bears its own value showing its potential as a solution. This value is called the "*fitness value*." In a GA, the population evolves under specified selection rules to a state that maximizes this fitness value. Individuals from the population mate with each other to produce unique offspring through the process of crossover. Mutation expands the set of plausible solutions, thus increasing the possibility of yielding a better solution every time crossover occurs. When these three steps are repeated for a fixed number of generations, a solution compliant with the objective is obtained.

The basic GA works to optimize a single objective function. However, many optimization and resource allocation problems involve tradeoffs between various objectives and parameters and, therefore, are called multiobjective [17], [18]. In the case of two conflicting objectives, each objective corresponds to a different optimal solution. Thus, in multiobjective problems, there is no "single" optimum solution, but many "acceptable" solutions. The main objective then shifts to finding an agreeable solution considering all the tradeoffs between the various objective functions. When such a set of acceptable solutions is obtained, a qualitative decision can be taken for selecting a single solution from the set.

B. NSGA

NSGA [17] uses an effective nondomination sorting algorithm to optimize multiple objective functions [17]. NSGA-II improves the computational complexity of NSGA and also incorporates elitism [17]. NSGA solves multiobjective problems by using the concept of domination. In NSGA-II, the initial population is sorted into fronts [18], where the individuals in the first front are not dominated by any other individuals in the current population, and the individuals in the second front are dominated only by the individuals in the first front, and so on. An individual solution is said to dominate another if its fitness value with respect to every objective fitness function is superior to the corresponding values for the other individual. The individuals in the rth front are assigned a rank of r. In addition, crowding distance, which is a parameter that measures how close an individual is to its neighbors, is also calculated for each individual. A larger average crowding distance indicates greater diversity in the population.

C. NSGA-II

Let $\vec{X}$ be an individual/chromosome (solution) and $f_i(\vec{X})$, $i = 1, \ldots, O_b$ be the value of the ith objective of $\vec{X}$, where O_b is the number of objectives. For the problem of resource allocation under consideration, each solution (see Fig. 2)

Subchannels/FBS	SC-1	SC-2	- - - -	SC-N
1	1, 17	3, 14	- - - -	F, 16
2	2, 19	F, 18	- - - -	2, 17
:	:	:	:	:
K	1, 14	F, 4	- - - -	2, 13
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Fig. 2. Schematic representation of an individual chromosome in the population.

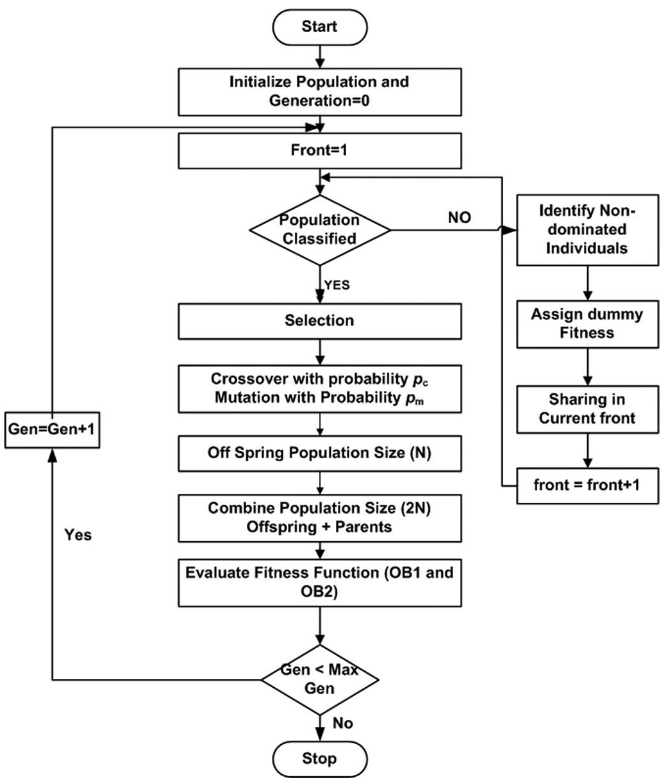

Fig. 3. Flowchart for resource allocation using NSGA-II.

corresponds to a subchannel and bit allocation in a two-tier femtocell network. Let N_p denote the population size and $P(t)$ and $Q(t)$ be the parent population (where elite solutions are kept) and the offspring population at generation t, respectively. The flowchart for resource allocation using NSGA-II is shown in Fig. 3.

In order to keep the elite individual found so far in the evolution process, in each iteration, the parent population $P(t)$ is combined with the offspring population $Q(t)$ to get combined population $S(t) = P(t) \cup Q(t)$ of size $2N_p$. Each individual in the combined population $S(t)$ is then subjected to fitness (or rank) evaluation (i.e., objective values $f_i(\vec{X}), i = 1, \ldots, O_b$ for individual $\vec{X}$ are calculated), and the population is sorted into different nondomination fronts [18]. Assuming minimization of fitness, each individual in the population is assigned a rank equal to its nondomination level (1 is the best level) [18]. Individuals in the population that are not dominated by any other individual are assigned rank 1, and the individuals that are dominated only by the individuals of rank 1 are assigned rank 2. This recursive process iterates until all of the individuals in combined population $S(t)$ are assigned a rank number. In order to realize the nondominated sorting, NSGA-II uses a domination count n_X (the number of individuals that dominate individual $\vec{X}$) and a set of individuals I_X that individual $\vec{X}$ dominates. Initially, every individual $\vec{X}$ in the population is compared with other individuals in order to get the sets n_X and I_X. Executing the above procedure, the individuals are sorted into fronts, i.e., an individual $\vec{X}$ with $n_X = 0$ is assigned rank 1 and becomes part of nondominated front 1. Once the first front individuals are determined, the nondominated sorting approach is used to determine second front individuals. For individuals in nondominated front 2 or higher, the domination count n_X can be, at most, $N_p - 1$. Hence, each individual $\vec{X}$ can be visited, at most, $N_p - 1$ times before n_X is reduced to zero. Note that $\vec{X}$ will never be visited again after it is assigned nondomination level. In addition, there are, at most, $N_p - 1$ individuals in nondominated front 2 and higher. Hence, to determine nondominated front 2 and higher requires a computational complexity of $O(O_b N_p^2)$, which is the same as to determine nondomination front 1. Therefore, the overall complexity of the nondominated sorting is $O(O_b N_p^2)$.

When comparing two individuals in parent selection, the crowded comparison operator is adopted to guide the selection process toward a uniformly spread-out Pareto-optimal front [18]. The individuals in combined population $S(t)$ are first sorted in ascending order on the basis of their nondomination rank. Between two individuals with differing nondomination ranks, the solution with the lower (better) rank is preferred. However, when two individuals have the same nondomination rank, the crowding distance is used to estimate the density of individuals surrounding a particular individual in the population. The individual with the larger crowding distance is preferred over individuals with smaller crowding distance. NSGA-II then applies crossover (with a crossover probability of p_c) and mutation (with a mutation probability of p_m) to the individuals in the mating pool to create the offspring population $Q(t)$. The final output is the set of all nondominated solutions in $P(t)$ and $Q(t)$.

D. Resource Allocation in Two-Tier Femtocell Network Using NSGA-II

In [19], the margin adaptive optimization problem for resource allocation in downlink OFDMA systems was addressed using GA, where each individual chromosome was coded as an array of elements that represented subchannels. Further, NSGA-II was used in [20] to solve joint subchannel and power allocation problem in the downlink of OFDMA systems with multiple antennas. In this paper, we extend the analogy to simultaneously allocate subchannels and power, while taking constraints (C1–C5) into consideration. Each individual chromosome is coded as a 2-D matrix of K (number of femtocell in the system) rows and N (number of subchannel in each femtocell) columns. Each element of the chromosome matrix is composed of two parts, i.e., the number on the left denotes the user in that femtocell to which that subchannel is assigned, whereas the number on the right denotes the uplink/downlink power (in dBm) assigned to that user on this particular subchannel. For each element in the chromosome matrix, fixing the upper and lower limits for the number on the right side (power

- **Initialization:**
- Set $t = 0$ and $Q(0) = \phi$;
- Randomly generate a initial population P_0 of N_p chromosomes. For the problem of resource allocation in two tier femtocells under consideration, each chromosome (Fig. 2) is a $K \times N$ matrix. Each cell in this matrix represents a particular subchannel in a particular femtocell and the values in that cell represents the user and the power allocated (in dBm) to that user on this subchannel.
- **repeat:**
- Set $t = t + 1$.
- $S(t) = P(t) \cup Q(t)$.
- Sort individuals in $S(t)$ using:
  (1) non-domination rank.
  (2) crowding distance.
- Set $P(t) = \phi$ and put first N_p individuals in to $P(t)$.
- **Selection:** Select N_p individuals from $P(t)$ in order to fill the matig pool employing tournament selection and crowding selection operator [18].
- **Crossover:** With a crossover probability (p_c) cross over the parents to form new offspring (children). If no crossover was performed, offspring is the exact copy of parents.
- **Mutation:** With a mutation probability (p_m) mutate new offspring at each locus (position in chromosome).
- **Accepting:** Place new offspring in the offspring population $Q(t)$.
- **Replace:** Use new generated population for a further run of the algorithm.
- **Test and loop:** If the end condition is satisfied (e.g. reaches a constant number of generations in this paper), stop, and return the best solution in current population. Otherwise go to Step 4.

Fig. 4. Pseudo-code for resource allocation in a two-tier femtocell network.

allocated to each user) to maximum power $P_{\max}$, which can be allocated to a user in downlink/uplink and 0.0001, respectively, satisfies constraints C1 and C2. Further, by fixing the upper and lower limits for the number on the left side (user to which that subcarrier is allocated) to a maximum number of users in each femtocell (F) and 1, respectively, satisfies constraints C4 and C5. Fig. 2 shows the structure of a chromosome (where we have assumed that there are K femtocells and F users in each femtocell) in the population. The last row of this figure depicts how chromosomes would be considered for crossover and mutation.

Note that it is assumed that there are F distinct users requesting for service in each femtocell, i.e., user 2 in one femtocell is different from user 2 in another femtocell. In other words, a particular user can be served only by one femtocell at a particular instant of time.

The flowchart and the pseudo-code for resource allocation in a two-tier femtocell network using the NSGA-II algorithm are given in Figs. 3 and 4, respectively.

E. Assumptions

In these simulations, as shown in Fig. 1, the spectrum-sharing femtocell and macrocell users are uniformly distributed their respective coverage areas. It is further assumed that the resource allocation in a macrocell is known beforehand. For both the uplink and downlink cases, the coverage radius of macrocells and femtocells is assumed to be 500 and 10 m, respectively. Moreover, the maximum transmit power $(P_{\max})$ of each macrocell and femtocell user is assumed to be 23 and 20 dBm in uplink and downlink, respectively. The carrier frequency is 2 GHz, bandwidth $B = 10$ MHz, $N = 50$, $M = 50$, $\sigma^2 = (B/N)N_0$, where $N_0 = -174$ dBm/Hz is the AWGN power spectral density. The path loss models for indoor femtocell users and outdoor macrocell users are based on [21], and block-fading channel gains are modeled as independent and identically distributed unit exponentially distributed random variables. The standard deviation of shadow fading between an MBS and a user is 8 dB, whereas that between an FBS and a user is 10 dB. However, as discussed in Section II, for the downlink case, the uplink channel power gains are replaced with their downlink counterparts. The "existing algorithm" included in the simulation for comparison is the subchannel allocation scheme proposed in [22] in conjunction with optimal power allocation proposed in [13].

F. NSGA-II Parameter Tuning

The effectiveness of any evolutionary algorithm depends on the choice of its parameters. Selection of best parameters is required in order to avoid premature convergence, to ensure diversity in the search space, and to intensify the search around best solution regions, etc. Inappropriate choice of parameters may lead to premature convergence or stagnation. Here, we present an empirical testing approach to find the best tuning parameters of the NSGA-II algorithm for the problem under consideration. In order to keep the number of combinations tractable, the population size was fixed *a priori* to 150. We have applied parameter tuning only for the crossover probability, mutation probability, and number of generations. We considered the following ranges for these parameters:

1) Number of generations: three levels (100, 200, and 300).
2) p_c: three levels (0.7, 0.8, and 0.9).
3) p_m: three levels (0.01, 0.02, and 0.03).

Due to this fact, the NSGA-II algorithm has three parameters, and each parameter has three levels; hence, we have 27 different conditions. In order to have more comprehensive analysis, each of these 27 conditions for NSGA-II was simulated ten times each, for two extreme cases of the problem set. The channel gain matrix, for each femtocell, once generated was kept constant during the tuning process. The number of subchannels in each femtocell and macrocell were fixed at 50. For the

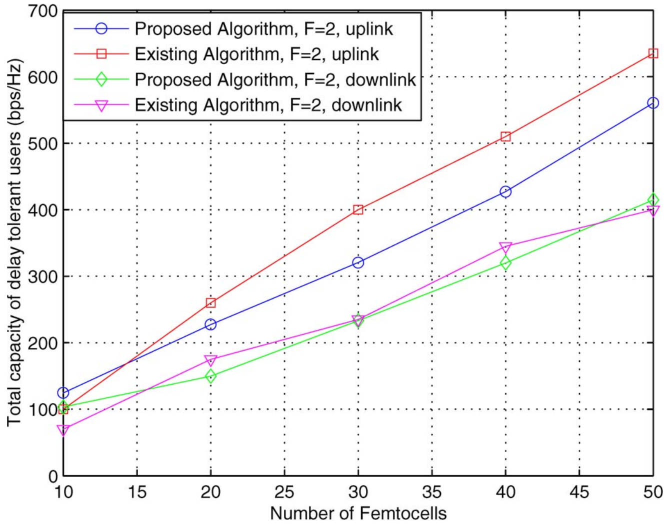

Fig. 5. Capacity of delay-tolerant users versus number of femtocells.

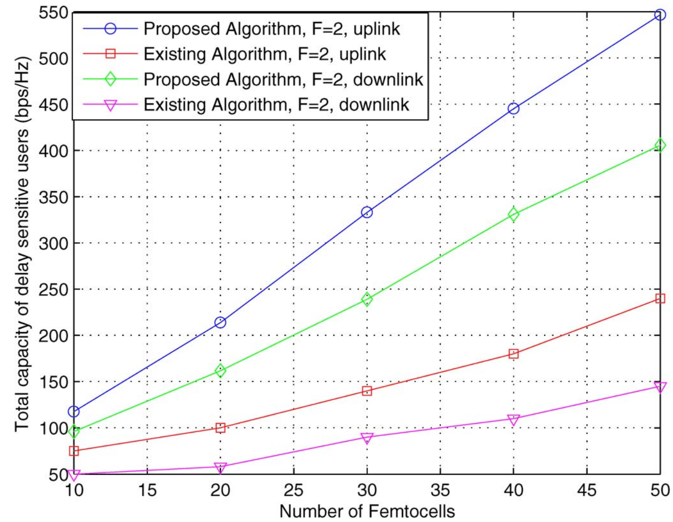

Fig. 6. Capacity of delay-sensitive users versus number of femtocells.

number of users in each femtocell F, number of femtocells K, and interference temperature limit I_n^{th}, two extreme levels were used. That is, F was considered as 2 and 4, K was taken as 10 and 50, whereas the I_n^{th} was -120 and -90 dBm. NSGA-II worked well for all the parameters considered, but the performance, in terms of CPU time and capacity, was found to be slightly better for the following set of values:

1) $p_c = 0.9, p_m = 0.03$
2) $p_c = 0.8\ p_m = 0.02$

IV. Analysis of Results

Here, the performance of the NSGA-II algorithm for resource allocation in a two-tier femtocell network is compared with the existing and optimal solution.

A. Capacity Versus Number of Femtocells

Here, we compare the results of different capacities obtained by the proposed algorithm with that of the existing algorithm. In order to have fair comparison with the method in [13], in our simulations, we modified the subchannel allocation proposed in [13] with the aim of maximizing the sum capacity of the two-tier femtocell network under consideration. This modified subchannel allocation combined with the power allocation method proposed in [13] is called the existing algorithm.

Figs. 5–7 depict the capacity of delay-tolerant users and delay-sensitive users and the sum capacity, which is the sum of delay-tolerant and delay-sensitive users' capacity, respectively. In each of these results, the number of femtocells was varied from 10 to 50 in increments of 10, and the capacity obtained in each case was plotted against the number of femtocells.

Fig. 5 shows the capacity of all delay-tolerant users versus the number of femtocells for the case of $F = 2$. The system parameters used for this set of results were: number of users in each femtocell $F = 2$, with one each as delay sensitive and delay tolerant, minimum data rate required by delay-sensitive users in each femtocell $R_u = 9$ b/s/Hz, maximum power allowed of each femtocell user $P_{\max} = 23$ dBm (in uplink),

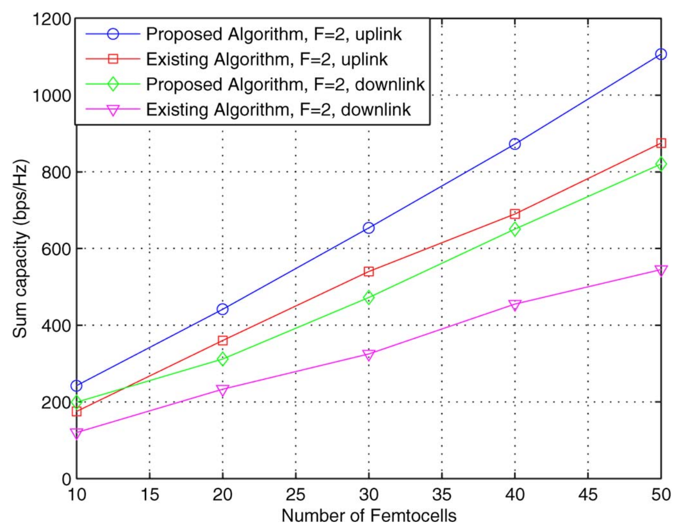

Fig. 7. Sum capacity of all users versus number of femtocells.

$P_{\max} = 20$ dBm (in downlink), and threshold interference level $I_n^{th} = 7.5 \times 10^{-14}$ W $(-101.2\ \text{dBm})$. The population and number of generations for NSGA-II were set to 170 and 200, respectively, whereas the probability of crossover and mutation were set to 0.9 and 0.03, respectively.

It can be observed in the figure that the capacity of delay-tolerant users obtained by the proposed algorithm is little lower than that of the existing algorithm for the uplink case. However, as can be observed in Fig. 6, the existing algorithm fails to provide the minimum capacity required by the delay-sensitive users for both the uplink and downlink cases. As the number of femtocells increases from 10 to 50, the gap between the minimum capacity requirement of delay-sensitive users and the actual capacity provided by the existing algorithm increases. On the other hand, the proposed algorithm, at the cost of delay-tolerant user capacity, always satisfies the constraint of minimum capacity for delay-sensitive users. Furthermore, it can be observed in Fig. 7 that the proposed algorithms always provides better sum capacity as compared with the existing algorithm.

TABLE I
TOTAL CAPACITY IN DOWNLINK, RESULTS FOR VARIOUS PERMUTATIONS OF POPULATION (*Pop*), GENERATIONS (*Gen*), PROBABILITY OF CROSSOVER (p_c), AND PROBABILITY OF MUTATION (p_m)

Set	Number of Femtocells (K)	Sum Rate (b/s/Hz)					
		Pop =80, Gen=100		Pop =170, Gen=200		Pop =250, Gen=300	
		p_c=0.9 p_m=0.03	p_c=0.8 p_m=0.02	p_c=0.9 p_m=0.03	p_c=0.8 p_m=0.02	p_c=0.9 p_m=0.03	p_c=0.8 p_m=0.02
1	10	193.83	194.75	199.41	200.14	207.12	207.31
2	20	308.21	307.11	311.64	311.23	316.32	315.83
3	30	468.35	468.54	472.22	473.50	477.33	477.82
4	40	647.97	648.27	650.72	650.73	655.43	655.19
5	50	815.15	814.78	820.05	821.36	825.76	824.89

TABLE II
TOTAL CAPACITY IN UPLINK, RESULTS FOR VARIOUS PERMUTATIONS OF POPULATION (*Pop*), GENERATIONS (*Gen*), PROBABILITY OF CROSSOVER (p_c), AND PROBABILITY OF MUTATION (p_m)

Set	Number of Femtocells (K)	Sum Rate (b/s/Hz)					
		Pop =80, Gen=100		Pop =170, Gen=200		Pop =250, Gen=300	
		p_c=0.9 p_m=0.03	p_c=0.8 p_m=0.02	p_c=0.9 p_m=0.03	p_c=0.8 p_m=0.02	p_c=0.9 p_m=0.03	p_C=0.8 p_m=0.02
1	10	235.41	234.23	242.32	241.54	247.87	248.12
2	20	433.23	432.72	441.31	440.75	446.44	447.32
3	30	645.41	648.44	653.74	654.23	657.46	656.62
4	40	865.43	868.74	872.37	872.44	877.38	877.78
5	50	1100.38	1100.45	1107.03	1107.75	1112.31	1111.94

In Fig. 7, it can be observed that the proposed algorithm provides an average gain of 27% in uplink and 31% in downlink over the existing algorithm. Further, in order to verify the robustness of NSGA-II to solve the problem under consideration, we tried different combinations of population size, number of generation, probability of crossover, and probability of mutation, keeping the system parameters the same as in previous results. The results obtained for different combinations of NSGA-II parameters are given in Tables I and II. It can be observed from these tables that NSGA-II provided almost similar results for different combinations of probability of crossover and mutation, whereas the results slightly improved with the increase in population size and number of generation. These results are in line with the expected performance of GAs.

B. Convergence Analysis

The results (shown in Tables I and II and Figs. 5–7) obtained for the various simulation cases reaffirm that applying multiobjective optimization to resource allocation problems in an OFDMA-based two-tier femtocell network provides efficient solutions in terms of sum capacity. In order to study the convergence behavior of NSGA-II in solving the resource allocation problem in femtocell networks, we evaluated the number of generations required by NSGA-II to converge. For this analysis, we fixed the population size to 80, the maximum number of generations to 100, and the probability of crossover and mutation to 0.9 and 0.03, respectively (column 1 of Table II). Fig. 8(a)–(e) depicts the convergence results corresponding to this set of NAGA-II parameters for different number of femtocells. As expected, the number of generations required for convergence increased with the increase in number of femtocells. However, even in the worst case with 50 femtocells, the number of generation required for convergence was around 55 only. Further, it can be observed in Fig. 8 that the difference between the maximum power budget (P_{Tot}) and actual transmit power increases with the increase in number of femtocells. This increase in difference of power with the increase in number of femtocells and, hence, sharing of subchannels can be attributed to the fact that the users are allowed to transmit less power to keep the interference generated within limits. Moreover, it can be noted from Tables I and II and Fig. 7 that there was no significant improvement in sum capacity with the increase in number of generations and population size. Furthermore, NSGA-II is capable of providing better sum capacity as compared with the existing algorithm even for a population size and number of generations as low as 80 and 100.

The fast converge of the proposed algorithm is an important result as our assumption of perfect channel state information is time dependent. The fast convergence rate of the algorithms makes it suitable for practical wireless applications. Because the channel gains are assumed to be constant during the period of allocation and considering the fact that wireless channels tend to quickly change, a fast-allocation algorithm is preferred. The algorithm can be made to work even faster if we can predict the expected power required to be transmitted by each user in all the femtocells and provide a partial feasible initial population to the algorithm. Further, in order to have a conceptual illustration of the nondominated Pareto sets (fronts), Fig. 9(a)–(d) depicts the Pareto fronts obtained corresponding to the uplink result (for 20–50 femtocells) in Fig. 7 (column 5, rows 2–5 in Table II). In Fig. 9, it can be observed that the proposed algorithm not only provides significant improvement in sum capacity but also utilizes the available.

C. Capacity Versus Interference Temperature Limit

Fig. 10 and Table III show the variation of total capacity with respect to the interference temperature level for both the uplink and downlink cases. For these simulations, the maximum power

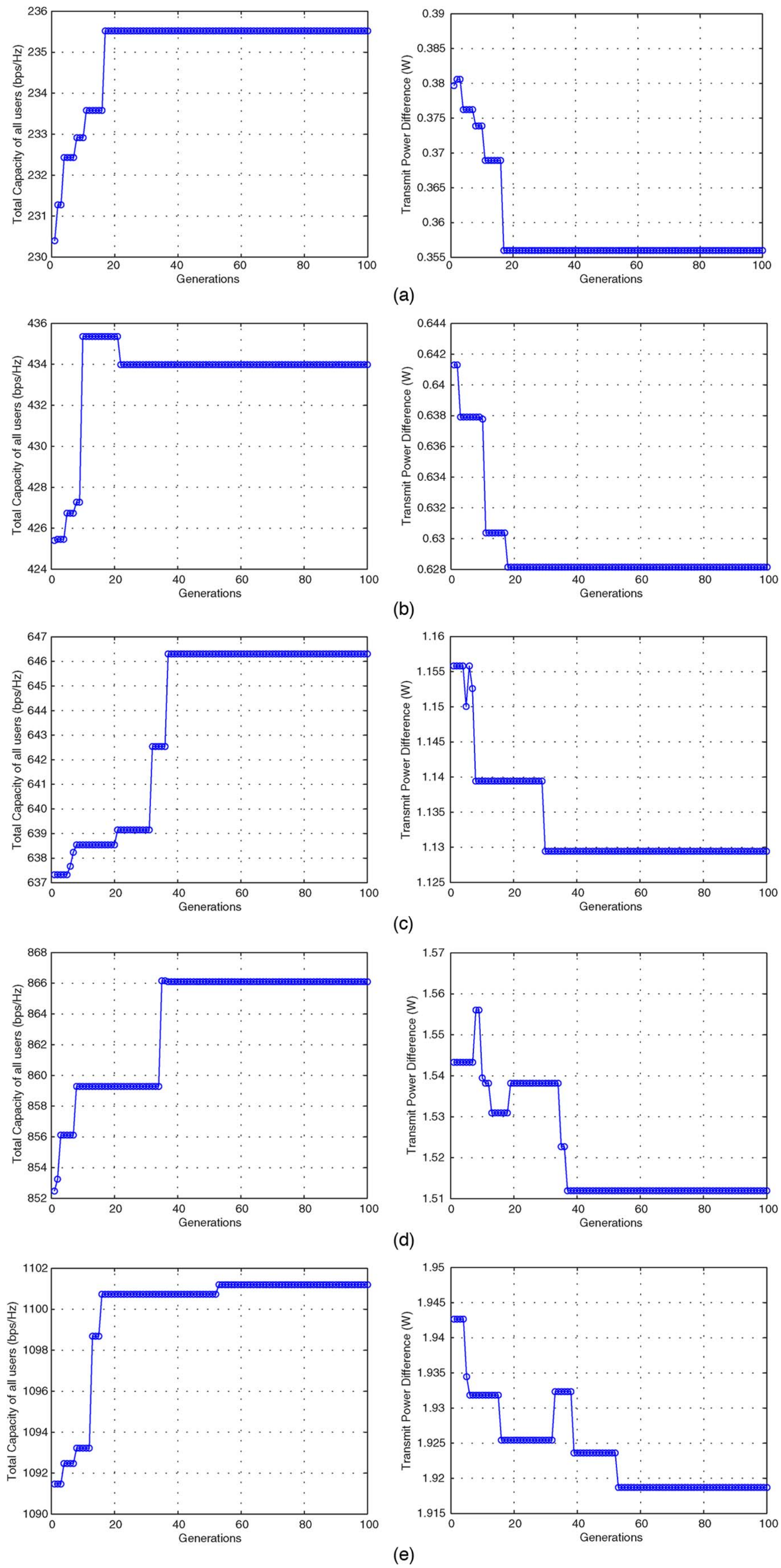

Fig. 8. Convergence curves for results corresponding to the uplink result (column 3 in Table II). Total capacity and power difference for the case of (a) 10 femtocells, (b) 20 femtocells, (c) 30 femtocells, (d) 40 femtocells, and (e) 50 femtocells.

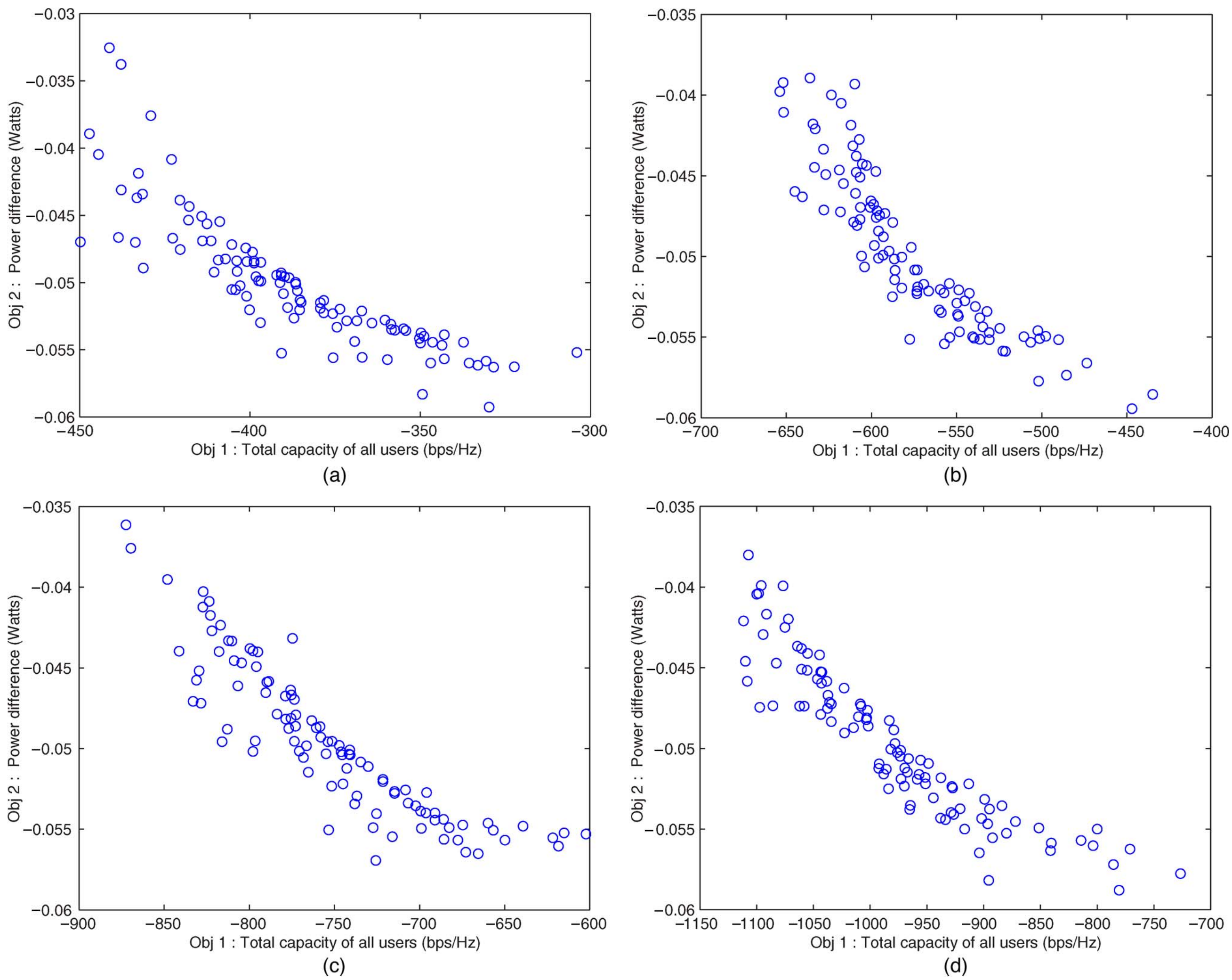

Fig. 9. Pareto fronts for results corresponding to the uplink result in Fig. 7 (column 5, rows 2–5 in Table II). (a) 20 Femtocells. (b) 30 Femtocells. (c) 40 Femtocells. (d) 50 Femtocells.

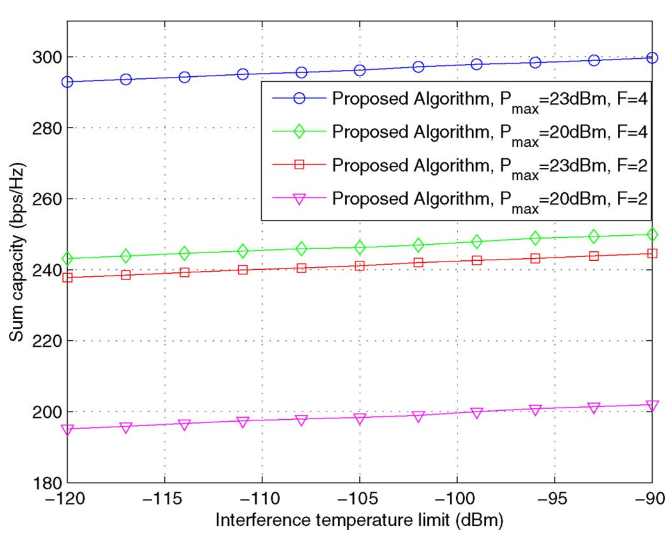

Fig. 10. Sum capacity versus interference temperature limit.

TABLE III
SIMULATION RESULTS FOR INTERFERENCE TEMPERATURE LIMIT VERSUS SUM CAPACITY

Set	Interference Temp. Limit (I_n^{th}) (dBm)	Sum Rate (b/s/Hz) Up-Link *F=4*	Up-Link *F=2*	Down-Link *F=4*	Down-Link *F=2*
1	-120	292.89	243.09	237.75	195.11
2	-117	293.55	243.80	238.42	195.86
3	-114	293.55	244.57	239.16	196.63
4	-111	294.22	245.20	239.89	197.39
5	-108	294.99	245.89	240.46	197.90
6	-105	295.56	246.22	241.08	198.34
7	-102	296.18	246.90	241.95	198.94
8	-99	297.80	247.87	242.60	199.98
9	-96	298.30	248.83	243.16	200.83
10	-93	298.92	249.29	243.84	201.38
11	-90	299.66	249.90	244.50	201.96

$P_{\max}$ of 23 dBm for uplink and 20 dBm for downlink with number of femtocells $K = 10$ were used. Further, the number of users in each femtocells was either $F = 2$ or 4 with half of the users in each case treated as delay sensitive and other half as delay tolerant, and the minimum data rate requirement of delay-sensitive users in each femtocell fixed to $R_u = 9\,\mathrm{b/s/Hz}$. As expected, it can be observed in Fig. 10 that the sum capacity increases with the decrease in the interference tolerance temperature limit. The reason for this increase in sum capacity is that

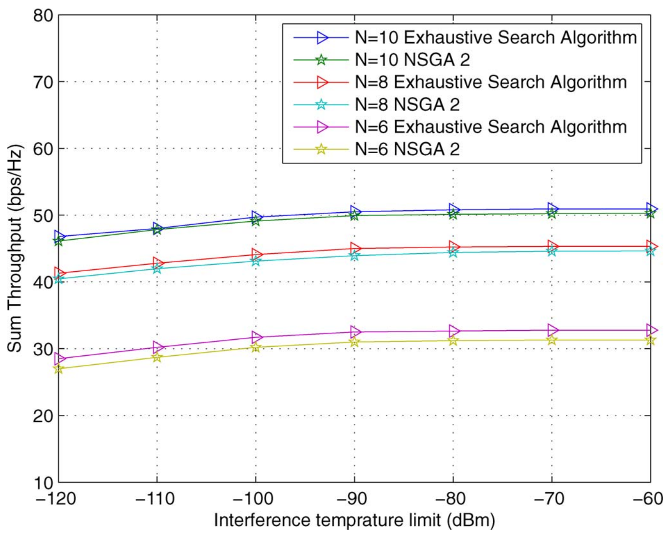

Fig. 11. Comparison with optimal solution of sum capacity achieved versus interference temperature limit.

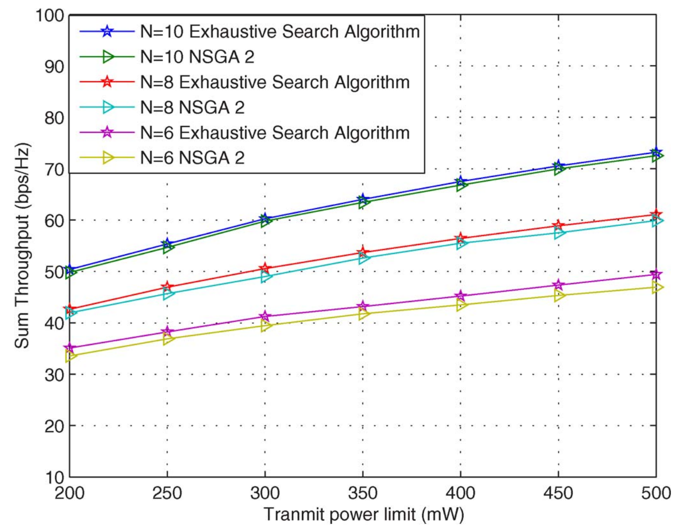

Fig. 12. Comparison with optimal solution of sum capacity achieved versus transmit power limit.

since decreasing the interference temperature limit increases the allowable tolerance of interference with macrocell users, this hence allows more subchannels to be shared between the macrocell and femtocell users. It can also be observed in the figure that with the increase in number of femtocell users F from 2 to 4, we get an increment of almost 20% in the sum capacity for both the uplink and downlink cases. Moreover, as the maximum allowed power $P_{\max}$ from downlink is 20 dBm as compared with 23 dBm for uplink, the sum capacity in uplink is almost 20% more than that in the downlink.

D. Comparison With Optimal Solution

Finally, in order to study the performance of the proposed solution with respect to the optimal solution, we compared the sum capacity obtained by NSGA-II with that by the exhaustive search method. For this comparison, we studied the effect of variation of interference threshold and transmit power limit on the sum capacity achieved by NSGA-II in comparison to the optimal solution. With the aim of reducing the time for calculating the optimal solution using exhaustive search, the number of femtocells and users in each femtocell was fixed to 2 each. A total of 200 channel realizations were simulated, and the the average of sum capacities obtained was then plotted.

Figs. 11 and 12 depict the comparison of sum capacities obtained by NSGA-II with optimal solution for different values of interference threshold and transmit power limit. As shown in these figures, we considered three different cases of number of subchannels in each femtocell. The sum capacity increased with the decrease in interference threshold and increase in the transmit power limit. The sum capacity also increased with the number of subchannels in each femtocell in both cases. Moreover, as the number of subchannels were increased, the gap between the optimal and the capacity obtained by NSGA-II decreased in both cases. This is in accordance with the expected performance of GAs; as the decision/solution space increases, GAs tend to provide better results. For the case of the number of subchannels equal to 10, the sum capacity achieved by NSGA-II was almost 93%–97% of the optimal. This reaffirms the fact that using NSGA-II for resource allocation in two-tier femtocell networks can provide close-to-optimal solution with significantly less computational cost. In the following subsection, we analyze the complexity of the proposed solution and compare it with the existing algorithm.

E. Complexity Analysis

In [18], the complexity for various stages of NSGA-II has been discussed. The complexity of the fitness function is combined at each stage of the algorithm to calculate the overall complexity. Evaluating the fitness function using objectives OB1 and OB2 [in (3) and (4)] involves three and two loops, respectively, to be executed for each individual in the population. The loop in OB1 involves summation over all the femtocells (K), and the number of users in each femtocell (F) and over all the subchannels (N) in each femtocell. These calculations are repeated for each individual N_p, where N_p is the population size, and hence involves a complexity of $O(N_pFKN)$. As discussed in Section III, the complexity of nondominated sorting is given by $O(O_bN_p^2)$.

The complexity of the crowding distance calculation part is governed by the sorting algorithm. Since M independent sorting of, at most, N_p solutions (when all population members are in one front I) are involved, the above algorithm has computational complexity $O(O_b \log_2 N_p)$. Finally, the tournament-selection algorithm requires selecting two individuals randomly from the entire population, resulting in a complexity of $O(N_p)$. Certain operations such as generation of random numbers, comparisons, accessing elements of array vectors, and mathematical operations have been assumed to take constant time. These operations occur for every generation. Hence, the total complexity can be calculated as

$$G \times \left[O(N_pFKN) + O\left(O_bN_p^2\right) + O(O_b \log_2 N_p) + O(N_p)\right] \cong O\left((N_pG)(FKN + O_bN_p)\right) \quad (5)$$

where $G =$ number of generations, N_p population size, $K =$ number of femtocells, $F =$ number of users in each femtocell, $N =$ number of subchannels in each femtocell, $O_b =$ number of objectives $= 2$. For some constant F, N, and K, the complexity of the algorithms is $O(GN_p^2)$ as compared with $O(FKN \log_2 N)$ for the existing algorithm and $O(K^{NF})$ for optimal exhaustive search. For the scenarios considered in comparison with exhaustive search, the exhaustive search algorithm took nearly 10–15 min to provide one solution as compared with a few seconds needed by NSGA-II. These simulations were executed on an Intel i-core 3 2.1-GHz processor with 4-GB RAM.

V. Conclusion

In this paper, the use of NSGA-II has been proposed for joint subchannel and power allocation in OFDMA-based two-tier femtocell networks. The results obtained by the algorithm are found to be suitable for different sets of femtocells and interference temperature limits, taking multiple conflicting objectives into account. The simulation results indicate that the optimized sum rates obtained by the proposed method are significantly higher than those obtained by the existing method. Specifically, the sum capacity, which is given by the sum of capacity of delay-tolerant and delay-sensitive users, obtained by the proposed algorithm was consistently higher than that obtained by the above method. The main advantage of our proposed algorithm is that it strictly satisfies the minimum capacity requirements of delay-sensitive users as compared with the existing methods. The proposed algorithm satisfies this and other constraints at the cost of slight reduction in delay-tolerant capacity; however, it provides much better results for our main objective of maximizing the sum capacity. Moreover, the proposed algorithm utilizes the maximum power available for transmission efficiently. Moreover, with increase in the number of subchannels, the proposed algorithm provides sum capacity close to optimal solution. For the case of the number of subchannels equal to 10, the sum capacity achieved by NSGA-II was almost 93%–97% of the optimal.

The proposed method can be modified and used for different scenarios involving resource allocation for cognitive femtocell systems, femtocells with multiple antennas, and any other such problem involving multiple conflicting objectives. Future work of this paper could be resource allocation in any such scenarios and for resource allocation with partial channel state information.

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