Telecommun Syst (2016) 63:99–110
DOI 10.1007/s11235-015-9976-x

Realistic framework for resource allocation in macro–femtocell networks based on genetic algorithm

Hanaa Marshoud · Hadi Otrok · Hassan Barada · Rebeca Estrada · Abdallah Jarray · Zbigniew Dziong

Published online: 17 March 2015

Abstract In this paper, we consider the problem of resource allocation in non-dense macrocell–femtocell networks. We build a comprehensive realistic framework that overcomes the limitations of previous research work such as (1) resources underutilization due to the equal transmitted power per subcarrier in macrocell, (2) lack of femtocells selection mechanism that grant access to public users without depriving their own subscribers. Orthogonal Frequency Division Multiple Access is a promising candidate for efficient spectrum sharing techniques as it eliminates intracell interference. We propose a base station selection and resource allocation model for two-tier networks that is able to: (i) maximize the overall network throughput, (ii) find the appropriate serving base station for each mobile user, and (iii) jointly assign bandwidth and power to each user. The proposed approach is based on Genetic Algorithm (GA) technique since this technique allows to find a near optimal solution and to speed up the optimization process. Simulations are conducted under realistic scenarios where user mobility and resource reservation are taken into account. The performance of the proposed approach is compared with a Mixed Integer Linear Programming (MILP) approach and the Weigthed Water Filling (WWF) algorithm.

Keywords Femtocell · Macrocell · Resource allocation · Optimization theories · Linear programming · Genetic algorithm

H. Marshoud (✉) · H. Otrok · H. Barada
Department of Electrical and Computer Engineering, Khalifa University of Science, Technology and Research, Abu Dhabi, UAE
e-mail: hanaa.marshoud@kustar.ac.ae

H. Otrok
e-mail: hadi.otrok@kustar.ac.ae

H. Barada
e-mail: hassan.barada@kustar.ac.ae

H. Otrok · A. Jarray · Z. Dziong
Department of Electrical Engineering, Universite du Quebec, Ecole de Technologie Superieure, Montreal, QC, Canada

A. Jarray
e-mail: Abdallah.Jarray.1@ens.etsmtl.ca

Z. Dziong
e-mail: Zbigniew.Dziong@ens.etsmtl.ca

R. Estrada
Electrical Engineering and Computer Science Faculty, ESPOL, Guayaquil, Ecuador
e-mail: restrada@espol.edu.ec

1 Introduction

Femtocells (FCs) are low-cost, low-power base stations deployed in homes or business enterprises. They can provide high signal-to-noise ratio (SNR) in a small coverage area to improve the quality of service (QoS) and data rates.

Femtocell deployment is expected to witness continuous growth in coming years. Despite all the advantages that this technology brings, there are still some challenges that need to be addressed such as interference management between femtocells and the overlaying macrocell (MC) and the resources allocation among the two tiers.

Femtocell access control mechanisms are classified as closed access or closed subscriber group (CSG) and open access (OA). In closed access, only a limited number of users known as subscribers is allowed to access the FC, while any user is allowed to connect to the FC in the open access mode. CSG is more demanded in home environments since it allows the subscriber to get full benefit from his FC, however this access mode has the drawbacks of limiting network capacity and increasing interference. Open access offloads traffic from MC and therefore network capacity is enhanced but it requires more communication between MC and FCs [32]. A hybrid access approach can find a trade-off between both access modes, since in this case the FC can share a part of its resources with public users without depriving its own subscribers.

Since the increasing demand for higher data rates is the key driver for femtocell technology, orthogonal frequency-division multiple access (OFDMA) is a good candidate for 4G femtocell networks [20]. In a non-dense two-tier network, subchannels assignment can be done by splitting the available spectrum into two parts (i.e. spectrum partitioning). In this way, different subchannels are used by the two tiers avoiding the interference.

Bandwidth allocation has been widely studied in literature. In [30], the main concern is the assignment of the licensed spectrum among both tiers and the majority of this work assumes fixed power transmission for all connections in the macrocell. In [12], frequency assignment and power control is performed in femtocells to minimize coverage holes at the macrocell edge. The work in [2] has shown the effect of changing the maximum transmitted power per connection basis in a multi-macrocell framework. A joint power and bandwidth assignment based on the Hungarian algorithm is carried out in [6] to minimize power consumption and improve QoS. Linear programming was used in [13] to solve the resource allocation problem together with base station selection. The main drawbacks of this approach are the high running time required to find the optimal solution and lack of the mobility incorporation.

The limitations of previous approaches can be summarized as follows:

- High complexity and long computation time makes the solution unpractical for real implementations.
- Lack of management techniques that consider user mobility.
- Lack of real traffic demand models that consider time-varying demand and time reservation.

In this paper, we propose a genetic algorithm (GA) based solution that performs base station selection together with resource allocation. The GA is a heuristic technique that generates solutions inspired by natural evolution. GA is a good candidate to bias the search toward a satisfying near-optimal solution while having the advantage of speeding up the optimization process [26]. The proposed model aims to maximize system throughput through the selection of the best serving BS and resources, i.e. bandwidth and power, for each user. This is done based on a spectrum partitioning approach, where each tier allocates a different part of the available bandwidth, which means that the cross-tier interference is avoided.

For comparison purposes, we implement the linear programming approach [13] that obtains the optimal solution and a heuristic approach using a modified version of weighted water filling (WWF) algorithm proposed in [16]. Simulations are conducted and the three models are tested under realistic conditions where user mobility and time reservation are considered.

In summary, our contribution is a GA-based model that is able to:

- Assign power and bandwidth based on spectrum partitioning.
- Select the set of users that will be connected to each BS.
- Maximize the throughput regarding users' demands and QoS requirements.
- Consider reservation of time slots in established calls.
- Reduce the impact of handover due to mobility.
- Have a near-optimal solution within short time compared to linear programming.

The remainder of this paper is organized as follows. Section 2 describes the problem statement. Proposed resource allocation model is described in Sect. 3. The implementation of GA and the benchmark models is described in Sect. 4. Section 5 illustrates simulation results. Section 6 presents related work. Finally, the conclusions are given in Sect. 7.

2 Problem statement

Dense femtocell deployment is expected in the coming years. This technology improves indoor coverage and provide high data rates inside homes and enterprises, but it should also be able to offload traffic from the expensive overlaying macrocell into the low cost public internet backhaul. To achieve this goal, a hybrid access mode should be applied for femtocells. It was shown in [17] that a hybrid access mode can improve the system capacity and QoS without causing unnecessary signaling overhead.

Let's assume a network with one macrocell and one femtocell as illustrated in Fig. 1, mobile user MU_1 is a femtocell subscriber and is located inside the femtocell coverage, so he is served by his own femtocell, while MU_2 is a public user that is passing near the femtocell. There are two possible ways to connect him to the mobile core network: (1) by femtocell, assigning low power, or (2) by macrocell, assigning high power. These two possible connections are indicated in Fig. 1 by L_1 and L_2 respectively. The L_1 link conditions depend on the modulation technique required in the FC, while the L_2 link conditions depend on the modulation technique in macrocell zone. For example, if FC uses 16-QAM as modulation technique and the macrocell zone Z_3 uses QPSK, the better option for user MU_2 is to be served by the femtocell instead of macrocell since it requires less power and

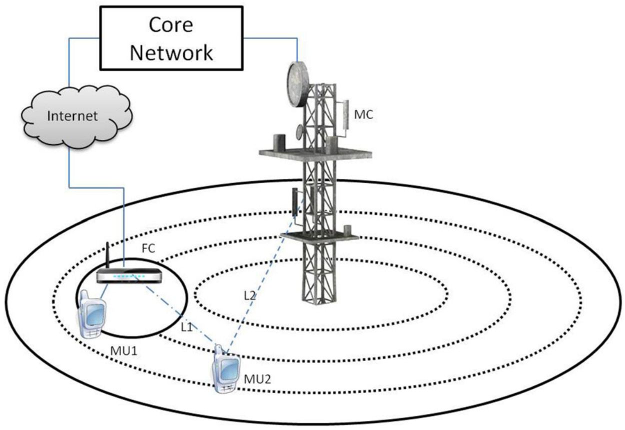


Fig. 1 Macrocell–Femtocell network

less bandwidth. It requires less bandwidth since the number of bits required for the modulation technique is higher in FC. In general, link conditions between public users and BS (i.e. macrocell and femtocells) should be investigated before choosing the serving base station.

Once base station selection is carried out, the amount of resources to be granted to the user should be determined. Bandwidth allocation [3,10,11] as well as power control [6,7,12] have been widely studied in literature. The main shortcoming of previous approaches is the lack of a base station selection mechanism that determines the optimal serving station for each user in order to improve two-tier network performance. To the best of our knowledge, resource allocation has not been evaluated under more practical circumstances such as user mobility and varying traffic conditions. In our approach, we support user mobility to offer a seamless voice and data service to users. The proposed model includes a mechanism to reduce the ping-pong effect when the handover is performed. Time-varying user traffic is also addressed since all users are not connected to the network at the same time and they do not withdraw from it after equal periods.

3 Problem formulation

In this section, we describe our proposed base station selection and resource allocation model and its implementation.

We investigate the resource allocation problem in non-dense femtocells deployment where spectrum partitioning is applied by means of orthogonal subcarriers allocation. We assume that a FC cluster is deployed under the coverage of an overlaying macrocell. This makes the resource allocation (RA) problem more clear, since a user of one femtocell could be connected to another femtocell or to the macrocell if he changes his location. We assume that the coverage area of macrocell is divided into four zones and each zone has a different modulation scheme and SNR target [28] as shown in Table 1. The parameters used in our model are described in Table 2.

Table 1 Zones assumptions

Zone	Modulation scheme	Bits/symbol	SNR target
Z_1	64-QAM	6	22.4
Z_2	16-QAM	4	16.24
Z_3	QPSK	2	9.4
Z_4	BPSK	1	6

Table 2 Model parameters

Name	Description
B_{tot}	Total available bandwidth
P_{tot}	Maximum Transmitted Power
R_m	MC's Radius
R_f	FC's Radius
γ_m	Outdoor attenuation factor
γ_f	Indoor attenuation factor
C_z^{max}	Maximum capacity per zone
$L_{m,z}^{mod}$	Bits per symbol per MC's zone
L_f^{mod}	Bits per symbol in FCs
N_0	Average noise power
N	Number of mobile users
N_f	Maximum number of users in FC
d_i	Distance from the user to the BS
S_i	Demand of mobile user (Mb/sec)

3.1 Objective function

Our objective is maximization of the network throughput, which is calculated using Shannon's Law and given by Eq. (1).

$$T = \sum_{k\in\{m,F\}} \sum_{i\in\{N\}} x_i^k b_i \log_2(1 + SNR_i) \tag{1}$$

where x_i^k is a binary parameter to represent that the base station k serves user i. Thus, x_i^k is set to 1 if the user i is being served by the base station k, and it is set to 0 otherwise. The variable b_i represents the bandwidth assigned to the user i and SNR_i is the signal-to-noise ratio of the connection between base station k and user i and is calculated as:

$$SNR_i = P_i \big/ (PL_i \times N_0) \tag{2}$$

where P_i is the variable that represents the power assigned to user i, PL is the path loss and N_0 is the average noise in the system. Path loss is calculated using non-line-of-sight (NLOS) propagation model in [1] and it is given by Eq. (3).

$$PL_i(dB) = \begin{cases} 10log_{10}(d_{im}^{\alpha_m}) + 149, & \text{for MC users} \\ 10log_{10}(d_{if}^{\alpha_f}) + 37, & \text{for FC users} \end{cases} \tag{3}$$

where d_{im} is the distance from the user i to the MC and is given in kilometers and d_{if} is the distance from the user i to the FC k and is given in meters.

In order to maximize the Eq. (1), we need to optimally utilize both power and bandwidth.

3.2 Model constraints

For our objective function presented in (1), we have the following constraints given in Eqs. (4–7) :

- **Total available bandwidth:** the sum of the assigned bandwidth should be less than or equal to the total available bandwidth B_{tot}.

$$\sum_{i=1}^{N} b_i \leq B_{tot}. \tag{4}$$

- **Maximum transmitted power:** the sum of power assigned to users should be less than or equal to maximin transmitted power allowed.

$$\sum_{i=1}^{N} P_i \leq P_{tot}. \tag{5}$$

- **Shannon's law capacity in MC:** the number of bits per symbol should be greater than target spectral efficiency in zone z.

$$\log_2(1 + SNR_i) \geq L_{m,z}^{mod} \tag{6}$$

- **Shannon's law capacity in FC:** the number of bits per symbol should be greater than target spectral efficiency of the femtocell f.

$$\log_2(1 + SNR_i) \geq L_{f}^{mod} \tag{7}$$

where SNR_i is the signal-to-noise ratio of the transmission between user i and the serving base station, i.e. the macrocell or near femtocell.

3.3 User mobility and time reservation

A mobile user may be moving while engaged in a call, this movement could imply that the user leaves the coverage area of his current serving BS and be handed over to another BS. In addition, the user movements might require an adjustment of the transmitted power to meet the SNR target. Our realistic framework considers the user mobility using the random walk as the mobility model [4]. In this mobility model, a mobile user changes his location by randomly choosing a direction between 0 and 2Π and a speed between 0 and 10 m/s.

We also consider the time reservation. Since users do not initiate their calls together and do not hold the calls for the same time period, our model allows users to join the network at different times and to end their calls after different time slots.

4 Resource allocation algorithms

In this section, we present the implementation of the GA based resource allocation model described in Sect. 3. For the comparison purposes, we implement two benchmark models

4.1 Genetic algorithm based model

Genetic algorithm is a heuristic technique premised on the evolutionary computing. This technique has been proven to reach a satisfying near-optimal solution for complex models where reaching the global optimum is complex and time consuming. GA represents the solutions as individuals or chromosomes and a group of individuals form a population. A fitness evaluation is done based on an objective function to choose parents for reproduction, where individuals with higher fitness have a bigger chance to survive and the next generation inherits even better characteristics. Crossover between the selected parents is done and then mutation is performed on the new generation in order to widen the search space and escape from local optima [27]. GA can be applied to any problem where the solution can be represented as a string and there is a way to evaluate the fitness of the solution [9].

The fitness function is the objective function given by (1). After the first population is randomly generated, the fitness evaluation is performed. Parents selection for reproduction is done using roulette wheel in such way that solutions with higher fitness have a bigger chance for survival. Double point cross-over is performed to produce the new solutions. Then, a mutation rate of 1 % is applied on the new offspring before including them in the population. The fitness of solutions notably improves as this process is repeated. A termination method stops the evolution when the fitness is estimated to converge. Two filters of different lengths are used to smooth the best fitness across the generations. When the best fitness from the long filter is less than 5 % away from the best fitness from the short filter, the evolution terminates.

4.1.1 BS selection

Femtocells are assumed to allow some public users to be connected to them together with own subscribers. A decision should be made for each user to determine whether he gets access to the core network via MC or a nearby FC. In

Table 3 System parameters

Name	Description	Value
B_{tot}	Total available bandwidth	200 MHz
P_{tot}	Total available power	56 dBm
R_m	MC's Radius	500 m
R_f	FC's Radius	20 m
γ_m	Outdoor attenuation factor	3.7
γ_f	Indoor attenuation factor	3
C_z^{max}	Maximum capacity per zone	(10, 7, 5, 1)
$L_{m,z}^{mod}$	Bits per symbol per MC's zone	(6,4,2,1)
L_f^{mod}	Bits per symbol in FCs	(6,4,2,1)
N_0	Average noise in the system	105 dBm
N	Number of mobile users	100
N_f	Maximum number of users in FC	5

order to guarantee the FC subscriber priority, a public user can be served by a FC if he is located inside FC's coverage as long as his connection does not deprive subscriber transmissions. In this way, MC traffic can be offloaded and allow a higher number of users to be served. Therefore, the following constraints should be considered during BS selection stage in order to determine the output parameter that associates each user to a BS, x_i^k.

– User i can be connected only to one BS.
– Number of users in each FC should be less than or equal to number of allowed users, N_f.

4.1.2 Dual bandwidth and power assignment

Dual bandwidth and power assignment is performed to distribute the available resources among users with the purpose of maximizing the overall system throughput. A portion of the available bandwidth is assigned to each user according to his demand and location. In macro tier, the bandwidth assigned to each user should be less than or equal to minimum value between his demand S_i, and the maximum allowed capacity per zone, C_z^{max}, divided by the number of bits per symbol required for the modulation scheme in the MC zone. In femto tier, bandwidth assigned to each user should be less than or equal to his demand divided by the number of bits per symbol required for the FC modulation scheme. Eqs. (8) and (9) give the upper bound for bandwidth to be allocated to a user in macro tier and femto tier respectively.

$$b_i^{max} = \frac{min(S_i, C_z^{max})}{L_{m,z}^{mod}} \tag{8}$$

$$b_i^{max} = \frac{S_i}{/} L_f^{mod} \tag{9}$$

where $L_{m,z}^{mod}$ and L_f^{mod} are the number of bits per symbol per MC's zone z and in FCs respectively as shown in Table 3.

After that, Downlink (DL) transmitted power assignment is done such that the SNR target values presented in Table 1 are met.

The GA based resource allocation model is presented in Algorithm 1.

Input: At each time interval the MBS collects
S: the demand of each user.
d: the location of each user.
L_f^{mod}: modulation scheme in the femtocell.
Output: Bandwidth, power and serving base station for each user.
while *new users join the network* **do**
1 . Find the serving base station for each user based on link-rate calculations.
2 .Randomly generate the first population. **repeat**
III . Calculate the fitness of each individual using the pre-defined objective function and save the best solution.
IV . Apply the selection process on the parents to select parents of the next offspring.
V . Produce a new generation by applying the cross-over operator on selected parents.
VI . Apply mutation to enrich the new generation with new solutions.
VII . Calculate the fitness of the new offspring and update the best solution if any.
until *stopping conditions are met*;
end

Algorithm 1: GA-based model

4.2 MILP based model

A mixed integer linear programming model was proposed in [13] to perform base station selection together with resource allocation. The proposed model aims to maximize the entire network throughput, which means optimizing the sum of achievable data rates according to Shannon's capacity law. Although MILP method can obtain the optimal solution, it has the drawback of time-consuming calculations which makes it unpractical for real implementations. In this work, we implement their MILP model to consider a realistic scenario with user mobility incorporation and the time varying demand.

4.3 Weighted water filling model

In [16], the resource allocation model for a macrocell–femtocells network is proposed using the weighted water filling algorithm. In this approach, bandwidth allocation is performed based on user demands. The analyzed scenario consists of a single FC located in the coverage area of one MC. The base station selection is pre-fixed and depends on link conditions. The drawback of this approach is that if the number of public users attempting to join the FC is greater than its capacity, it might result in public users being blocked and there is no procedure defined to redirect the blocked users to the MC.

This approach introduces the concept of weights to prioritize the subscriber transmissions over public users inside their FC. After BS selection is performed, the macrocell algorithm runs taking into account each FC as a macro user with demand and weight equal to the sum of demands and weights of all the users associated to it. Then, the FC algorithms run independently using as available bandwidth the value allocated from the MC algorithm. In each BS, users are sorted according to their weighted demand. The user weighted demand is equal to his demand divided by his weight. Then, bandwidth allocation is done round by round until users demands are satisfied or the total available bandwidth is exhausted.

The modifications included on this algorithm are:

1. We consider several femtocells located under the coverage of the macrocell. Thus, BS selection is done by calculating the link rate from each user to each BS and the base station with highest link rate serves the user.
2. Power assignment is calculated based on the SNR target.

Our modified version of the WWF algorithm is presented in Algorithm 2.

Input:
S: the demand of each user.
d: the distance between user and MBS.
d_f: distance between FBS and MBS.
L_f^{mod}: modulation scheme in the femtocell.
Output: Bandwidth, power and serving base station for each user.

```
/* MC's Algorithm */
```
while *new users join the network* **do** the MC
1 . Find the serving base station for each user based on link-rate calculations.
2 . Sort macro users according to their weighted demand
Solve:
3 . Calculate the bandwidth to be assigned for each user $i \in M + F$.

$$b_i = min\left(\frac{b_i^{required} - b_i^{k-1}}{w_i^m}, \frac{B - \sum_{k=1}^{i-1}\sum_{j=k}^{M+F} b_j}{\sum_{j=i}^{M+F} w_j^m}\right)$$

4 . Calculate the power to be assigned for each user $i \in N_f$ according to SNR value
end

```
/* FC's Algorithm */
```
while *new users join the network* **do** the FC
1 . At each time interval t the FBS do:
2 . Sort femto users according to their weighted demand
Solve:
3 . Calculate the bandwidth to be assigned for each user $i \in N_f$.

$$b_i = min\left(\frac{b_i^{required} - b_i^{k-1}}{w_i^m}, \frac{B - \sum_{k=1}^{i-1}\sum_{j=k}^{N_f} b_j}{\sum_{j=i}^{N_f} w_j^m}\right)$$

4 . Calculate the power to be assigned for each user $i \in N_f$ according to SNR value
end

Algorithm 2: WWF algorithm

5 Simulation results

In this section we present the network configuration and simulation results using the three different approaches: GA, MILP and WWF. Simulation results were conducted using: (1) Visual C++ Studio 8.0 and (2) IBM ILOG Cplex 12.1: Concert Technology Environment.

5.1 Network configuration

We used the same physical layer assumptions as in [28], where MC coverage area is decomposed into 4 zones which are assumed to be concentric circles. Each zone uses different modulation technique and requires different SNR target as shown in Table 1. This is very helpful in the study of two-tier MC-FC networks as the spectral efficiency decreases when users get further from the BS. SNR target value depends on the modulation scheme and represents the minimum SNR that the user should receive to avoid data losses. Five femtocells are located in the macrocell coverage area forming a cluster. The number of bits per symbol required for the FC modulation scheme should be higher than the number of bits per symbol required for the modulation scheme in the MC zone where the user is located. Thus, the FC transmission link requires less bandwidth than the MC transmission link. The number of bits per symbol in the femtocells are randomly generated with values of 6, 4 or 2 with equal probability, which corresponds to have different modulation techniques (64-QAM, 16-QAM and 4-QPSK respectively). FCs are not located in Z_1 since the user can be connected to the near MC and achieve higher data rate. Table 3 shows the system parameters used in the simulations.

Simulations are conducted periodically for 20 consecutive time periods where each time period has the duration of 5 s. Simulation starts with 50 mobile users initiating their calls in the macrocell–femtocells network. User locations are randomly generated such that 50 % of them are in the FC vicinity and 20 % are femtocell subscribers. The percentage of users leaving the network at any time interval is 5–20 %, while percentage of arriving users is 5–25 %. Every 5 s interval, the control module in the macrocell updates its data by collecting statistics from the mobile users, then the resource allocation problem is carried out to assign power, bandwidth and serving base station to the new users.

5.2 Performance analysis

In the following, we show the performance of the three RA models: MILP, GA and WWF used to solve the resource allocation problem described in Sect. 3.

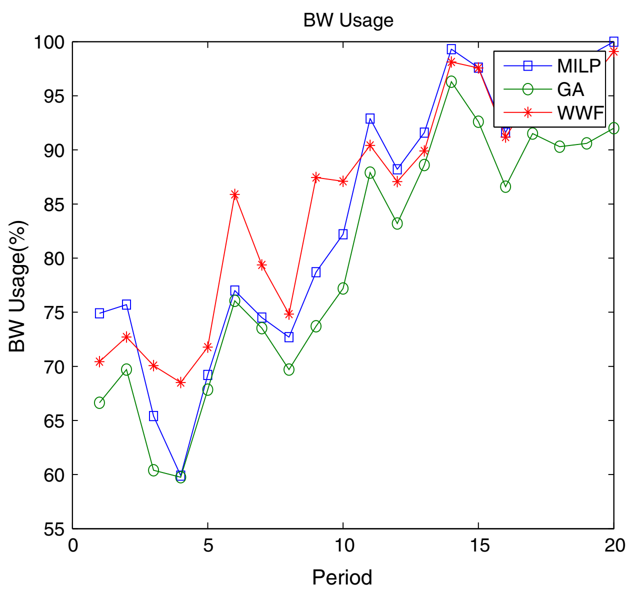


Fig. 2 BW usage

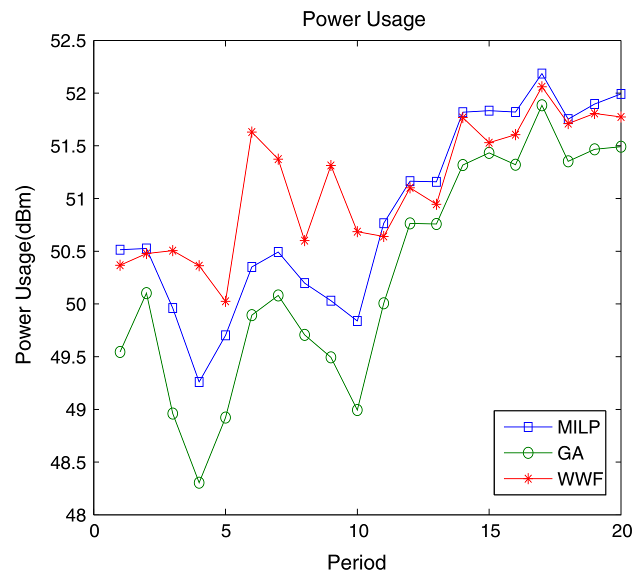


Fig. 3 Power usage

Bandwidth usage is the ratio between the bandwidth allocated to macro and femto users and the total available bandwidth and it is given by Eq. (10).

$$BW_{usage} = \frac{\sum_{i=1}^{N} b_i}{B_{tot}} \tag{10}$$

Power usage indicates the sum of assigned power for DL transmission from the MC to macro users, which is given by Eq. (11). Power usage in FCs is not considered due to low power levels.

$$P_{usage}(dBm) = 10log_{10}\left(\frac{(\sum_{i=1}^{N} x_i^m P_i)}{1mW}\right) \tag{11}$$

Figures 2 and 3 shows bandwidth and power usage for the three algorithms. Bandwidth allocation is performed to maximize the objective function defined in Eq. 1. The performance of the GA algorithm is very close to the MILP algorithm. The WWF algorithm is able to utilize a large portion of the available bandwidth, which is due to the fair resource allocation criteria described in Sect. 4.3.

The MILP model utilizes more transmitted power than the GA model by assigning the optimal power for each DL transmission. In the GA model, power was assigned according to SNR calculations as shown in Eq. (2). Thus, the power assigned for a DL transmission should be high enough to reach the target SNR of the MC zone, which is considered by means of Shannon's law in Eqs. 6 and 7. While the power allocation in WWF algorithm is also based on SNR calculation, the power consumption is different from the GA algorithm case. This is due to the different BS selection procedure in both algorithms. In WWF, resources are allocated to users after sorting them in a descending-demand order, thus some users may be connected to a far BS because the near BSs are already occupied by users who were handled first. Therefore, the WWF algorithm gives the largest power consumption.

5.2.1 System throughput and user satisfaction

User satisfaction is defined as the ratio between the sum of assigned user data rates and the sum of demands and it is given in Eq. (12).

$$D = \frac{\sum\limits_{k\in\{m,F\}} \sum\limits_{i\in\{N\}} x_i^k b_i L_{k,z}^{mod}}{\sum_{i=1}^{N} S_i} \tag{12}$$

The system throughput is calculated as the sum of Shannon's link capacities given by Eq. (1) in Sect. 3. Shannon's Capacity gives the maximum data rate over a communication channel.

As seen from Figs. 4 and 5, MILP achieves the highest system throughput and user satisfaction whereas GA performs better than WWF algorithm. The weak performance of WWF is due to the BS selection criteria, mentioned previously, causing that some users may be connected to a non-optimal base station where the base station that have the highest link rate from the user is fully-loaded.

Incremental Traffic Scenario: Under incremental traffic scenario, simulations start with 20 users in the network. Then the number of users continues to increase in each interval. Bandwidth usage and the achievable system throughput versus number of users for such scenario are shown in Figs. 6 and 7. It can be seen that both MILP and GA maintain

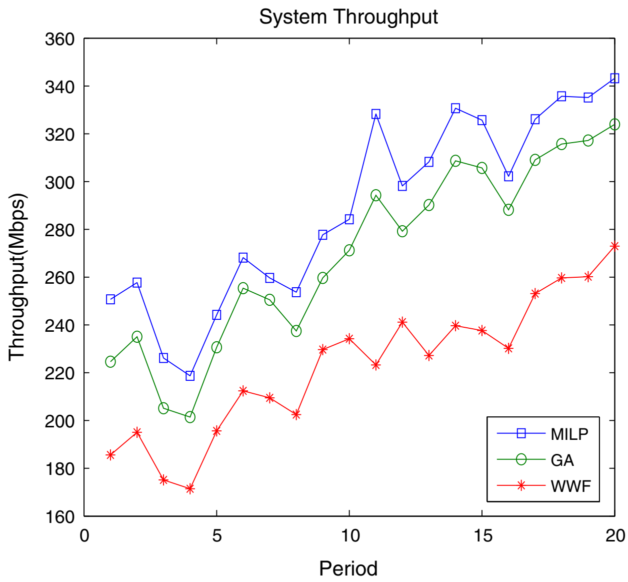


Fig. 4 System throughput

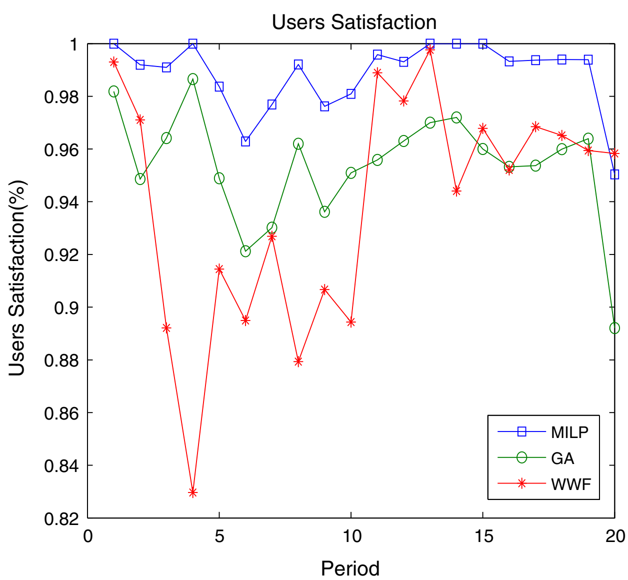


Fig. 5 User satisfaction

high system throughput despite the continuous increase in the number of users being served. In case of WWF, the system throughput drops rapidly although it utilizes a large part of the available spectrum.

5.2.2 Mobility analysis

Figure 8 shows the number of executed handovers. Frequent handovers have a bad impact on the system performance and may lead to an increase in the call-drop probability [25]. As we can see from Fig. 8, the number of handovers in the GA and WWF models is higher than in the MILP model. To

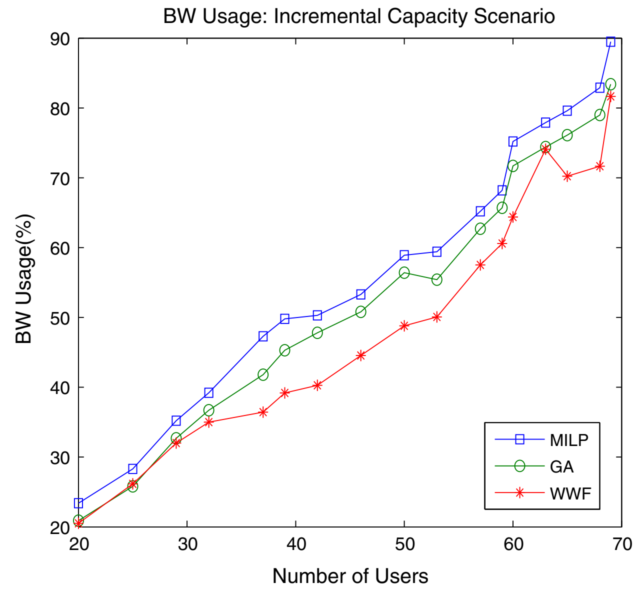


Fig. 6 BW usage: incremental capacity scenario

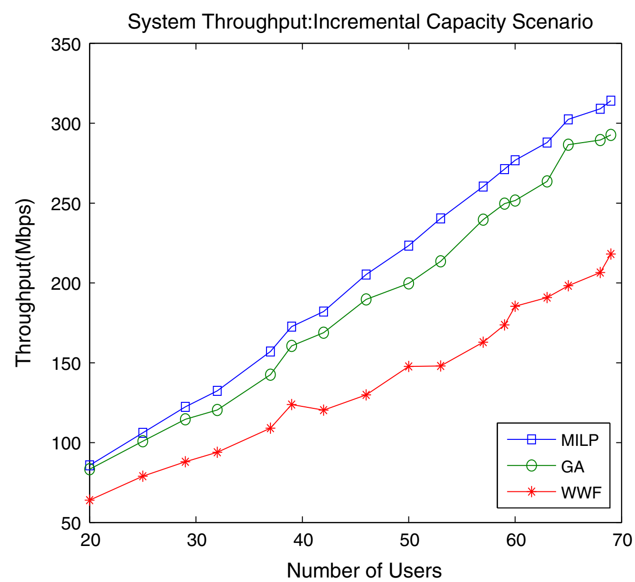


Fig. 7 Throughput: incremental capacity scenario

reduce the number of unnecessary handovers, we propose a mechanism to avoid the so-called ping-pong effect. Ping-pong effect is undesirable and occurs when a mobile station is handed over to an adjacent BS and then returns back to the original BS in short time [29]. Since the FC coverage area is small, it is very likely that too many handovers take place for a mobile user that is moving in the proximity of neighboring FCs. The elimination of the ping-pong effect is done by saving a record of the BSs that the mobile station joins in a particular call. If the mobile station is handed over from FC A to FC B and then attempts to join A again, the handover is not performed and the mobile station is directly connected

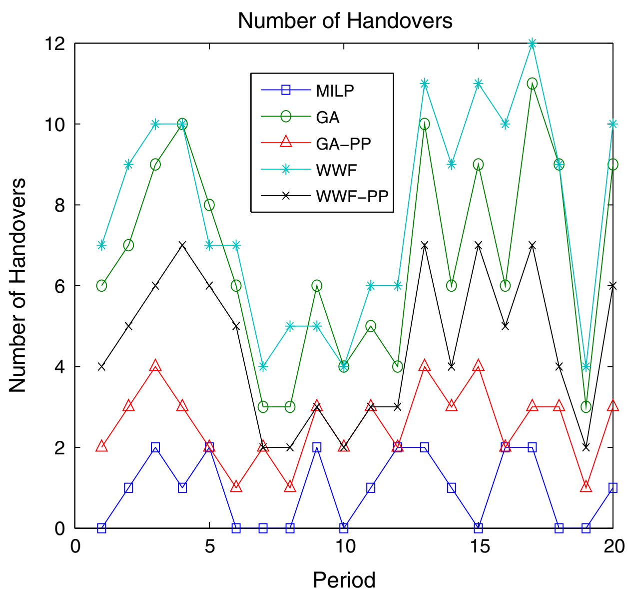


Fig. 8 Reduction of unnecessary handovers

to the MC. In this way, a better connection is guaranteed by avoiding frequent handovers that could cause a call drop. Figure 8 shows the number of executed handovers for both GA and WWF models, where $GA\text{--}PP$ and $WWF\text{--}PP$ indicate the ping-pong free GA and WWF algorithms respectively.

5.3 Complexity

Table 4 presents the running time for the three algorithms. It is worth to notice that the MILP consumes much higher time for simulations [13]. This is the main reason to find alternative optimization techniques to solve the proposed resource allocation problem. As can be seen from the table, when number of users changes from 40 to 50, the MILP running time was almost doubled, while the GA maintains the lowest calculation time. This is due to the stopping criteria that exits the search when a semi-steady solution is produced. Simulation results show that the GA succeeds to reach near-optimal solutions in a very short time which makes it a viable candidate for practical implementations. This is because the GA based approach solves the RA problem for new users each period of time taking into account time reservation, while MILP and WWF needs to work on the whole network users at once. Moreover, MILP looks at all the possible solutions, which results in high computational complexity. The convergence of the GA is shown in Fig. 9.

6 Related work

In this Section, the prior work in the field is presented in three parts: RA in two-tier networks, mobility management in two-tier networks and the implementation of heuristic techniques in solving RA problems.

Table 4 Running time (s)

No. of users	MILP	WWF	GA
10	0.04	0.02	0.02
20	0.14	0.06	0.05
30	0.42	0.09	0.07
40	1.06	0.12	0.09
50	2.07	0.16	0.11

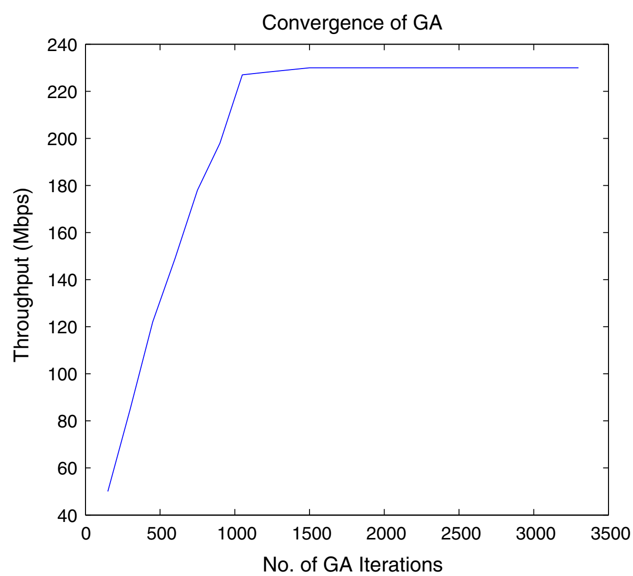


Fig. 9 Convergence of GA

6.1 Resource allocation in OFDMA two-tier networks

Most of the research work using OFDMA technology assumes equal distribution of transmitted power among all the subcarriers in macrocell. Thus, RA problem is reduced to allocate subcarriers with equal power in macrocell that maximizes network capacity under scenario with sparse or dense deployment of femtocells. In sparse deployment, subcarrier allocation uses dedicated subcarriers in each tier as in [10]. Conversely, subcarriers must be shared between MC and FCs in dense deployment and interference management techniques must be implemented to enhance network throughput such as adaptive or combined spectrum usage and power control [8,19].

In [10], a spectrum allocation that separates MC and FCs frequency channels in a hierarchical cell arrangement is proven to have a higher data rate satisfaction rather than the shared spectrum, in addition to avoiding the co-channel interference resulting from spectrum sharing.

A distributed resource assignment scheme is proposed in [11]. In this scheme, MC utilizes the entire available bandwidth while FCs can access only a randomly chosen limited portion of the bandwidth to reduce the number of femtocells interfering with MC per time interval. The limitation appears in dense deployments where the spectrum portion assigned to FCs may not be adequate to fulfill their users' needs.

Hybrid spectrum usage is used in [3], where each femtocell is allowed to choose its spectrum usage mode, either shared or dedicated according to its location and traffic. The proposed method aims to increase the area spectral efficiency which is defined as the achievable throughput per unit area.

In [7], power control is carried out in femtocell tier through the determination of the maximum allowed connection transmitted power in FCs in such a way that they do not degrade the service given to macro users operating in same channel. In [12], power control is carried out in FCs to minimize coverage holes at the macrocell edge. A joint power and bandwidth assignment based on the Hungarian algorithm is carried out in [6] to minimize power consumption and improve QOS provided for users.

In [22], we have proposed a joint power and bandwidth resource allocation (RA) together with base station selection in a hybrid-access two-tier network with spectrum partitioning approach. In [21], we have considered a dense deployment of femtocells where full spectrum sharing approach is needed. In such a scenario, severe interference can be generated for femto and macro users. Thus, interference mitigation techniques are required to ensure good system performance.

6.2 Mobility management in two-tier networks

Mobility of femtocell users is considered in [5], where orthogonal sub-bands are assigned to adjacent FCs to eliminate inter-cell interference and enhance the system performance. Probabilistic mobility prediction is carried out in [15] to decide whether a FC should accept an arriving new call or handover. This is done in order to optimize bandwidth utilization and reduce call blocking probability. In [31], handover parameters optimization method is proposed based on Ant Colony Algorithm. Simulations shows that the proposed scheme outperforms the fixed parameters strategy.

6.3 Implementation of heuristic techniques in RA models

Heuristic techniques have been widely proposed for solving resource allocation problems in mobile networks. GA has been used in femtocells network to perform power control such as the distributed approach in [14] to minimize coverage holes and balance users' distribution among FCs or the centralized approach in [23] to increase coverage and reduce femto-femto interference. In [24], frequency allocation and power control in femtocells network is carried out using both centralized and distributed GA in order to maximize the network capacity. The work in [33] showed that the genetic algorithm performed well at satisfying QoS requirements of users in an OFDMA wireless communication system. Joint power control and channel allocation is proposed in [18] where particle swarm optimization is used to maximize the minimal throughput of the femtocells.

Main concern of prior work was the resources allocation among both tiers such that interference effects are minimized or avoided but it did not specify a mechanism for base station selection for each user. In addition, it did not specify the amount of access that should be granted to public users in FCs. Moreover, noise effects has not been evaluated in spectrum partitioning approaches where noise is the only capacity-limiting parameter that affects SNR. Genetic Algorithm was proven to be a good candidate to solve resource allocation problems and it has the advantage of speeding up the optimization process.

7 Conclusion

A spectrum partitioning based resource allocation model was introduced for non-dense femtocell deployments. User mobility and time reservation were considered in a network with one macrocell and a cluster of five underlaid femtocells. The proposed model was able to (1) find the best serving base station for each user, and (2) allocate power and bandwidth resources among the users. Simulations showed that the GA was able to provide very good results that are close to the optimal results, while GA reduces the calculation time which is a major requirement in mobile communications. On the other hand, GA performed better that the modified WWF algorithm in terms of resources utilization, system throughput and user satisfaction. Therefore, the proposed approach is a good candidate to solve the resource optimization problem for macro–femtocell networks.

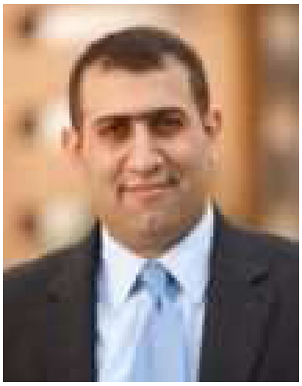
References

1. Guidelines for evaluation of radio transmission technologies for imt-2000. In *ITU-R Recommendations ITU R M.1225*.
2. Alsawah, A., & Fijalkow, I. (2008). Resource allocation in ofdma downlink with reduced feedback overhead. In *IEEE 19th International Symposium on Personal, Indoor and Mobile Radio Communications, PIMRC 2008. September 2008* (pp. 1–5).
3. Bai, Y., Zhou, J., & Chen, L. (2009). Hybrid spectrum usage for overlaying lte macrocell and femtocell. In *2009 IEEE GLOBECOM* (pp. 1–6).
4. Camp, T., Boleng, J., & Davies, V. (2002). A survey of mobility models for ad hoc network research. *Wireless Communications & Mobile Computing (WCMC): Special Issue on Mobile Ad Hoc Networking: Research, Trends and Applications*, *2*, 483–502.
5. Cao, G., Yang, D., An, R., Ye, X., Zheng, R., & Zhang, X. (2011). An adaptive sub-band allocation scheme for dense femtocell envi-

ronment. In *Wireless Communications and Networking Conference (WCNC), IEEE, March 2011* (pp. 102–107).

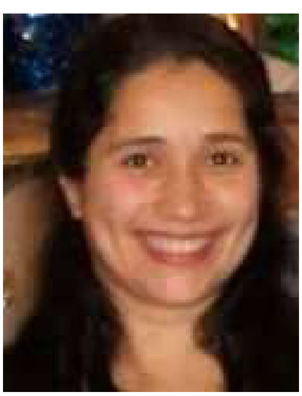
6. Cao, G., Yang, D., Ye, X., & Zhang, X. (2011). A downlink joint power control and resource allocation scheme for co-channel macrocell-femtocell networks. In *Wireless Communications and Networking Conference (WCNC), IEEE, March 2011* (pp. 281–286).
7. Chandrasekhar, V., Andrews, J., Muharemovic, T., Shen, Z., & Gatherer, A. (2009). Power control in two-tier femtocell networks. *IEEE Transactions on Wireless Communications*, *8*(8), 4316–4328.
8. Cheng, S.-M., Ao, W. C., Tseng, F.-M., & Chen, K.-C. (2012). Design and analysis of downlink spectrum sharing in two-tier cognitive femto networks. *IEEE Transactions on Vehicular Technology*, *61*(5), 2194–2207.
9. Chinneck, J. W., & Canada, C. U. (2006). *Practical Optimization: A Gentle Introduction*. Ottawa: Carleton University.
10. Cho, K., Lee, W., Yoon, D., Hyun, K., & Choi, Y.-S. (2009). Resource alloation for orthogonal and co-channel femtocells in a hierarchical cell structure. In *IEEE 13th International Symposium onConsumer Electronics, 2009. ISCE '09.* (pp. 655–656).
11. Chu, X., Wu, Y., Benmesbah, L., & Ling, W.-K. (2010). Resource allocation in hybrid macro/femto networks. In *Wireless Communications and Networking Conference Workshops (WCNCW), 2010 IEEE* (pp. 1–5).
12. Espino, J., & Markendahl, J. (2009). Analysis of macro femtocell interference and implications for spectrum allocation. In *IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications, 2009* (pp. 2208–2212).
13. Estrada, R., Jarray, A., Otrok, H., & Dziong, Z. (2013). Base station selection and resource allocation in macrofemtocell networks under noisy scenario. *Wireless Networks: The Journal of Mobile Communication, Computation and Information*, *20*(1), 115–131.
14. Ho, L., Ashraf, I., & Claussen, H. (2009). Evolving femtocell coverage optimization algorithms using genetic programming. In *IEEE 20th International Symposium on Personal, Indoor and Mobile Radio Communications, 2009* (pp. 2132–2136).
15. Huang, C.-J., Chen, P.-C., Guan, C.-T., Liao, J.-J., Lee, Y.-W., Wu, Y.-C., Chen, I.-F., Hu, K.-W., Chen, H.-X., & Chen, Y.-J. (2010) A probabilistic mobility prediction based resource management scheme for wimax femtocells. In *International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), 2010* (vol. 1, pp. 295–300).
16. Ko, C.-H., & Wei, H.-Y. (2011). On-demand resource-sharing mechanism design in two-tier ofdma femtocell networks. *IEEE Transactions on Vehicular Technology*, *60*(3), 1059–1071.
17. Li, L., Zheng, W., Zhang, H., Wen, X., & Liu, D. (2012). Improved performance analysis based on a novel hybrid access algorithm in femtocell networks. In *19th International Conference on Telecommunications (ICT), 2012* (pp. 1–5).
18. Li, Z., Guo, S., Li, W., Lu, S., Chen, D., & Leung, V. (2012). A particle swarm optimization algorithm for resource allocation in femtocell networks. In *Wireless Communications and Networking Conference (WCNC), 2012 IEEE* (pp. 1212–1217).
19. Liang, Y.-S., Chung, W.-H., Ni, G.-K., Chen, I.-Y., Zhang, H., & Kuo, S.-Y. (2012). Resource allocation with interference avoidance in ofdma femtocell networks. *IEEE Transactions on Vehicular Technology*, *61*(5), 2243–2255.
20. Lopez-Perez, D., Valcarce, A., de la Roche, G., & Zhang, J. (2009). Ofdma femtocells: A roadmap on interference avoidance. *IEEE Communications Magazine*, *47*(9), 41–48.
21. Marshoud, H., Otrok, H., Barada, H., Estrada, R., & Dziong, Z. (2013). Genetic algorithm based resource allocation and interference mitigation for ofdma macrocell-femtocells networks. In *Wireless and Mobile Networking Conference (WMNC), 2013 6th Joint IFIP* (pp. 1–7).
22. Marshoud, H., Otrok, H., Barada, H., Estrada, R., Jarray, A., & Dziong, Z. (2012). Resource allocation in macrocell-femtocell network using genetic algorithm. In *IEEE 8th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob), 2012* (pp. 474–479).
23. Mohjazi, L., Al-Qutayri, M., Barada, H., & Poon, K. (2011). Femtocell coverage optimization using genetic algorithm. In *Telecom World (ITU WT), 2011 Technical Symposium at ITU* (pp. 159–164).
24. Ponente, G., & De Marinis, E. (2011). Femtocell system optimization by genetic algorithm in clustered scenarios. In *Future Network Mobile Summit (FutureNetw), 2011* (pp. 1–9).
25. Ramanath, S., Kavitha, V., & Altman, E. (2010). Impact of mobility on call block, call drops and optimal cell size in small cell networks. In *IEEE 21st International Symposium on Personal, Indoor and Mobile Radio Communications Workshops (PIMRC Workshops), 2010* (pp. 157–162).
26. Sait, S.M., & Youssef, H. (1999). Iterative Computer Algorithms with Applications in Engineering: Solving Combinatorial Optimization Problems. 1st IEEE Computer Society Press Los Alamitos, CA, USA.
27. Sivanandam, S.N., & Deepa, S.N. *Introduction to Genetic Algorithms*. Springer.
28. Tarhini, C., & Chahed, T. (2007). On capacity of ofdma-based ieee802.16 wimax including adaptive modulation and coding (amc) and inter-cell interference. In *15th IEEE Workshop on Local Metropolitan Area Networks, 2007. LANMAN 2007* (pp. 139–144).
29. Walke, B. H. (2001). *Mobile Radio Networks: Networking and Protocols*. New York, NY: Wiley.
30. Zhang, H., Jiang, C., Beaulieu, N., Chu, X., Wen, X., & Tao, M. (2014). Resource allocation in spectrum-sharing ofdma femtocells with heterogeneous services. *IEEE Transaction on Communications*, *62*(7), 2366–2377.
31. Zhang, H., Liu, H., Ma, W., Zheng, W., Wen, X., & Jiang, C. (2012). Mobility robustness optimization in femtocell networks based on ant colony algorithm. *IEICE Transactions*, *95–B*(4), 1455–1458.
32. Zhang, J., & de la Roche, G. (2010). *Femtocells: Technologies & Deployment*. New York, NY: Wiley.
33. Zhou, J., She, X., Chen, L., & Otsuka, H. (2011) Qos guaranteed radio resource allocation scheme using genetic algorithm for ofdma. In *6th International ICST Conference on Communications and Networking in China (CHINACOM), 2011* (pp. 594–599).

Hanaa Marshoud received in 2011 the Bachelor of Science in Electrical Engineering with specialization in Communication from Ajman University of Science and Technology , Ajman, UAE. The Master degree with specialization in communication in 2013 from Khalifa University of Science, Technology and Research, Abu Dhabi, UAE. Currently doing PhD at Khalifa University. Her research work is about resource allocation in two-tier mobile networks.



Hadi Otrok holds an associate professor position in the department of ECE at Khalifa University. Also, he holds an affiliate assistant professor in the Concordia Institute for Information Systems Engineering at Concordia University, Montreal, Canada. Moreover, he has an affiliate associate professor in the electrical department at cole de technologie suprieure (ETS), Montreal, Canada. He received his Ph.D. in ECE from Concordia University where he worked on Intrusion Detection System (IDS) using Game Theory and Mechanism Design. He worked as a postdoctoral on Security issues and resource management for virtual private networks at ETS. Dr. Otrok has co-supervised to accomplishment several graduate students at Khalifa University, Lebanese American University (LAU), ETS and Concordia University. He is a senior member at the IEEE and a TPC member of several prestigious conferences and reviewer of several highly ranked journals. Also, he co-chaired several tracks at international conferences.

Hassan Barada holds the Associate Dean position in the department of computer engineering at Khalifa University. Prior to becoming a Professor at Khalifa University, Dr. Barada held academic and administration positions at Etisalat University College in Sharjah, UAE; King Fahd University of Petroleum and Minerals, KSA; and Lehigh University, USA. He holds PhD (1989), MS (1986) and BS (1984) degrees in Electrical Engineering from Louisiana State University, USA. Also he is an active member of the engineering community. He is a member of a number of distinguished engineering associations.



Rebeca Estrada received in 1995 the Engineer Diploma in Computer Science from Escuela Superior Politécnica del Litoral (ESPOL), Guayaquil, Ecuador, the Master degree with specialization in Telecommunication in 1998 from Instituto Tecnológico de Estudios Superiores de Monterrey, Monterrey, México, and the Ph.D. degree in 2014 from École de Technologie Supérieure, Montreal, Canada. Before her Ph. D. studies, she worked as leader of telecommunication research group of program VLIR-ESPOL, between 2005 and 2009 and as assistant professor in the Electrical and Computer Science Engineering Department of ESPOL from 1998 to 2010. During her Ph. D., she worked on several optimization models for resource allocation in two-tier networks using different optimization techniques. Currently, she is working with ESPOL as the Telematics Engineering coordinator and aggregated professor. Her research work involves resource allocation in wireless/cellular network, wireless mesh networks and D2D communications.

Abdallah Jarray received in 1997 the National Engineer Degree from École Nationale des Sciences de l'Informatique, Tunis, Tunisia, the Master and the Ph.D. degrees in 2005 and 2010 respectively from University of Montreal, Quebec, Canada. During his PhD, he worked on the dimensioning and the planning of optical backbone network. Prior to starting his master degree in 2003, he gained industrial experience in network design and Web development from 1997 to 2002.During 2010 and 2011, he was working as Postdoctoral fellow at the Ecole de Technologie Supérieure, University of Quebec. Currently, he is working as a postdoctoral fellow at School of Information Technology at University of Ottawa.

Zbigniew Dziong received his M.Sc. and Ph.D. degrees from the Warsaw University of Technology, Poland, both in Electrical Engineering. After graduation he was with the Warsaw University of Technology as an Assistant Professor. During this period, he was on sabbatical leaves at the Centre National d'Etudes des Telecommunications, Paris, France, and at the Department of Communication Systems, Lund Institute of Technology, Sweden. From 1987 to 1997 he was with INRS-Telecommunications, Montreal, Canada, as a Professor. From 1997 to 2003 he worked for Performance Analysis Department at Bell Labs, Lucent Technologies, Holmdel, New Jersey, USA. Since 2003 he is with cole de technologie suprieure (University of Quebec), Montreal, Canada, where he teaches on both undergraduate and graduate level as a Professor.